Employment Protection and the Direction of Technology Adoption*

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Abstract

We study the impact of employment protection legislation (EPL) on firms' innovation, through an event-study analysis of labor market reforms occurring in Europe over 2000-2016. Data from the Community Innovation Survey reveal that substantial drops in EPL for temporary workers prompt a reallocation of innovation towards the introduction of new products, away from process innovation aimed at cutting labor costs. Among innovative firms, the share of product innovators increases by 15% of the pre-reform value, while the share of firms specializing in process innovation falls by 35%. We develop a theoretical framework of directed technical change to rationalize our findings.

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In recent years, the increase in inequality and the progress of automation have put labor standards back on center stage, and intensified the calls for stricter employment regulation. In the US, the proposed Schedules that Work Act of 2019—"to require employers to provide more predictable and stable schedules for employees"—, and the New Jersey S3170 bill—increasing advance notices and mandating severance payments for workers in mass layoffs—are just two of numerous examples.[1] The proponents of these measures often see them as a way of mitigating the adverse employment effects of technological trends.

However, employment protection measures may *themselves* impact firms' technology choices. We test this hypothesis empirically, analyzing the role of employment protection legislation (EPL) on firms' innovation choices across Europe over the years 2000-2016, when several countries substantially loosened regulations on fixed-term contracts. We combine data from the European Community Innovation Survey (CIS) with measures of strictness of EPL compiled by the OECD to assess the effects of this deregulation on the direction of innovation. In a departure from the literature, we focus on technology *adoption*, rather than patenting, and analyze the choice between process innovation—aimed at modifying production techniques—and product innovation—aimed at the development and introduction of new or improved goods and services. This distinction is important, since product and process innovation entail different welfare and distributional effects.[2]

[1]See `https://www.congress.gov/bill/116th-congress/house-bill/5004/text` and `https://www.njleg.state.nj.us/2018/Bills/S3500/3170_I1.HTM`

[2]While variety-expanding product innovation is unambiguously beneficial, automation—a type of process innovation—may reduce welfare by displacing too many workers (Acemoglu and Restrepo, 2020b). Process and product innovation may also produce different knowledge spillovers, arising from differential patenting activity (Hall et al., 2014).

Our baseline analysis studies manufacturing firms in 18 European countries through an event-study design around large reductions in EPL for temporary workers, employees hired on fixed-term contracts with duration up to three years. The labor market reforms underlying these changes vastly expanded the take-up of fixed-term contracts, raising the share of temporary workers by an average of 30 – 50% across countries. Our estimates show that, in the long run, EPL reductions boosted product innovation at the expense of process innovation.

Specifically, large EPL reductions increased the share of innovative firms engaging in product innovation by 10pp (15% of the pre-reform share), and reduced the fraction of firms engaged exclusively in process innovation by 10pp (35% of the pre-reform share). At the same time, overall innovation activity was essentially unchanged. This suggests that firms which were not conducting any product innovation started to do so, partially reallocating their efforts away from process innovation.

Our findings are robust to the inclusion of reforms in EPL for permanent workers, extend to all sectors beyond manufacturing, and are robust to alternative sample definitions, as well as flexible covariate-specific time trends capturing features of the labor market, macroeconomic conditions, and industry composition. We thoroughly discuss threats to identification and provide suggestive evidence in support of the identifying assumptions underlying the event-study design through an interaction-weighted estimation of pre-trends (Sun and Abraham, 2021) and a randomization exercise (Hsiang and Jina, 2014).

We interpret our results through a three-period model of firms' innovation choices based on Fornino and Manera (2021). In the model, temporary workers adjust instantly to idiosyncratic productivity shocks, while permanent workers are a predetermined stock in each period. Permanent workers are more productive than temporary workers due to accumulated firm-specific capital, and the amount of temporary workers available to each firm is limited by regulatory constraints. We model innovation as the choice between a Hicks-neutral technology that increases the product quality (product innovation), and a technology that increases the productivity of permanent workers (process innovation). In this setting, process innovation is more profitable when temporary work is strictly regulated, while product innovation is more beneficial when firms are free to adjust, consistently with our empirical findings.

Related Literature. Our paper contributes to the literature on the effects of EPL on firm and worker outcomes, as well as macroeconomic variables.[3] Recent empirical studies directly identify the effect of labor regulations on specific types of innovation. Griffith and Macartney (2014), Acharya et al. (2014) and Aghion et al. (2019) focus on the distinction between incremental and radical innovation, finding contrasting results. García-Vega et al. (2021) show that a reduction in the strictness of labor laws leads to an increase in product-related inventions, and Bena et al. (Forthcoming) show that process-related patents increase with EPL strictness. We depart from the bulk of this literature by focusing on the *adoption* of process and product innovation—which includes, but is not limited to, patented inventions (Maclaurin, 1953). In our dataset, only 8% of innovative firms report patenting inventions, confirming that our study extends and complements previous findings based on patent data. Moreover, we conduct

[3]We refer the interested reader to Boeri et al. (2015), Duval and Furceri (2018), Daruich et al. (2019), García-Pérez et al. (2019), and Acabbi and Alati (2021) for recent examples of studies in this area and a complete discussions of the related literature.

a joint analysis of multiple reform episodes across countries, and highlight a pattern of substitution between these two innovation types, which is novel to the literature.

The theoretical literature on this topic has primarily focused on the impact of labor rigidity on overall innovation activity, with varying conclusions (positive according to Acemoglu, 1993; Acemoglu and Pischke, 1998, 1999; Belot et al., 2002; Acharya et al., 2014; negative for Malcomson, 1997; Cuñat and Melitz, 2012; Aghion et al., 2019).[4] Few papers have focused on the *direction* of innovation activity, generally finding that highly regulated labor markets encourage process innovation, which may or may not come at the expense of product innovation (Boone, 2000; Saint-Paul, 2002; Alesina et al., 2018; Fornino and Manera, 2021).[5]

In particular Saint-Paul (2002) models the tension between labor laws imposing high firing costs and risky investments in product innovation, while Boone (2000) highlights the role of process innovation in reducing fixed labor costs, compared to product innovation affecting variable costs. Our model connects to both these frameworks, underscoring the importance of risk, against which temporary workers act as a buffer, and by modeling process innovation as a reduction of labor costs associated to permanent workers. However, it deviates from them by not relying on specific assumptions on the relative riskiness of process and product innovation (as in Saint-Paul, 2002), nor requiring that process innovation only affect overhead costs (as in Boone, 2000).

Our framework also connects with the insights in Acemoglu (2007, 2010), which provide a complementary explanation of our theoretical results. In our model, pro-

[4]See Kleinknecht et al. (2014); Griffith and Macartney (2014) for further references.

[5]Bassanini and Ekkehard (2002) argue instead that high firing costs discourage labor-saving (process) innovations among incumbents.

cess innovation is strongly temporary-labor saving, and product innovation is strongly temporary-labor complementary. Since labor regulations restrict the effective supply of temporary workers, temporary-labor-saving process technology is discouraged by a relaxation of EPL in favor of the temporary-labor-complementing technology.

The paper is organized as follows. Section 1 describes the data; Section 2 presents our findings; Section 3 describes the model that guides the interpretation of our results, and Section 4 concludes.

1 Data and Sample Selection

1.1 Community Innovation Survey (CIS)

The Community Innovation Survey (Eurostat, 2000-2016a) asks a sample of European enterprises about their innovation activities. This survey is particularly suitable for our analysis for several reasons. First, it allows us to distinguish product from process innovation, which is usually unfeasible in administrative data sources, which mainly report overall R&D investments. Second, the survey inquires about both technological innovation and adoption, regardless of whether they required in-house R&D activity, or whether they lead to inventions and patenting. This provides a more complete picture of innovation than balance-sheet and patent data sources. Finally, firms also report the intended objectives of their innovation activities, shedding light on their motives.

The CIS surveys enterprises with 10 employees or more, using a repeated cross-section design.[6] Coordinated by Eurostat (the EU statistical agency), it is carried out

[6]Appendix Table A.1 reports coverage summary statistics.

by national statistical agencies but designed to ensure comparability across countries. We restrict our attention to the eight waves carried out between 2000 and 2016, which feature consistent variable definitions.

Invention, Innovation and Adoption. Before proceeding, we wish to clarify the important distinction between the concepts of invention, innovation and adoption, which is crucial to delineate the scope of our analysis and to interpret our findings. In doing so, we follow the definitions provided by Maclaurin (1953). In his work, he states that "the significant feature of an *invention* is that it discloses an operational method of creating something new." It is only through a sequence of events "by no means automatic" that "an invention is introduced commercially as a new or improved product or process," becoming an *innovation*. Thus, innovation is the first or improved commercial implementation of (patented or non-patented) inventions. Finally, *adoption* occurs when firms which were not necessarily involved in the two above steps introduce the innovation into their activity. In what follows, we will use the terms "innovation" and "adoption" interchangeably, to denote the practical implementation of technologies or products that are new to the firm, but not necessarily to the market, and that may or may not have resulted from inventions by the said firm. This definition is consistent with the CIS, where firms are considered "innovators" if they "introduce onto the market" product or process improvements, even if not developed in-house.

Product and Process Innovation. We focus on two main variables: product innovation and process innovation. A firm is a "product innovator" if it answered affirmatively to the question: "During the period [year of survey minus 2 - year of survey], did your enterprise introduce onto the market any new or significantly improved products (goods or services)?"[7] A firm is instead classified as "a process innovator" based on the answer to the question: "During the period [year of survey minus 2 - year of survey], has your enterprise introduced any new or significantly improved production processes including methods of supplying services and ways of delivering products?" In both cases, the CIS questionnaire specifies that "the innovation (new or improved) must be new to your enterprise, but it does not need to be new to your sector or market. It does not matter if the innovation was originally developed by your enterprise or by other enterprises." Finally, "Innovative" firms are those that fall in either of the above classifications.[8]

The CIS refers surveyed firms to the Oslo Manual (OECD, 2005), which reports some clarifying examples of innovation types. Examples of process innovation include: installation of new or improved manufacturing technology, such as automation equipment; new equipment required for new products; new or improved software. Examples of product innovation are: integrating products (e.g. cameras in phones); improvements in energy efficiency of products; new or improved services (e.g. internet banking). Both designations explicitly exclude marginal or purely cosmetic changes.

Table 1 summarizes these key variables for the manufacturing sector across the countries in our sample.[9]

[7] See e.g. `https://ec.europa.eu/eurostat/documents/203647/203701/CIS_Survey_form_3.pdf`.

[8] The sample of innovators also includes firms that have ongoing or abandoned activities, which are reported separately and not classified as either product or process. They represent 8.8% of innovators in the sample.

[9] Appendix Table A.2 expands to all sectors.

Process innovation as a proxy for labor-cost-cutting technology. The survey also inquires about innovators' motives. One of the questions asks: "How important was [to reduce labour costs per unit output] as objective for your activities to develop product or process innovations during [the last three years]?" [10] Respondents choose between "High," "Medium," "Low," and "Not relevant." Panel (a) of Figure 1 shows the share of process and product innovators grouped by answers to this question. Only 48% of the respondents who consider labor cost reductions irrelevant are process innovators, as opposed to 80% carrying out product innovation (firms can carry out both activities at once). As the objective to reduce labor costs moves from low to high, the fraction of respondents carrying out process innovation increases from 65% to 80%, compared to a decrease in product innovators. This pattern emerges starkly in Panel (b), reporting the fraction of firms which conduct only one innovation activity at time.

Alternative Data Sources on Innovation. In closing this subsection, we detail why both patent data and the CIS microdata are unsuitable to answer our research question.

First, patent data provide an incomplete view of the overall direction of technology, due to the distinction between invention and adoption detailed above. In the CIS microdata, we verify that only about 8% of firms reporting any innovation activity patent any inventions. This indicates that the set of innovators is much larger than that of patenting inventors. Nevertheless, as noted above, complementary studies using patent data report results that are consistent with our findings (Bena et al., Forth-

[10] This question comes from the 2010 survey (`https://ec.europa.eu/eurostat/documents/203647/203701/CIS_Survey_form_2010.pdf`). Other waves ask comparable questions.

coming; García-Vega et al., 2021) .

Second, the CIS microdata available to researchers only includes a subset of countries and periods, severely limiting the potential scope of the analysis.[11] Further, many variables are binned due to privacy regulations, preventing us to leverage the microdata to develop firm- or sector-level exposure measures.[12] These two facts prompt us to use aggregate CIS measures (at the country-sector-wave level) available on the Eurostat website for our main analysis, and the microdata available as SUFs to compile relevant aggregate statistics. Given that treatment is at the country level, and that we cannot build measures of exposure to the reform in the microdata, we believe that there is no loss from using aggregate data in our empirical analysis.

1.2 OECD Indicators of Employment Protection

We obtain our indicator of strictness of Employment Protection Legislation (EPL) from the OECD (OECD, 2000-2018). EPL refers to the body of legislation that regulates procedures and costs involved in hiring and dismissing workers, individually or collectively, and that governs fixed-term and temporary work. The OECD has developed three main numerical indicators of EPL that are comparable across countries and over time. Two of these indices refer to legislation regulating open-ended employment contracts, focusing on individual and collective dismissals. The third index measures employment protection for temporary workers. All three indices range from 0 to 6 and aggregate a

[11]In particular, Scientific Use Files (SUF) that are available remotely only provide us with an unbalanced panel of 6 countries in our sample, which excludes Italy from treated countries. The Safe Centre in Luxembourg would allow only a marginal improvement, leaving us with either a balanced sample of 8 countries, or an unbalanced sample of 12.

[12]For example, size is only provided in very large bins. Moreover, it is virtually impossible to merge it with other data sources, for example administrative sources indicating the share of temporary workers.

number of sub-components. We focus on the index of EPL strictness for temporary employment.[13] In what follows, we refer to this indicator as "EPL for temporary workers," "EPL Temp," or simply "EPL."

The EPL for temporary workers measures the strictness of regulations on fixed-term contracts and temporary work agency employment. This index is constructed as the simple average of two sub-components relating to fixed-term contracts and temporary work agencies. Each of these two sub-components is itself constructed as the weighted average of three indices, measuring: the scope of application of temporary contracts (with weight 1/2); their maximum number of renewals (1/4); and their maximum duration in months (1/4). For example, the sub-component relative to the scope of application of fixed-term contracts takes a value of 6 (strictest EPL) if these contracts can only be used for tasks that require a fixed amount of time to be carried out; a value of 4 if either employers or employees can be exempted from restrictions (2 if both can be exempted); and a value of 0 (lightest EPL) if there are no restrictions. The other two indices are constructed discretizing the underlying quantities.

We focus on EPL for temporary workers mostly because there was very little variation in EPL for regular workers over the sample period. Indeed, when considering the distribution of yearly percentage changes, the mean is 0.5% and the standard deviation is 2.4 pp, while the corresponding figures for the EPL for temporary workers are 4% and 65.5 pp. See Appendix B.5 for further details.

Big EPL Drops. We consider a country as experiencing a "big EPL drop" in a specific year, if the country-year pair registers a change in EPL for temporary workers smaller

[13] For further details on this measure and its evolution over our sample period, see Appendix A.3.

than −20% (2.5 percentile of EPL changes). This procedure singles out five countries as treated: Germany, Greece, Italy, Portugal and Sweden. All these countries implemented measures to extend the duration or scope of fixed-term contracts.[14] By contrast, the majority of countries experienced no or small changes in this measure over the sample period (see the standard deviations in column 5 of Table 1), and provide suitable controls for our analysis. Appendix A.3 presents a detailed description of level and changes in EPL across Europe over the sample years.

We validate the selection of large EPL drops against the database of "major narrative labor market reforms" assembled by Duval et al. (2019). All the drops that we select appear in the database; excluded episodes do not appear, or represent reforms that were subsequently reversed.[15] We set the treatment date to the year in the sample that sees a reduction in EPL, reported in column 6 of Table 1.[16]

1.3 Sample Selection

Our raw sample consists of 27 countries appearing in both the CIS and OECD dataset of EPL strictness. We drop Croatia and Slovenia, for which we have less than two matched observations across these two datasets, and seven other countries that see a large increase in EPL for temporary workers over the sample period (20% or more, the 97.5

[14] In Italy, for example, Law 368 of 2001 introduced a "generic reason" for the use of temporary contracts to a previously highly restrictive list, which decreased EPL Temp by 26.8%. We provide a short summary of reform episodes in Appendix Table A.3 .

[15] For example, we exclude the EPL drop which occurred in Spain in 2011, when restrictions on temporary work agencies were reduced. The following year, EPL was tightened through a reduction in the maximum duration of temporary contracts.

[16] In all treated countries reforms happened in odd years, except for Germany (2002), and the CIS only reports data biannually. Therefore, we harmonize the treatment variable attributing to Germany the treatment year 2001, the last odd year before the reform.

percentile in the distribution of changes).[17] This leaves 18 countries in the baseline sample. We focus on the manufacturing sector, which is consistently surveyed by all countries for all waves in which they participated. We verify the robustness of our results to including all available sectors in Appendix B.4.

2 Empirical Strategy and Results

2.1 Empirical Strategy

We run the event-study regression

$$Y_{it} = \alpha_i + \delta_t + \sum_{e=m}^{n} \kappa_e \times \mathbb{1}\{(t - (\text{Event Year})_i) \in [e-2, e]\} \times \mathbb{1}\{\text{Treated}\}_i + \epsilon_{it}, \qquad (1)$$

where Y_{it} indicates outcome Y for country i in year t, α_i and δ_t are country and time fixed effects respectively, $\mathbb{1}\{(t - (\text{Event Year})_i) \in [e-2, e]\}$ are indicators for the two-year period ending in year e relative to the "big drop in EPL" event taking place at $t = (\text{Event Year})_i$, and $\mathbb{1}\{\text{Treated}\}_i$ indicates that country i is treated. Thus, coefficients κ_e capture the effect of treatment at event times $[e-2, e]$ (so for example κ_7 estimates the treatment effect 5 to 7 years after the large drop in EPL). This is due to the biannual nature of the survey, which inquires about innovation activity the year of the survey and the preceding two years. The data structure implies that the range $[m, n]$ is composed of odd

[17] These countries are: Czechia, Estonia, Hungary, Ireland, Poland, Slovakia and the United Kingdom. Five of these are countries where EPL changes occur around the date of EU accession, and unsurprisingly exhibit significant pre-trends in all our variables of interest. Ireland and the UK additionally experience significant data quality issues. In particular, Ireland does not report data for the pre-period, and the UK only participates to the survey in 2000 and after 2010, reporting highly volatile data.

numbers in $[-7, +15]$ (excluding -5).[18]

We also run the difference-in-differences specification

$$Y_{it} = \alpha_i + \delta_t + \beta_{SR} \times \mathbb{1}\{t - (\text{Event Year})_i \leq 5\} \times \mathbb{1}\{\text{Treated}\}_i + \\ + \beta_{LR} \times \mathbb{1}\{t - (\text{Event Year})_i > 5\} \times \mathbb{1}\{\text{Treated}\}_i + \epsilon_{it}, \tag{2}$$

which splits the post-treatment period into "short run" (up to five years after treatment) and "long run" (year six and beyond).

All the regressions are weighted by the number of respondent firms. When the outcome is share of temporary employment, we instead weight by total employment. We report standard errors clustered at the country level, as well as wild-bootstrap confidence intervals (Cameron et al., 2008).

Identification Assumptions. We require three main assumptions for our baseline specification to identify the average treatment-on-the-treated effects of EPL reductions (Sun and Abraham, 2021): parallel trends between treated and never-treated countries; no anticipation effects; and no selection into early versus late treatment.

In our context, the parallel-trends assumption relies on other European countries being a good comparison group for the treated countries. Table 2 suggests that the two groups were indeed observationally comparable in 2000 according to all the outcome and explanatory variables we use in the analysis (labor market institutions, GDP growth, trade exposure to Euro-area and accession countries, sectoral composition,

[18] We normalize $\kappa_{-1} = 0$. κ_{-5} cannot be estimated due to a four-period lag between the first two waves. As the κ_{-7} coefficient is always estimated very imprecisely, we report event-study graphs from lag -3. Full results are available on request.

etc.).[19] Econometrically, we take several steps to mitigate concerns about a violation of the parallel-trends assumption. First, when estimating Equation (1) we test for, and always reject, the presence of significant pre-trends. This is also true when adopting the specification from Sun and Abraham (2021), which addresses the concern of spurious pre-trend test results. We futher analyze the validity of this assumption through a randomization exercise (described in detail in Appendix C.2). Randomizing treatment within and between countries produces distributions of simulated t-statistics centered around zero. This suggests that treatment effects do not stem from permanent heterogeneity across treated and control countries, nor from time trends unrelated to treatment, respectively.

The biennial structure of our panel, combined with the absence of pre-trends, comforts us about the absence of substantial anticipation effects on our variables. In addition, these variables seem to react slowly to policy, as suggested by treatment effects manifesting in the long run.

We confirm the robustness of our results to relaxing the assumption of treatment effect homogeneity through the use of the interaction-weighted estimator (Sun and Abraham, 2021, , described in Appendix C.1), which produces unchanged estimates relative to our baseline.

Finally, event-study coefficients could also be biased by the omission of relevant time-varying covariates, like other features of the labor market and industry composition. We tackle this threat by restricting our baseline analysis to firms in the manufacturing sector, and conducting a robustness exercise where we include interactions of

[19] The only statistically significant difference between treatment and control countries in 2000 is in the average protection of collective dismissals. This issue is addressed separately in Appendix B.5.

time dummies with a rich set of covariates.

2.2 Results

EPL Temp and Share of Temporary Workers. Panel (a) of Figure 2 summarizes the results of the event study analysis when the dependent variable is the EPL index itself. The figure shows that the event "big EPL drop" reflects a permanent level shift in EPL Temp, allowing us to interpret the event-study estimates as responses to *permanent* changes in EPL for temporary workers. In panel (b), we report event-study coefficients for the share of temporary workers over total employment in manufacturing. The midpoints of our estimates reveal a sizable—albeit noisy—increase in the share of temporary workers following these reforms, corresponding to 30 – 50% of the pre-reform value. This pattern is consistent with micro-level results in Daruich et al. (2019). We interpret the increase in the share of temporary workers as suggestive that the reforms succeeded in promoting the take-up of fixed-term contracts.

Main Results. Figure 3 displays our main results. We plot the event-study coefficients around large EPL drops from specification (1) together with the confidence bands resulting from cluster-robust standard errors and a wild bootstrap procedure. Common to all panels is the absence of significant pre-trends in the variables of interest. Recall that the event coefficients capture the effects that manifest in the two-year period *ending* at event time e. For example, the coefficient for $e = 7$ captures the effects that occur 5-7 years after the reform.

Panel (a) depicts the path of the share of innovators over the total number of firms surveyed. The event-study coefficients are mostly non-significant, suggesting that labor market reforms did not increase overall innovation activity. The remaining panels present a pattern of reallocation across different types of innovation. In particular, panel (d) displays the significant drop in the ratio of process innovators to product innovators in the years following the event. This ratio falls by an average of 0.25 in the long run (starting 5-7 years from the event), about 25% of the pre-treatment average (1.03). Panels (b) and (c) show that this result is driven by an essentially unchanged share of process innovators coupled with a sizable and significant increase in product innovation—the long-run increase of 0.1 in the fraction of product innovators corresponds to about 15% of the pre-treatment average (0.67).

We believe that effects manifest in the long run for three reasons. First, in view of high firing costs for regular workers, firms might be slow to adjust the composition of their workforce, relying on retirement and voluntary separations to replace regular workers with newly-hired temporary workers. Second, aggregate innovation activity can respond with a lag to reforms, both because of the slow workforce adjustment mentioned above, and because firms might be reluctant to interrupt multi-year innovation projects close to completion. Third, and perhaps most importantly, invention responds slowly to EPL changes and adoption follows invention with a significant lag. In particular, our findings resonate with previous studies reporting that patenting activity responds significantly to employment protection only 3, 4, or 5 years after the relevant changes (respectively, García-Vega et al., 2021; Acharya et al., 2014; Bena et al., Forthcoming), and that the lag between patenting and adoption can be as long as 10 years (Popp, 2016; Shambaugh et al., 2017).

Panels (e) and (f) extend our main findings to firms that exclusively conduct either process or product innovations.[20,21] The share of innovative firms that implement only process innovations fell sharply and significantly by about 0.1—more than 35% of the pre-treatment average, resulting in a fall of about 60% of the "process only" to "product only" innovators ratio. Thus, labor market reforms seem to reduce the attractiveness of process innovation when this is the sole activity of the firm. This contrasts with panel (c), which shows that overall process innovation—including firms that also carry out product innovation—is not significantly affected by EPL reductions. These findings suggests that firms cut on innovations aimed exclusively at labor costs reductions, while they keep conducting other process innovations that are needed to support the introduction of new products. These results depose in favor of a general reallocation of innovation activity from process innovation—often motivated by a desire to reduce labor costs—towards product innovation.

Table 3 reports the coefficients from the difference-in-differences model (2). These results highlight that significant effects only emerge in the long run. In particular, columns (2), (4) and (5) confirm the significant long-run increase in product innovation, decrease in exclusive process innovation, and reduction in the ratio of process innovators to product innovators.

[20]Recall that our measure of product (process) innovators includes any firm that implemented product (process) innovations, regardless of whether said firm has also introduced other types of innovation.

[21]Note that the presence of firms with ongoing or abandoned activities, not classified as either product or process innovators but included in the count of innovators, makes it such that this exercise is not redundant with respect to the above. The fact the results that we find for "process only" and "product only" mirror the results for "product" and "process" reassure that this group did not change systematically.

2.3 Robustness

Robustness to Additional Covariates. Table 4 assesses the robustness of our results to the inclusion of time dummies interacted with the value in year 2000 of several variables, which capture institutional features of the labor market, macroeconomic conditions, and sectoral composition. Data sources are reported in Appendix A.1 and B.1. We focus on the ratio of process innovators to product innovators as our outcome, a measure that neatly summarizes the reallocation across different innovation activities.

Column 1 reports the baseline specification, which includes only country and time fixed-effects, for reference. Column 2 includes controls for other labor market institutions: employment protection legislation for regular workers (both individual and collective dismissal), and total spending on labor market policies as a percentage of GDP (which combines active labor market policies and unemployment benefits). Column 3 controls for macroeconomic conditions and trade openness: GDP growth (average annual growth between 1998 and 2000), trade with Euro area countries (as of 2001) as a fraction of GDP, and trade with accession countries (meaning countries that joined the EU between 2004 and 2013). Column 4 controls for characteristics of the underlying manufacturing sectors: automation potential (an employment-weighted average of adjusted robot penetration), task offshoring, and the manufacturing capital-labor ratio.

The inclusion of interacted controls naturally results in a substantial degree of freedom reduction, as well as a sample restriction due to data availability (reported in Appendix Tables B.2 and B.4). Estimates for the long-run treatment effect remain negative, significant, and quantitatively close to the baseline. Appendix B.1 discusses further robustness exercises.

Sectoral Composition. A possible explanation for the observed shift from process to product innovation involves sectoral reallocation through entry of firms in more product-intensive sectors and exit from process-intensive sectors. While reallocation could be a channel through which EPL affects innovation, we provide three pieces of suggestive evidence that this is unlikely to be the main driver of our results. First, our main analysis focuses on the manufacturing sector only, but results are unchanged when we expand to include all available macro-sectors (Figure B.5). This suggests that the shift, if any, did not take place across macro-sectors. Second, including various controls for sectoral composition within manufacturing does not change the main estimates (column 4 in Table 4). Third, while the CIS data available does not allow us to perform the analysis at a finer level than macro-sectors, we can study how the sectoral composition of manufacturing has evolved around the events and compute the changes in process and product innovation implied by the sectoral changes only. This latter exercise, explained more in detail in Appendix B.2, suggests that there was little change in the sectoral composition of manufacturing around large drops in EPL (Figure B.1). The only sectors that changed significantly (albeit little in magnitude) are: chemical-pharmaceutical, electronics, and transport equipment, which we control for in Table B.5 , and which do not alter our estimates.

Using the estimated changes in sectoral shares, if we assume random entry and exit in subsectors, the implied change in the fraction of product and process innovators and their ratio is negligible (-0.4 pp versus the estimated effect of -25 pp for the process-to-product ratio). Even in the most extreme scenario, in which we assume that only product innovators enter in the sectors that expand and only process innovators exit from the sectors that shrink, and we use the bounds of the confidence intervals instead of the point estimates for the sectoral changes, we still would only be able to explain around half of the estimated drop in the process to product ratio and only a third of the estimated increase in the fraction of product innovators.

Treatment Effect Heterogeneity. Appendix B.3 discusses three additional sets of results. First, we find that the effect of weakening EPL on the process-product innovators ratio is strongest for small firms (10-49 employees) and decreases with size. This is likely because large firms have enough funds to pursue multiple projects, which dampens their response on the extensive margin of innovation. Second, we split countries by their initial EPL level, so that we compare high(low)-EPL treated countries to high(low)-EPL control countries, and run separate regressions on both sample partitions. Third, we divide treated countries into two groups according to the size of the EPL drop, and separately compare these groups to all control countries. All these exercises restrict the size of the treatment group, resulting in imprecise estimates. Nevertheless, our results suggest that labor market reforms have a sizable and significant effect on innovative activities only when the starting EPL is high, and that only relatively large EPL reductions trigger the reallocation of innovation from process to product.

Robustness to Alternative Sample Definitions. We consider two alternative sample definitions in Appendix B.4. First, we expand the sample of firms to include all sectors (in addition to manufacturing). Our main results carry over to this setting, and are robust to the inclusion of country-sector and sector-time fixed-effects. Second, we limit the sample to two panels of eleven countries each, balanced around the time of the event. Coincidentally, the latter exercise corresponds to the heterogeneity by size of the EPL drop discussed in the above paragraph.

Robustness to EPL for Regular Workers. Three of the treated countries (Greece, Italy and Portugal) and two control countries (Spain and Denmark) face large relaxations of EPL for regular workers over the sample period. In Appendix B.5, we propose three exercises to account for these episodes. First, we run our baseline specification excluding countries that see large drops in EPL for *regular* workers, which produces broadly similar estimates. Second, we include a set of event-time dummies around big drops in EPL for regular workers, constructed following the same criteria for the EPL Temp measure. This produces estimates that are almost identical to our baseline. Finally, we also run the analysis using drops in EPL for regular workers as the main event. The smaller import of these episodes results in non-significant estimates for the outcomes of interest.

2.4 Alternative Estimation Strategies.

Treatment Effect Heterogeneity part 2 - Interaction-Weighted estimator Sun and Abraham (2021) show that when multiple cohort are treated at different times, and true treatment effects are heterogeneous, event-study coefficients estimated with standard procedures are weighted averages of coefficient at all time horizons, complicating their interpretation. As a result of this, pre-trend estimates might also be spurious. Sun and Abraham's (2021) "interaction-weighted" (IW) estimator, which consists in estimating the treatment effects by cohort and then averaging across them, addresses both these issues.[22] Figure 4 shows the estimated event-study coefficients by treated country (panels (a) through (e)) and the resulting IW estimates in panel (f), which produces results that are comparable to our main results. In addition, the estimated pre-trends are not significally different from zero. Appendix C.1 explains the procedure in detail and shows that, for all our outcome variables, results are comparable to our main specification.

Randomization Inference In order to assess the role of permanent heterogeneity across treated and control countries and for confounding time trends occurring simultaneously to treatment, we conduct three permutation experiments reassigning treatment status and/or year relative to treatment (Hsiang and Jina, 2014; MacKinnon and Webb, 2020). In particular we randomize treatment: (1) across periods within treated countries (within); (2) across countries preserving the treatment periods (between); and (3) across both countries and periods.

We run the diff-in-diff specification (2) and focus on the "long run" coefficient. First, we check whether the distribution of estimated t-statistics for long-run treatment effects is centered around 0. In particular, if the distribution resulting from (1) is non-centered, baseline treatment effects stem partly from permanent heterogeneity across countries. That is, random assignment across countries is not satisfied. If the distribution resulting from (2) is non-centered, baseline treatment effects stem from differences in the time path of variables. That is, random assignment over time is not satisfied. Then, we use the distribution from (3) to compute an overall randomization p-value.

[22]We do not adopt this specification as our baseline because cluster-robust standard errors—an input for the computation of the IW variance-covariance—are not reliable with the few clusters we have (Cameron and Miller, 2015). At the same time, the bootstrap properties of the IW estimator with few clusters have not yet been explored.

A detailed explanation of the methodology and the full set of results is provided in Appendix C.2.

Figure 5 displays the resulting distributions of t-statistics from the randomization exercises described above, for the outcome variable product-to-process ratio. Panel (a) shows that the distribution of t-statistics from the "within" randomization experiment is well-centered around zero, which suggests that never-treated countries are a good control group for treated countries. The distribution resulting from "between" randomization in panel (b) is less well-behaved but still centered around zero and implies a small p-value for the t-statistic estimated in our baseline specification. The p-value of 1.6% resulting from the total randomization (panel (c)) is well below the conventional 5% level. The results from this procedure confirm the significance of our main results, and suggest that they are not driven by systematic bias in time and country assignment to treatment.

3 Conceptual Framework

In this section, we develop a stylized three-period model that links firms' innovation choices to the rigidity of the labor market, building on Fornino and Manera (2021). The aim of this exercise is to clarify which assumptions can generate implications that align with our empirical findings, and clarify the economics at play.

In the model, permanent workers are a stock that the firm chooses in advance, while temporary workers can be adjusted in response to idiosyncratic productivity shocks. We assume that permanent workers are more productive than temporary workers, and that the amount of temporary workers available to each firm is limited by regulatory constraints. Thus, the firm uses temporary workers to increase output in response to positive idiosyncratic shocks. We model innovation as the choice between a Hicks-neutral technology that increases the product quality (product innovation), and a technology that increases the productivity of permanent workers (process innovation).

We show that this set of assumptions is sufficient to give rise to the prediction that firms prefer process innovation when the use of temporary workers is restricted, while product innovation becomes more viable when restrictions are lifted. Intuitively, the benefit of process innovation is to expand the effective amount of labor available to the firm when it is constrained by regulatory limits on temporary work, while product innovation increases the returns from each additional temporary worker employed. Therefore, process innovation is more profitable when regulatory constraints on temporary work are stricter, while product innovation is more beneficial when firms are freer to adjust their workforce.

We close this section by showing that our model admits a simple interpretation in the setting of Acemoglu (2007, 2010). In our model, process innovation is strongly temporary-labor saving, and product innovation is strongly temporary-labor complementary. Since labor regulations restrict the effective supply of temporary workers, temporary-labor-saving process technology is discouraged by a relaxation of EPL in favor of the temporary-labor-complementary technology.

3.1 Discussion of main assumptions

Before presenting our theoretical framework formally, we motivate our main modeling choices, which aim to capture the distinction between temporary and permanent work, as well as between process and product innovation.

First, we distinguish between permanent workers that cannot be fired at-will, and own firm-specific human capital as a result of their high attachment to the firm, and temporary workers that can be hired and fired in the short-run to cope with high periods of high demand for its product. We capture this distinction by assuming that permanent and temporary workers are perfect substitutes, with a marginal rate of technical substitution strictly larger than one. Moreover, firms competes monopolistically, and thus face a downward-sloping demand schedule for their product. These two assumptions provide a rationale for firms to hire both type of workers. While permanent workers are more productive, due to lower turnover and the accumulation of firm-specific capital, they are also harder to fire and less flexible than temporary workers when responding to shocks.

Second, we assume that product innovation is Hicks-neutral. As such, it complements both temporary and permanent workers. We believe this assumption to be natural, as by definition product innovation increases the value of products without necessarily involving changes in production technologies.

Third, we assume that process innovation only increases the marginal product of permanent workers. This captures the fact that firms need to train their employees to the use of new production technologies, and that the required human capital to use these technologies may well be firm-specific and require time to be accumulated. This assumption is backed by empirical results in Cingano et al. (2014), who find a positive relation between capital deepening—a form of process innovation—-and the number of high-tenure workers following an EPL increase. More generally, theory suggests that firms' incentives to provide specific training increase with expected employee tenure (Acemoglu, 1997).

Finally, we model EPL for temporary workers as a limit on the quantity of temporary workers that can be hired. We make this choice to capture two types of real-world restrictions that pose a limit to the number of temporary workers available to the firm. The first type of restrictions concerns limitations to the scope of application of fixed-term contracts to specific sectors or tasks, as well as limitations to the share of the workforce that can be employed under a temporary contract.[23] The second type of restrictions concerns the amount of successive contract renewals that a firm can carry out, or the duration of such contracts. Both these restrictions limit the effective amount of temporary work available to the firm in each time period, as the temporary job must be converted into a permanent position after the maximum duration or number of renewals for the contract have been reached.

3.2 Environment

Timing. The world lasts three periods, $0, 1, 2$, and the economy is populated by a continuum of monopolistically competitive firms, whose output is aggregated into the final consumption good by a competitive sector. In period 0, firms choose the stock of

[23]Many countries require specific reasons for the use of fixed-term contracts, which usually relate to the type of work (e.g. seasonal) that can form the object of this contract (see footnote 14 for the Italian example). Limitations to the share of fixed-term workers in individual firms are applied in Lithuania and Italy (both of which set the maximum share to 20%).

permanent workers, L, and a representative union bargains a wage w, which depends negatively on the expected unemployment rate in period 2. All firms are endowed with the same process and product technology at time 0, and both firms and workers expect this technology and the limit on temporary work, u, to be fixed until the end of period 2.[24] In period 1, the regulatory limit on temporary workers is changed unexpectedly, and firms are able to adjust their technology mix to respond to this shock. In period 2, each firm receives an idiosyncratic productivity shock, chooses temporary workers, T, and realizes profits. There is no aggregate uncertainty in period 2.

Final Good. The consumption good in the economy, Y, is supplied by a competitive final good producer who aggregates differentiated intermediate goods, y_i. Intermediates are produced by a measure-one continuum of monopolistically competitive firms, so that the final good's production function is

$$Y = \left[\int_0^1 \left(z_i q_i y_i^{\theta} \right) \mathrm{d}i \right]^{\frac{1}{\theta}}.$$

Here y_i denotes the quantity of intermediate good i, q_i their quality, and z_i is s good-specific shock, capturing idiosyncratic productivity shocks affecting intermediate goods producers. The parameter $\theta \in [0,1]$ governs the elasticity of substitution between intermediates, and consequently market power of each intermediate good producer. In what follows, we take the final good as the numeraire. Standard cost-minimization by

[24]Our findings are qualitatively unaffected if we assume that firms can choose their initial technology and expect u to change in period 1. We only require that firms do not know exactly the future level of u and that they are allowed to change their technology mix in period 1.

the intermediate producer gives rise to the firm-specific downward-sloping demand:

$$p_i = z_i q_i \left(\frac{Y}{y_i}\right)^{1-\theta}.$$

For ease of notation, we define $A \equiv Y^{1-\theta}$, which enters as a parameter in the problem of the intermediate producer.

Intermediate producers: static problem. In period 2, firms produce output y_i using labor according to the production function:

$$y_i = T + \Gamma L,$$

where L is a stock permanent workers chosen in period 0 as detailed below, T is the number of temporary workers, and $\Gamma > 1$, parametrizes the marginal rate of technical substitution between permanent and temporary workers. We assume that permanent workers are more productive than temporary workers, to capture firm-specific capital accumulated between period 0 and period 2. We also assume that the amount of temporary workers is constrained by the stock of permanent workers in the firm:

$$T \leq uL,$$

where u can take values in $[0, \infty)$, with the extremes of this interval capturing the scenarios where temporary work is not permitted, and where there are no restriction on its use. As discussed above, we assume that the amount of temporary workers depends on the stock of permanent workers to capture institutional features present in many

European countries.[25]

Under this assumption, given the intermediate good demand from the final good producer and a wage w, we have that each firm, i, maximizes profits:[26]

$$\begin{aligned} \max_{T \geq 0} \quad & zqA\left(T+\Gamma L\right)^{\theta} - w\left(L+T\right) \\ \text{s.t.} \quad & T \leq uL, \end{aligned}$$

which gives the candidate interior solution:

$$T^{\star} = \left(\frac{\theta zqA}{w}\right)^{\frac{1}{1-\theta}} - \Gamma L.$$

This condition highlights the role of temporary workers as a buffer to respond to positive productivity shocks. Indeed, the firm's monopolistic position gives rise to decreasing returns to scale in the profit function. As a result, each productivity shock z has an associated optimal output. If the productivity shock is sufficiently high, this output cannot be produced using only the available stock of permanent workers, and the firm chooses to hire temporary workers in order to achieve the output level, $\left(\frac{\theta zqA}{w}\right)^{\frac{1}{1-\theta}}$. In particular this occurs if the shock is larger than a threshold $\bar{z}$, the productivity level at which the firm does not wish to hire temporary workers,

$$\bar{z}(L) = \left[\Gamma L\right]^{1-\theta} \frac{w}{\theta qA},$$

[25]While realistic, this structure is not essential to our results, which carry over to a case where the maximum number of temporary workers does not depend on L.

[26]The first term in the expression for profits arises by plugging in p_i from intermediate's demand and the production for y_i into revenues $p_i y_i$.

which can be found by setting $T^{\star} = 0$ in the above expression. The constraint on temporary workers, in turn implies that the firm hires at most uL temporary workers when z is sufficiently large, that is $z > \hat{z}$, where:

$$\hat{z}(L) = [(u + \Gamma)\, L]^{1-\theta} \, \frac{w}{\theta q A}.$$

Inspecting these two thresholds immediately reveals that, ceteris paribus, a higher productivity of permanent workers, Γ, acts to reduce the probability that the firm hires temporary workers, while an increase in product quality increases the likelihood that the firm will want to hire temporary workers. Indeed, an increase in product quality lowers the productivity threshold at which the firm finds itself constrained by restrictions on temporary work. Equivalently, product innovation raises the marginal profits from additional temporary workers for any demand shock, z. Given the above, profits at time 2 read:

$$\Pi(z, L; u, q, \Gamma) = \begin{cases} zqA\,(u+\Gamma)^{\theta}\,(L)^{\theta} - w\,(1+u)\,L & z \geq \hat{z} \\ (1-\theta)\, zqA \left(\frac{\theta z q A}{w}\right)^{\frac{\theta}{1-\theta}} + (\Gamma - 1)\, wL & \bar{z} < z < \hat{z} \\ zqA\,(\Gamma L)^{\theta} - wL & z \leq \bar{z} \end{cases}$$

Two features are worth emphasizing. First, the firm is contractually bound to pay the wage w to its permanent workers. Therefore, profits can be negative if the productivity shock is sufficiently low. This immediately implies that the firm optimally chooses not to hire enough permanent workers to meet all possible shocks z. Second, the profits function makes clear that permanent workers allow the firm to save on labor costs incurred when hiring temporary workers. In particular, in the region, $\bar{z} < z < \hat{z}$, each additional permanent worker allows the firm to realize savings $(\Gamma - 1)\, w$ on the hiring of temporary workers. This second observation clarifies why the firm does not rely solely on temporary workers even in the absence of limits to their use.

Labor markets. In period 0, before knowing the realization of the shock z, all intermediate producers are endowed with the same product and process technologies defined by the pair (q_0, Γ_0). Further, firms and workers assume the *current* level of EPL, u will persist until the end of period 2. Given a distribution for z with CDF $F(z)$, we can define expected profits for a generic pair $\left(q, \Gamma\right)$:

$$\begin{aligned}
\mathbb{E}_z \Pi\left(z, L; u, q, \Gamma\right) = & \int_0^{\underline{z}(L)} \left\{ zqA\,(\Gamma L)^{\theta} - wL \right\} \mathrm{d}F(z) \\
& + \int_{\underline{z}(L)}^{\bar{z}(L)} \left\{ (1-\theta)\, zqA \left(\frac{\theta zqA}{w} \right)^{\frac{\theta}{1-\theta}} + (\Gamma - 1)\, wL \right\} \mathrm{d}F(z) + \\
& + \int_{\bar{z}(L)}^{\infty} \left\{ zqA\,(u+\Gamma)^{\theta}\,(L)^{\theta} - w\,(1+u)\, L \right\} \mathrm{d}F(z).
\end{aligned}$$

In period 0, the firm chooses the amount of permanent workers L, given the technology (q_0, Γ_0), and the limit u on temporary workers. Thus the firm's problem reads:

$$\max_L \mathbb{E}_z \Pi\left(q, \Gamma, z, L; u\right),$$

which gives an optimal permanent labor demand L^*. Given that there is no aggregate uncertainty on firms' productivity, the total amount of labor that will be demanded in period 2 is known (agents expect u not to change in period 1):

$$\begin{aligned} L^d(w) &= L^*(w) + T^*(w) \\ &= L^*(w) + \int_{\bar{z}(L^*(w))}^{\hat{z}(L^*(w))} \left\{ \left(\frac{\theta z q A}{w} \right)^{\frac{1}{1-\theta}} - \Gamma L^*(w) \right\} \mathrm{d}F(z) + u L^* \int_{\hat{z}(L^*(w))}^{\infty} \mathrm{d}F(z). \end{aligned}$$

Given this labor demand, a representative union negotiates a statutory wage, w, which depends inversely on the level of unemployment arising in period 2. There is a representative family with a mass one of individuals that are assigned to temporary and permanent labor or unemployment, and supply labor inelastically. Unemployment arises as a result of union bargaining, which establishes a wage based on the expected employment level in period 2. Following Boone (2000), the wage solves:

$$w = b\left(1 - L^d(w)\right),$$

where $b'(\cdot) > 0$, capturing the assumption that the union's bargaining power declines with higher unemployment. This wage level cannot be changed in future periods. While this assumption might appear stringent, it is not far from the reality of many EU countries, where wage levels are set by unions and are only renegotiated at fixed time intervals, e.g. every two years in Italy.

3.3 Technology choices and EPL

Given the above structure, the firm enters period 1 with a fixed wage, w, and a fixed stock of permanent labor $L^*(w)$. At this stage, the limit on temporary work is changed unexpectedly from u to u', and the firm is given the option to modify its technology to adjust to the changed regulatory framework. We follow Boone (2000) and assume that there is a continuous differentiable concave innovation possibility frontier (IPF) described by $G(q', \Gamma') = 0$, which defines the menu of technologies that the firm can choose from, $\left(q_1, \Gamma_1\right) \in \left[q_0, \bar{q}\right] \times \left[\Gamma_0, \bar{\Gamma}\right]$. This assumption can capture the fact that there is a limited quantity of human capital to allocate to innovation activities, and that each research activity has diminishing returns. Thus, the firm's problem in period 1 reads:

$$\max_{(q,\Gamma):G(q,\Gamma)=0} \mathbb{E}_z \Pi\left(q, \Gamma, u', L^*(w)\right)$$

An interior solution satisfies the F.O.C.'s:[27]

$$\frac{(\partial \mathbb{E}_z \Pi / \partial \Gamma)}{\left(\partial \mathbb{E}_z \Pi / \partial q\right)} = \frac{(\partial G / \partial \Gamma)}{\left(\partial G / \partial q\right)},$$
$$G(q, \Gamma) = 0,$$

with the usual interpretation that the firm equals the slope of the isoprofits to the slope of the (innovation) possibility frontier.

The effect of regulation on innovation. In this model, employment protection is captured by the parameter u, the limit on the share of temporary workers in employment. The higher u, the more firms facing high demand shocks, z, are able to hire temporary workers. Appendix Proposition 2 shows formally that the ratio of product to process

[27] Corner solutions are possible, and desirable in light of the empirical evidence that many firms specialize on a single type of innovation. Our main theoretical result in Proposition 2 does not rely on the existence of an interior solution.

innovation increases with u.

To understand why, note that the partial derivatives of the profit function with respect to Γ, q are continuous in z, which allows us to neglect the effects of changes in the thresholds $\bar{z}, \hat{z}$ caused by changes in u.[28] Thus, the effect of a small change in u on the difference of returns in process versus product innovation is simply given by:[29]

$$\frac{\partial\left[\partial \mathbb{E}_z \Pi / \partial \Gamma - \partial \mathbb{E}_z \Pi / \partial q\right]}{\partial \bar{u}} = \int_{\hat{z}(L^*)}^{\infty} \frac{\partial\left[\partial \Pi(z, L^*) / \partial \Gamma - \partial \Pi(z, L^*) / \partial q\right]}{\partial \bar{u}} \mathrm{d}F(z),$$

the difference in marginal profits from the two types of innovation when the shock z is sufficiently high. Recall that, when $z > \hat{z}(L^*)$, the firm optimally employs exactly uL temporary workers, so u is the ratio of temporary to permanent workers employed in high-demand states. Thus, an increase in u raises the amount of temporary workers relative to permanent workers in these states, making product innovation, which augments both worker types, more attractive than process innovation, which only augments permanent workers.

To further this intuition, recall that each firm faces a downward-sloping demand for its products. Thus, given a permanent worker stock, it finds itself producing above or below its profit-maximizing quantity depending on the realization of demand shocks. In particular, the firm produces less quantity than optimal when demand is high enough that it cannot be met by hiring the maximum amount of temporary workers. Investment in process innovation increases the productivity of permanent workers, reducing the need for additional temporary workers when a high demand shock is realized,

[28]This result is proved formally in Appendix Proposition 1.

[29]We provide this differential argument for ease of exposition. Proposition 2 in Appendix D shows that our results hold regardless of the size of the change in u.

which is more attractive if regulation on fixed-term contracts is stricter. Conversely, product innovation increases the productivity of workers in all states, in particular raising the marginal profits from adjusting temporary workers upwards. Thus, the gains from product innovation are more pronounced if the firm faces less restrictions on temporary employment.

Discussion. Our assumptions have three main implications, which allow a complementary interpretation of our model according to the framework in Acemoglu's (2007, 2010).[30] First, the fact that product innovation is Hicks-neutral implies that it is also *strongly temporary-labor complementing*. Second, perfect substitution between temporary and permanent workers, coupled with the fact that process innovation augments only permanent workers, implies that process innovation is *strongly temporary-labor substituting*. As a result, the firm prefers to invest in product innovation when the supply of temporary workers is high, while it invests in process innovation when it is low. Finally, we model EPL regulations as restrictions on the quantity of temporary workers. Therefore an EPL reduction results in an expansion of the effective supply of temporary workers, tilting firms' choices in favor of product innovation.

4 Conclusion

In this paper, we have investigated the effect of changes in employment protection legislation across European countries on the direction of technology adoption. Our find-

[30]Proposition 3 in the Appendix proves formally the analogue of Acemoglu's (2010) Theorem 1. That is, firms' revenues are supermodular in $\left(T, (q, -\Gamma)\right)$, and product (process) innovation is *strongly temporary-labor substituting (complementing)*.

ings show that countries that eased the use of temporary contracts have experienced an increase in product innovation activities. Our results also suggest that this increase occurred through a reallocation away from process innovation—which is generally motivated by a desire to cut labor costs. The effects are sizable, implying an increase in the share of innovative firms engaging in product innovation by about 10pp, and a corresponding decrease in innovation activity directed exclusively to production process improvements. We have interpreted our results in light of a model which features an endogenous choice between product and process innovation. In our framework, limits on temporary work directly affect the direction of innovation since process innovation augments more experienced permanent workers, while product innovation complements both permanent and temporary workers alike.

From a policy standpoint, our findings add a new rationale for structural labor market reforms, by highlighting their impact on the direction of innovation activity. Our results suggest that countries with strict EPL naturally direct their research efforts toward process innovations to reduce labor costs, at the detriment of innovations that might expand the range or increase the quality of existing products. Depending on which type of innovation is more relevant for economic growth, the direction of innovation activity towards product or process innovation might be more or less desirable.

We identify two avenues for future research. First, further theoretical work is warranted to draw formal normative conclusions on the effects of EPL on the direction of innovation. Mapping our results to aggregate welfare is not straightforward. Indeed, while spillovers from the two activities could provide a sufficient statistic in a representative agent economy, welfare evaluation in more general settings is complicated by their distributional effects (such as worker displacement from labor-substituting technologies, or product innovation that is biased towards wealthier agents). Second, we would like to expand our research to the analysis of the direction of process innovation towards labor-complementing or labor-substituting technologies, building groups of "complementing" and "substituting" innovators. This could be accomplished through the use of the full CIS firm-level data, beyond the subset currently available to researchers.

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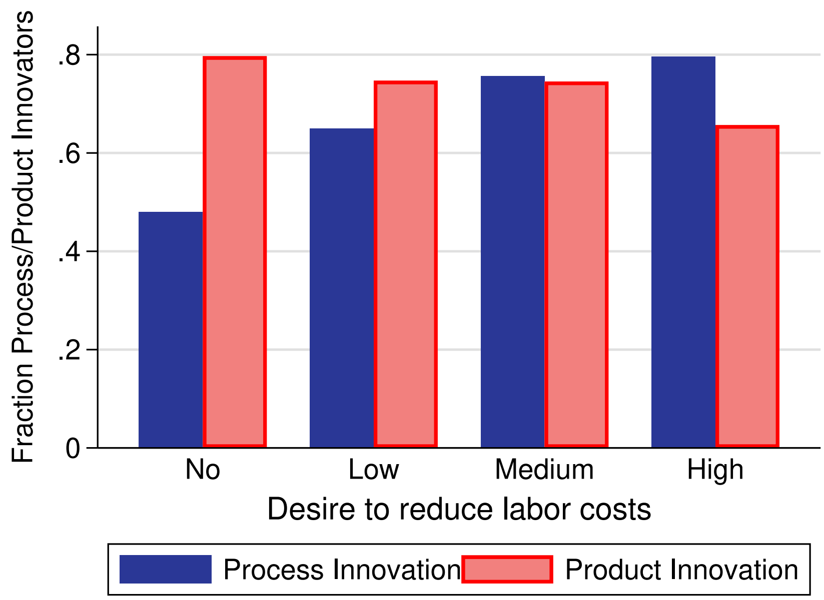
Figures and Tables

(a)



(b)

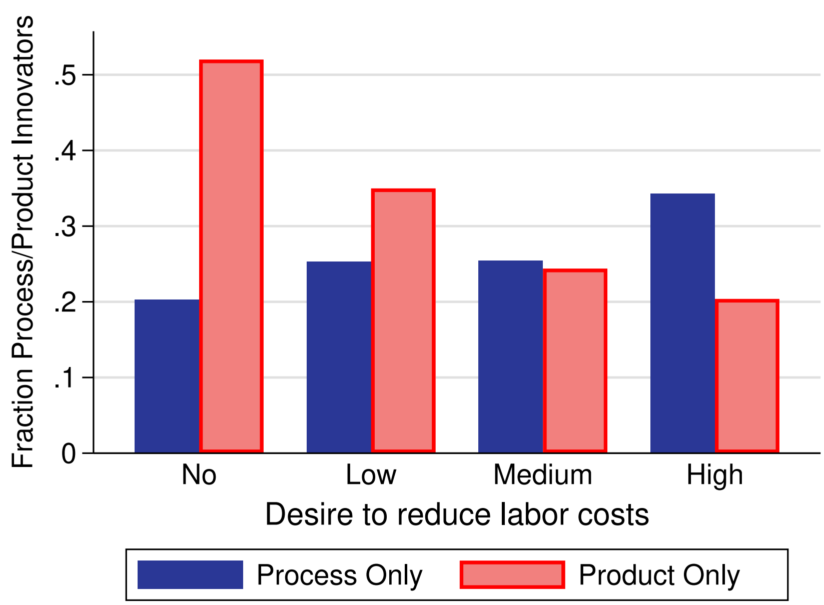


Figure 1: Fraction of innovators conducting product and process innovation, by desire to cut labor costs

Note: For each possible response to the question of whether the objective/effect of innovation was the reduction in labor costs (how much innovation "reduced labour costs per produced unit"), this figure shows the fraction of respondents who reported doing product/process innovation. Panel (a) does not condition on whether firms carry out the other innovation type, while panel (b) reports statistics for firms that carry out only one type of innovation. More details are in the text. We use CIS firm-level data, which include only a subset of surveyed countries. We restrict the sample to the year 2000 (before EPL changes), include all available industries, and consider only countries that feature also in our baseline regression sample (Belgium, Germany, Greece, Iceland, Latvia, Lithuania, and Spain).

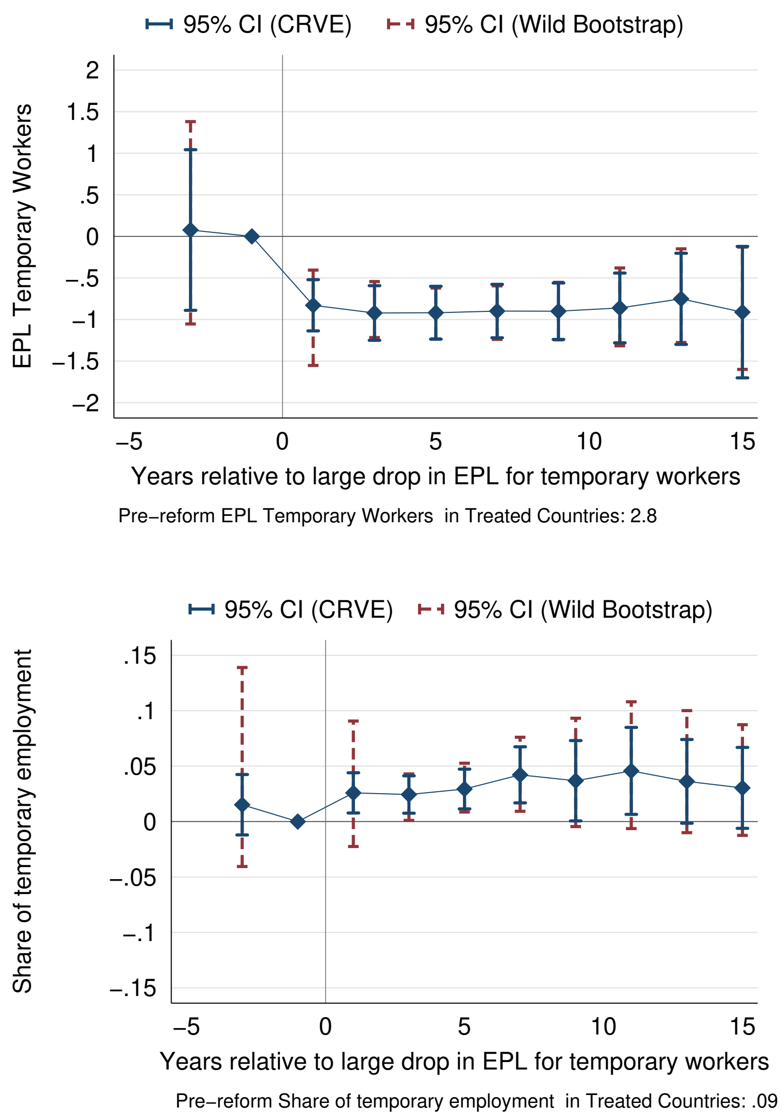


Figure 2: Evolution of EPL for temporary workers and the share of temporary employment around a big EPL drop

Note: Panel (a) shows the path of the index of strictness of Employment Protection Legislation (EPL) for temporary workers around the event (a big drop in EPL for temporary workers). A drop in EPL is considered large if the measure of EPL drops by 20% or more from one year to the next. The figure reports the coefficients κ_e from regression (1) with "EPL for temporary workers" as outcome variable. Panel (b) reports the same coefficients for the share of temporary workers over total dependent employment in the manufacturing sector, from Eurostat (2000-2016b). The latter regression is weighted by total employment.

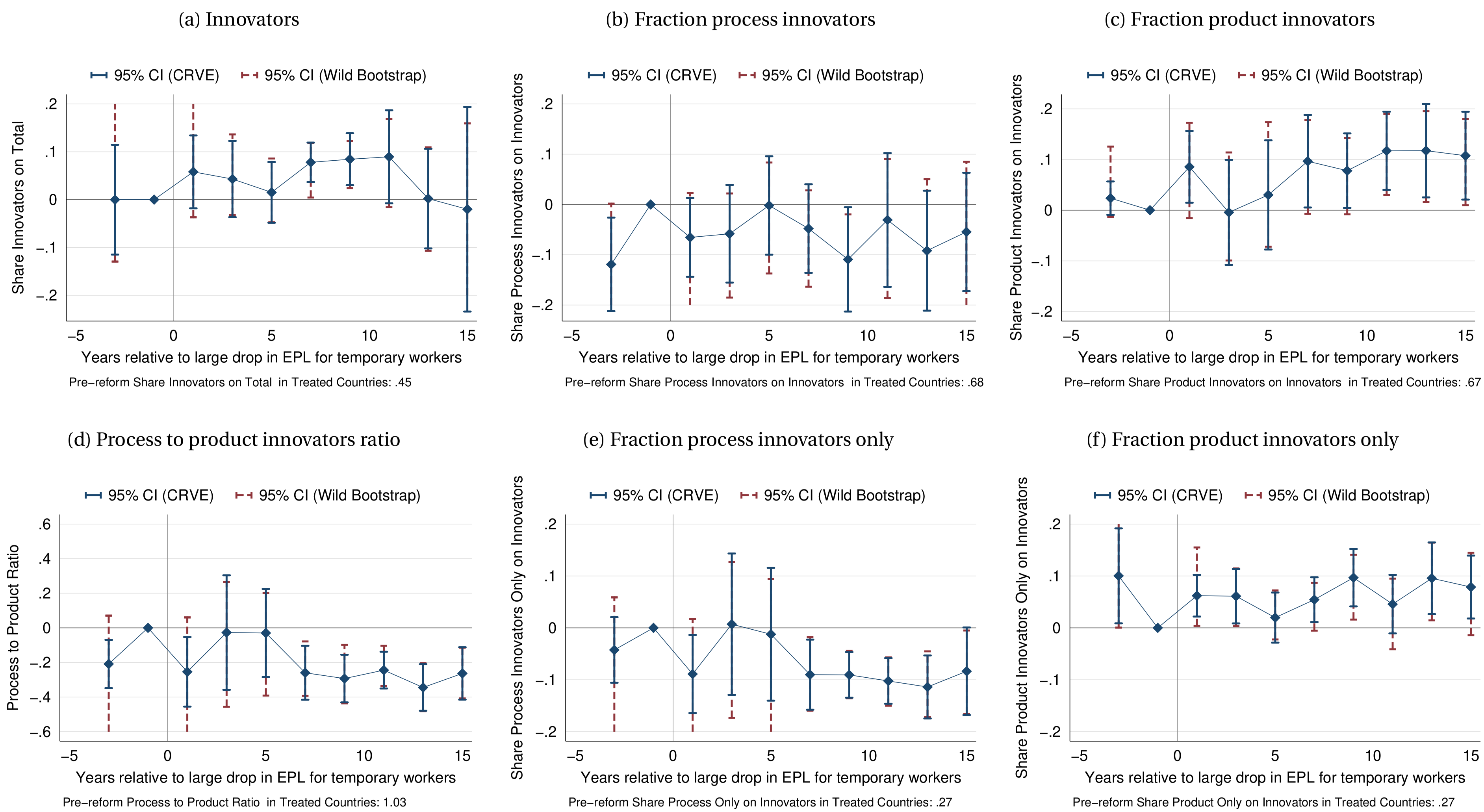


Figure 3: Main Results: effect of large EPL drop on innovators and product/process innovation

Note: This exhibit plots the coefficients κ_e from the estimation of Equation (1) on the main sample. The coefficient κ_{-1} is normalized to zero, and $e = 0$ denotes the event year. The outcomes are: share of innovating firms out of all respondents (panel a), share of process/product innovators over innovators (panels b/c), total number of process innovators over total number of product innovators (panel d), share of innovating firms that carry out exclusively process/product innovation (panel e/f). Regressions are weighted by the number of respondent firms. The solid bars are 95% confidence intervals constructed using a cluster-robust variance estimator, clustering at the country level. Dashed bars are 95% wild cluster bootstrap confidence intervals (Rademacher weights, 999 repetitions). The absence of a horizontal dash at the endpoints indicates that bars have been truncated to fit the graph area.

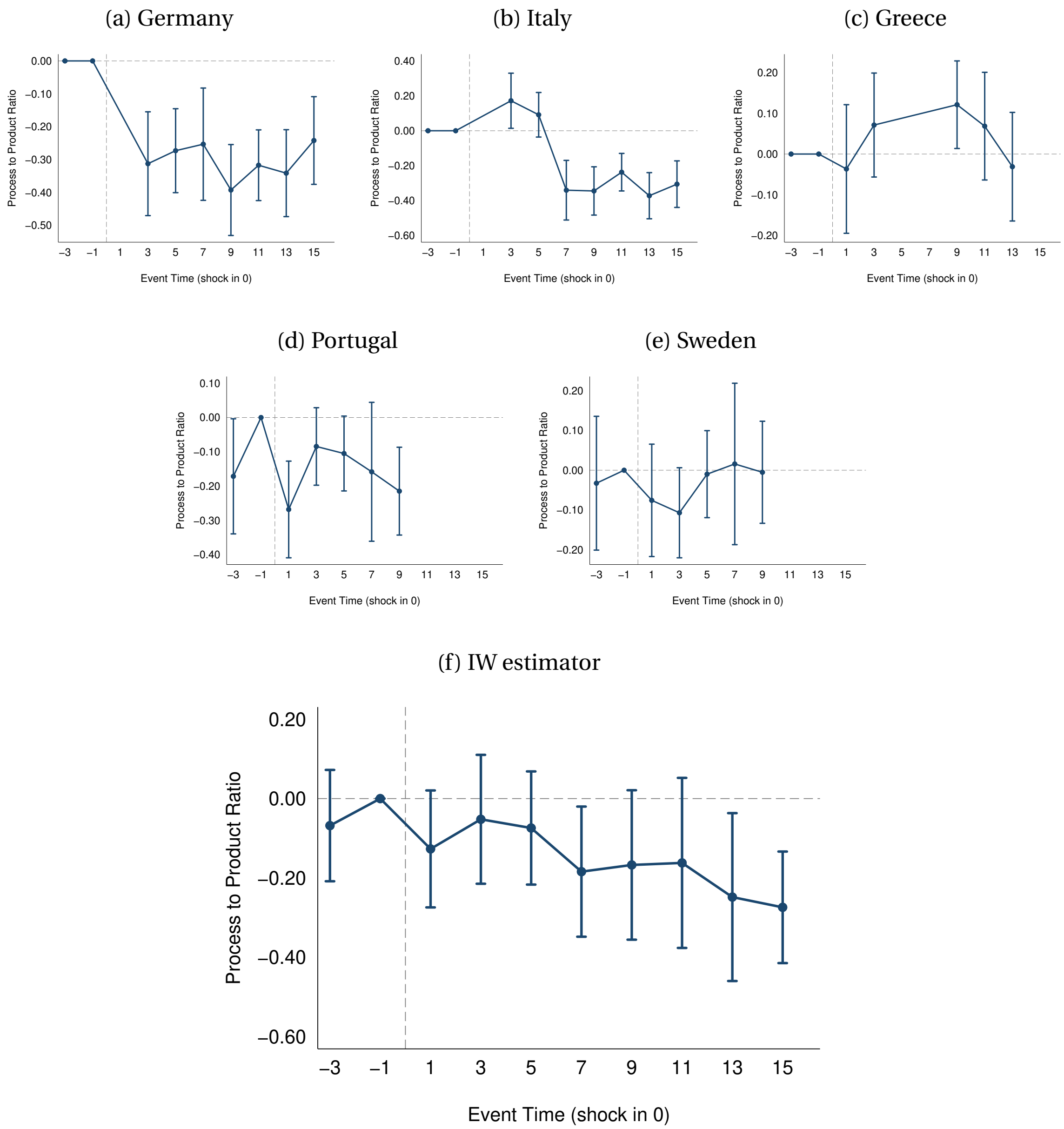
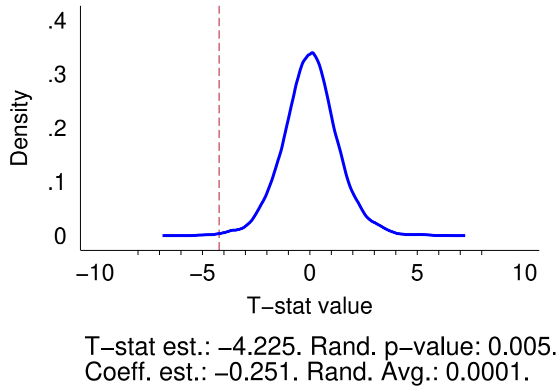


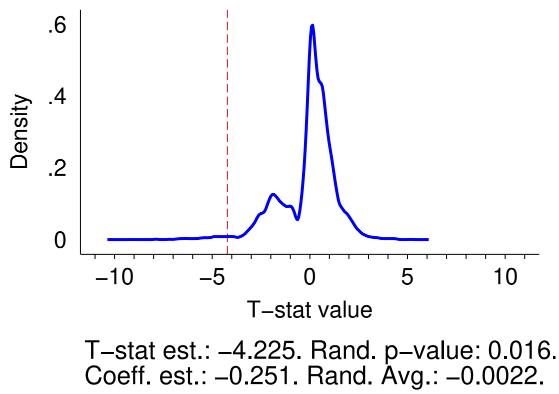
Figure 4: Process to product ratio: Country-specific coefficients and IW estimator

Note: The figure shows event-study coefficients by treated country and averaged across countries following Sun and Abraham (2021), for the outcome variable process-to-product ratio. The method is summarized in Appendix C.1. Panels (a) to (e) report country-specific event-study coefficients, $\kappa_{e,c}$, from Equation (3). Panel (f) displays the interaction-weighted event-study coefficients obtained from their aggregation, $\hat{\beta}_e^{IW}$, from Equations (4) and (5). Regressions are weighted by the number of respondent firms. Panels (a) to (e) report cluster-robust standard errors, while panel (f) reports IW standard errors constructed following Proposition 6 in Sun and Abraham (2021).

(a) Within randomization



(b) Between randomization



(c) Total randomization

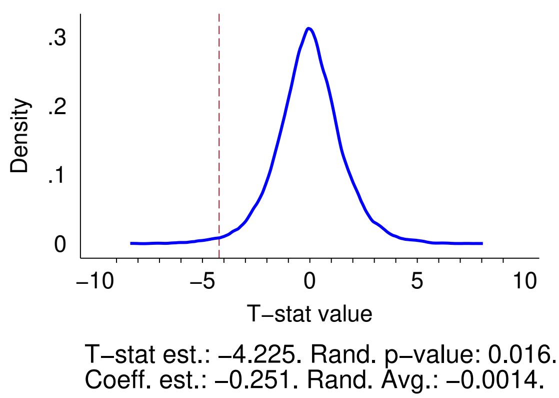


Figure 5: Process on product ratio: Permutation tests

Note: The figure shows the distribution of the t-statistic on the hypothesis that the "long run" coefficient is equal to zero from randomization inference. In panel (a), countries are kept fixed while time periods are randomized, in panel (b), treatment periods are preserved while countries are randomized, and in panel (c) both countries and time periods are randomized. More details are provided in Section 2.4 and in Appendix C.2. The vertical dashed line indicates the t-statistic from the original sample, and its value is also reported below ("T-stat est."). "Coeff. est." indicates the coefficient on the long-run dummy estimated in the main sample. "Rand. p-value" indicates the fraction of replications in which the t-stat is more extreme than the one estimated in the main sample. "Rand. Avg." indicates the mean of the distribution of estimated t-statistics displayed.

Table 1: Summary statistics on main variables - Manufacturing

Country	(1) Innovators	(2) Fraction Process	(3) Fraction Product	(4) Process over Product	(5) EPL Temp	(6) Year EPL Drop
Austria	0.52	0.72	0.72	1.00	1.31	.
	(0.04)	(0.10)	(0.03)	(0.14)	(0)	.
Belgium	0.59	0.71	0.67	1.06	2.21	.
	(0.05)	(0.04)	(0.06)	(0.11)	(0.08)	.
Denmark	0.49	0.63	0.67	0.97	1.43	.
	(0.08)	(0.03)	(0.10)	(0.15)	(0.11)	.
Finland	0.54	0.67	0.70	0.96	1.56	.
	(0.05)	(0.06)	(0.04)	(0.12)	(0)	.
France	0.43	0.68	0.67	1.02	3.11	.
	(0.06)	(0.07)	(0.03)	(0.15)	(0.04)	.
Germany	0.67	0.52	0.69	0.76	1.14	2001
	(0.06)	(0.05)	(0.03)	(0.08)	(0.32)	.
Greece	0.37	0.78	0.65	1.20	2.91	2003
	(0.07)	(0.09)	(0.06)	(0.14)	(1.02)	.
Iceland	0.49	0.69	0.74	0.94	0.63	.
	(0.02)	(0.03)	(0.06)	(0.05)	(0)	.
Italy	0.43	0.75	0.65	1.18	2.14	2001
	(0.05)	(0.04)	(0.08)	(0.22)	(0.50)	.
Latvia	0.21	0.68	0.67	1.02	0.88	.
	(0.04)	(0.01)	(0.00)	(0.01)	(0)	.
Lithuania	0.41	0.83	0.69	1.21	2.38	.
	(0.02)	(0.03)	(0.04)	(0.11)	(0)	.
Luxembourg	0.51	0.73	0.70	1.05	3.75	.
	(0.05)	(0.06)	(0.08)	(0.16)	(0)	.
Netherlands	0.49	0.64	0.73	0.88	0.96	.
	(0.07)	(0.04)	(0.04)	(0.07)	(0.08)	.
Norway	0.44	0.55	0.69	0.79	2.91	.
	(0.08)	(0.11)	(0.07)	(0.09)	(0.18)	.
Portugal	0.45	0.81	0.63	1.28	2.23	2007
	(0.06)	(0.06)	(0.03)	(0.08)	(0.40)	.
Spain	0.34	0.71	0.54	1.31	2.98	.
	(0.04)	(0.05)	(0.06)	(0.16)	(0.32)	.
Sweden	0.50	0.61	0.67	0.90	1.06	2007
	(0.02)	(0.06)	(0.03)	(0.08)	(0.33)	.
Turkey	0.40	0.75	0.67	1.13	4.88	.
	(0.09)	(0.03)	(0.04)	(0.08)	(0)	.

Note: This table reports means and standard deviations (in parentheses) of selected variables in our sample. Variables in columns 1 through 4 come from the CIS (restricting to manufacturing firms). Column 1 reports the share of respondents that report carrying out at least one type of innovation (product and/or process); column 2/3 report the shares of innovating firms that engage in process/product innovation and column 4 reports their ratio. Columns 5 and 6 report the OECD index of EPL strictness for temporary workers, and the treatment year (if any) in which EPL drops by 20% or more. Note that we attribute treatment year 2001 for Germany, although the reform occurred in 2002, in order to harmonize the treatment variable across countries to odd years, given the biannual data structure.

Table 2: Balance table

	Control			Treatment			
	N	Mean	SD	N	Mean	SD	Difference
Share Innovators on Total	8	0.45	0.08	5	0.50	0.14	0.049
Share Process Innovators on Innovators	8	0.62	0.09	5	0.65	0.10	0.037
Share Product Innovators on Innovators	8	0.73	0.06	5	0.68	0.04	−0.041
Process to Product Ratio	8	0.86	0.16	5	0.96	0.18	0.103
EPL Temporary Workers	8	2.67	0.90	5	2.73	0.80	0.064
EPL Collective dismissals	9	3.14	0.56	5	3.77	0.47	0.625**
EPL Regular Workers	9	2.57	0.45	5	2.97	0.57	0.392
EPL Regular and Collective dismissal	9	2.74	0.25	5	3.20	0.39	0.458**
Spending on Active LMP ex admin (pct GDP)	8	0.82	0.24	5	0.74	0.31	−0.076
Out-of-work income maintenance and support (pct GDP)	9	1.34	0.25	5	1.01	0.68	−0.327
Trade Union Density (Adminstrative Sources)	10	22.78	18.26	3	32.97	15.79	10.196
Collective Bargaining Coverage (pct employees)	8	53.63	40.76	5	76.68	8.81	23.056
Capital-Labor ratio	7	0.76	0.07	3	0.82	0.08	0.056
Labor Share	10	0.62	0.03	5	0.65	0.07	0.036
Automation potential	12	8.64	1.79	5	7.79	2.90	−0.843
Task offshoring	12	37.67	0.75	5	39.08	2.54	1.403
GDP Growth (average previous two years)	13	3.73	1.20	5	2.79	0.60	−0.948
Trade with 2001 Euro Area (fract GDP)	13	0.29	0.19	5	0.23	0.05	−0.065
Trade with post-2004 Accession Countries (fract GDP)	13	0.02	0.03	5	0.03	0.01	0.011
Employment in Chem-Pharma (frac manuf empl)	10	0.06	0.02	5	0.05	0.01	−0.009
Value Added in Chem-Pharma (frac manuf VA)	10	0.11	0.04	5	0.09	0.02	−0.022
Employment in Electronics (frac manuf empl)	9	0.04	0.02	5	0.03	0.02	−0.005
Value Added in Electronics (frac manuf VA)	9	0.06	0.05	5	0.05	0.03	−0.012
Employment in Transport (frac manuf empl)	9	0.08	0.03	5	0.09	0.04	0.004
Value Added in Transport (frac manuf VA)	9	0.10	0.03	5	0.11	0.04	0.010

Note: For each of the variables used in the analysis, the table reports summary statistics for the year 2000 by treatment status, and the difference in means between treatment and control. Countries are weighted by the total number of firms across all waves of the CIS. Stars indicate significance level (* 10%, ** 5%, *** 1%). Data sources (detailed in Appendix A.1): innovation variables from Eurostat (2000-2016a); EPL and labor market institutions from OECD (2000-2018); capital-labor ratio, labor share and subsectors' share in manufacturing from EU KLEMS (Stehrer et al., 2019; Adarov and Stehrer, 2019); automation potential and task offshoring from Acemoglu and Restrepo (2020a); Autor and Dorn (2013); GDP from OECD (1998-2020); trade variables from IMF (2000).

Table 3: Difference-in-differences results

	(1) Share Innovators on Total	(2) Share Product Innovators on Innovators	(3) Share Process Innovators on Innovators	(4) Share Process Innovators Only on Innovators	(5) Process to Product Ratio
Short Run	0.033	0.019	-0.007	-0.005	-0.013
	(0.027)	(0.046)	(0.041)	(0.051)	(0.111)
	[−0.027, 0.123]	[−0.095, 0.153]	[−0.141, 0.069]	[−0.194, 0.114]	[−0.449, 0.232]
Long Run	0.061	0.097	-0.051	-0.090	-0.251
	(0.033)	(0.039)	(0.045)	(0.022)	(0.059)
	[−0.023, 0.122]	[0.005, 0.172]	[−0.164, 0.047]	[−0.144, −0.044]	[−0.353, −0.074]
Constant	0.546	0.805	0.669	0.163	0.778
	(0.013)	(0.023)	(0.035)	(0.014)	(0.037)
N	119	119	119	119	119
Number of Clusters	18	18	18	18	18
Number of Firms	2298051	2298051	2298051	2298051	2298051

Note: This table reports difference-in-differences coefficients from the estimation of Equation (2) on the main outcomes of interest. “Short-Run” is a dummy equals to 1 if the treatment occurred between 1 and 5 years prior. “Long-Run” is a dummy for the treatment occurring 6 or more years prior. All specifications are weighted by the number of respondent firms and include country and time fixed-effects. Cluster-robust standard errors in parentheses (clustered at the country level); wild-boostrap 95% confidence intervals in brackets.

Table 4: Difference-in-differences including controls, process to product ratio

	Baseline	Labor Market Institutions	Macroeconomic Conditions	Sectoral Characteristics
	(1)	(2)	(3)	(4)
Short Run	-0.013	-0.001	0.041	-0.268
	(0.111)	(0.086)	(0.105)	(0.092)
	[−0.347, 0.193]	[−0.318, 0.199]	[−0.290, 0.450]	[−0.422, −0.008]
Long Run	-0.251	-0.176	-0.182	-0.273
	(0.059)	(0.068)	(0.100)	(0.029)
	[−0.337, −0.122]	[−0.290, −0.013]	[−0.448, −0.005]	[−0.315, −0.193]
Constant	0.778	0.769	0.839	0.795
	(0.037)	(0.056)	(0.133)	(0.045)
EPL total		3		
Total LMP spending		3		
GDP Growth (av. two years)			3	
Trade with Euro Area			3	
Trade with Accession Countries			3	
Automation potential				3
Task offshoring				3
Capital-Labor Ratio				3
Observations	119	101	119	79
Number of Clusters	18	13	18	10
Number of Firms	2298051	2085006	2298051	1922666
DoF Residual	92	65	71	39
DoF Model	26	35	47	39

Note: This table displays the estimates for our baseline diff-in-diff specification (2) using the ratio of process to product innovators as outcome variable. All specifications are weighted by the number of respondent firms and include country and time fixed-effects. Column 1 includes no additional controls (it replicates column 5 of Table 3), columns 2 through 4 control for the interactions of year dummies with the variables listed below, taken at their level in the year 2000. Cluster-robust standard errors in parentheses (clustered at the country level); wild-boostrap 90% confidence intervals in brackets. “DoF Residual” and “DoF Model” denote the degrees of freedom of the residuals and the model respectively.

A Data Appendix

A.1 Data Sources

Our data sources are:

- **Innovation data** from the Community Innovation Survey[31]
  - Aggregate data from Eurostat website: `https://ec.europa.eu/eurostat/web/main/data/database`, Database by themes > Science, Technology and Digital Society > Science and technology (scitech) > Community Innovation Survey (inn). Relevant series: CIS3 through CIS2016 (Eurostat, 2000-2016a);
  - Micro-data (Scientific Use Files) for a subset of countries from Eurostat under RPP 94/2020-CIS-SES-MMD;[32]
  - Questionnaires from Eurostat website: link to all; paths are `https://ec.europa.eu/eurostat/documents/203647/203701/CIS_Survey_form_XXX.pdf` where "XXX" are 3, 4, 2006-2016.
- Index of **strictness of Employment Protection Legislation (EPL)** from the OECD (2000-2018). Main source: `https://stats.oecd.org/Index.aspx?DataSetCode=XXX`, where "XXX" is to be replaced by the dataset code; Main references: `https://www.oecd.org/employment/emp/oecdindicatorsofemploymentprotection.htm`, OECD (2020) and OECD (2014). Series used:
  - EPL Temp: "Strictness of hiring regulation for workers on temporary contracts" (EPT version 1) [Dataset code: EPL_T];
  - EPL Regular: "Strictness of regulation of individual dismissals of workers on regular contracts" (EPR version 1) [Dataset code: EPL_R];
  - EPL Collective: "Strictness of regulation of collective dismissals of workers on regular contracts" (EPC version 2) [Dataset code: EPL_CD];
  - EPL Total: "Strictness of dismissal regulation for workers on regular contracts (both individual and collective dismissals)" (EPRC version 2). Weighted average of EPL Regular (5/7 of the weight) and of EPL Collective (2/7 of the weight) [Dataset code: EPL_OV].
- **Permanent and temporary employment** (aged 15-64, both sexes) from the Labour Force Survey (Eurostat, 2000-2016b). Main source: `https://ec.europa.eu/eurostat/`

[31] CIS results were collected under European Commission Regulation (EC) No 1450/2004 until 2010 and under regulation EC No 995/2012 starting in 2012.

[32] We specify that the results and conclusions are those of the authors and not those of Eurostat, the European Commission or any of the national statistical authorities whose data have been used.

web/main/data/database, Database by themes > Population and social conditions > Labour market (labour) > Employment and unemployment (Labour force survey) (employ) > LFS series - detailed quarterly survey results (from 1998 onwards) (lfsq) > Employment - LFS series (lfsq_emp). Series used:

  - Employment by economic activity: lfsq_egana (1998-2008), lfsq_egan2 (from 2008 onwards);
  - Employment by detailed economic activity: lfsq_egana2d (1998-2008);
  - Temporary employees by economic activity: lfsq_etgana (1998-2008), lfsq_etgan2 (from 2008 onwards);
  - Share of temporary workers: ratio of temporary employment over total employment by economic activity.

- **Labor market institutions and policies** from the OECD (2000-2018). Main source: https://stats.oecd.org/Index.aspx?DataSetCode=XXX, where "XXX" is to be replaced by the dataset code. Series used:
  - Collective bargaining coverage [Dataset code: CBC];
  - Trade union density [Dataset code: TUD];
  - Spending on unemployment benefits (% of GDP) [Dataset code: LMPEXP, #80];
  - Spending on active labor market policies (% of GDP) [Dataset code: LMPEXP, #112];
  - Total spending on labor market policies (sum of unemployment benefits and active labor market policies).

- **Gross domestic product (GDP)** from the OECD (1998-2020). Main source: https://stats.oecd.org/viewhtml.aspx?datasetcode=SNA_TABLE1&lang=en.
  - GDP Growth (average previous two years): we take the average of GDP growth in 1999 and 2000. Series used: Growth rate (code: G);
  - GDP: value in 2000. Series used: Current prices, current exchange rates, in USD (code: CXC).

- Value of **trade** from the IMF (2000). Main source: the Direction of Trade Statistics (DOTS). https://data.imf.org/?sk=9D6028D4-F14A-464C-A2F2-59B2CD424B85.
  - Value of exports in 2000. Series used: Goods, Value of Exports, Free on board (FOB), US Dollars (code: TXG_FOB_USD);

- Value of imports in 2000. Series used: Goods, Value of Imports, Cost, Insurance, Freight (CIF), US Dollars (code: TMG_CIF_USD);
- Value of imports from (export to) Euro area countries: sum of imports from (exports to) Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain (countries part of the Euro area as of 2001);
- Value of imports from (export to) accession countries: sum of imports from (exports to) Bulgaria, Croatia, Cyprus, Czechia, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia, Slovenia (countries that joined the European Union between 2004 and 2013);
- Trade with 2001 Euro Area: sum of imports from and export to Euro area countries over GDP in 2000;
- Trade with post-2004 Accession Countries: sum of imports from and export to accession countries over GDP in 2000.

- **Automation and offshoring** for detailed manufacturing sectors from the replication package of Acemoglu and Restrepo (2020b). Variables used:
  - Automation potential: average robot penetration for detailed manufacturing sectors in the US for 2004 (apr_us_lv_04);
  - Task offshoring: task offshoring at the broad industry level from Autor and Dorn (2013) (task_offshore_manuf).

- **Labor share and capital-labor ratio** for the manufacturing sector from EU KLEMS (Stehrer et al., 2019; Adarov and Stehrer, 2019). Main source: `https://euklems.eu/`. Database: Growth Accounts - statistical. Variables used:
  - Labor share: LAB / (LAB+CAP) ;
  - Capital-labor ratio: CAP_QI / LAB_QI .

- **Value added and employment** by detailed manufacturing sectors (groups of 1-3 level 2 NACE Rev.2 codes) from EU KLEMS (Stehrer et al., 2019). Main source: `https://euklems.eu/`. Database: National Accounts - statistical. Variables used:
  - Employment: EMP (Number of persons employed, th.);
  - Value Added: VA (GVA, current prices, NAC mn);
  - emp. share / manufacturing employment share: share of manufacturing employment in the subsector;
  - VA share / manufacturing value added share: share of manufacturing value added in the subsector.

A.2 Additional Descriptive Statistics

Table A.1 : Number of respondents in CIS

Country	Industry			Services		
	Innovative Firms (1)	Total Respondents (2)	Percentage Innovative (3)	Innovative Firms (4)	Total Respondents (5)	Percentage Innovative (6)
Austria	3,727	7,251	51	3,673	8,754	42
Belgium	3,585	6,126	59	3,646	7,827	46
Denmark	1,931	3,948	47	1,916	4,953	39
Finland	2,133	4,025	53	1,826	4,211	43
France	14,140	33,608	43	11,709	35,685	33
Germany	40,140	61,308	66	32,801	62,752	53
Greece	2,334	6,332	38	2,192	5,684	38
Iceland	213	422	50	223	400	56
Italy	34,635	82,119	42	12,250	38,897	31
Latvia	476	2,266	21	409	2,612	16
Lithuania	920	2,998	31	901	3,474	25
Luxembourg	169	342	49	570	1,223	47
Netherlands	4,803	9,824	49	6,413	16,647	39
Norway	1,677	3,930	43	1,917	5,013	38
Portugal	5,766	12,875	45	3,598	7,405	49
Spain	13,465	40,279	33	8,430	34,439	25
Sweden	3,603	7,278	49	4,271	9,874	44
Turkey	16,476	41,726	39	10,382	32,630	31

Note: This table reports the average number of respondents to the Community Innovation Survey per wave by country and macro-sector. The macro sectors are Industry (sectors C-E in NACE Rev.1) and Services (Innovation core services activities; G51, I, J, K72, K74.2 and K74.3 in NACE Rev.1 for years 2004-2016, sectors G-K in year 2000). Columns 2 and 5 report the average of all respondents, while columns 1 and 4 of the innovative firms, where a firm is innovative if it carries out at least one type of process or product innovation in the three years preceding the survey. Columns 3 and 6 report the average number of innovative firms out of all respondents.

Table A.2 : Summary statistics on main variables - all sectors

Country	Innovators	Fraction Process Innovators	Fraction Product Innovators	Process to Product Innovators Ratio
	(1)	(2)	(3)	(4)
Austria	0.46	0.73	0.67	1.11
	(0.13)	(0.11)	(0.09)	(0.30)
Belgium	0.48	0.68	0.64	1.09
	(0.14)	(0.09)	(0.11)	(0.33)
Denmark	0.41	0.64	0.62	1.12
	(0.11)	(0.07)	(0.14)	(0.49)
Finland	0.47	0.67	0.66	1.09
	(0.13)	(0.09)	(0.12)	(0.40)
France	0.30	0.73	0.58	1.36
	(0.11)	(0.09)	(0.11)	(0.53)
Germany	0.59	0.54	0.64	0.88
	(0.14)	(0.07)	(0.10)	(0.25)
Greece	0.37	0.79	0.64	1.26
	(0.08)	(0.09)	(0.08)	(0.28)
Iceland	0.48	0.66	0.71	0.96
	(0.10)	(0.08)	(0.11)	(0.22)
Italy	0.33	0.75	0.60	1.35
	(0.11)	(0.08)	(0.12)	(0.58)
Latvia	0.17	0.71	0.52	1.72
	(0.07)	(0.10)	(0.19)	(1.20)
Lithuania	0.34	0.86	0.55	1.71
	(0.09)	(0.05)	(0.15)	(0.59)
Luxembourg	0.45	0.69	0.67	1.08
	(0.11)	(0.10)	(0.13)	(0.32)
Netherlands	0.35	0.64	0.67	0.98
	(0.12)	(0.08)	(0.10)	(0.26)
Norway	0.34	0.55	0.61	0.99
	(0.15)	(0.12)	(0.16)	(0.43)
Portugal	0.45	0.80	0.61	1.35
	(0.07)	(0.07)	(0.08)	(0.76)
Spain	0.23	0.71	0.43	1.88
	(0.10)	(0.09)	(0.14)	(0.82)
Sweden	0.49	0.59	0.69	0.87
	(0.08)	(0.10)	(0.07)	(0.19)
Turkey	0.36	0.73	0.65	1.14
	(0.09)	(0.05)	(0.06)	(0.12)

Note: This table replicates columns 1 through 4 of Table 1 but including all sectors available (that is, without restricting to the manufacturing sector). See note to Table 1 for details.

A.3 Details on EPL Reforms

In this subsection, we describe how the index of strictness of Employment Protection Legislation for temporary workers varies across countries and over time, and we provide more details on the identification of the treatment and the selection of controls.

Figure A.1 shows the level of EPL for temporary workers for each country in our sample at the beginning and at the end of the sample period. About a third of the countries in our sample experienced no change at all, while the remaining two thirds introduced at least some change to this measure over the period of interest, with a few presenting substantial variation—induced by large reforms that lifted regulatory burdens on temporary contracts, as described in Table A.3 .

This pattern is apparent in Figure A.2, which depicts the frequency distribution of year-to-year percentage changes in EPL for temporary workers. The figure groups changes into three categories: large drops, small changes, and large increases; we define a change as large if it is smaller than −20% or greater than 20%. These cutoffs correspond to the 2.5 and 97.5 percentiles of EPL changes, respectively. Small or zero changes represent the vast majority of the observations (95%). We use large drops as treatment, while countries with only small or no changes in EPL form our control group. We drop countries with large positive changes as they do not constitute a valid control group. In particular, many of these are eastern European countries, where EPL changes occur around the date of EU accession.[33] Finally, Figure A.3 reports the path of the EPL measure around the time of the event for treated countries. EPL is mostly stable before and after reform episodes, and only Sweden and Portugal experience (minor) increases in EPL in the ten years following the event.

[33]When these large increases are studied as events, there are clear pre-trends in all our outcomes of interest.

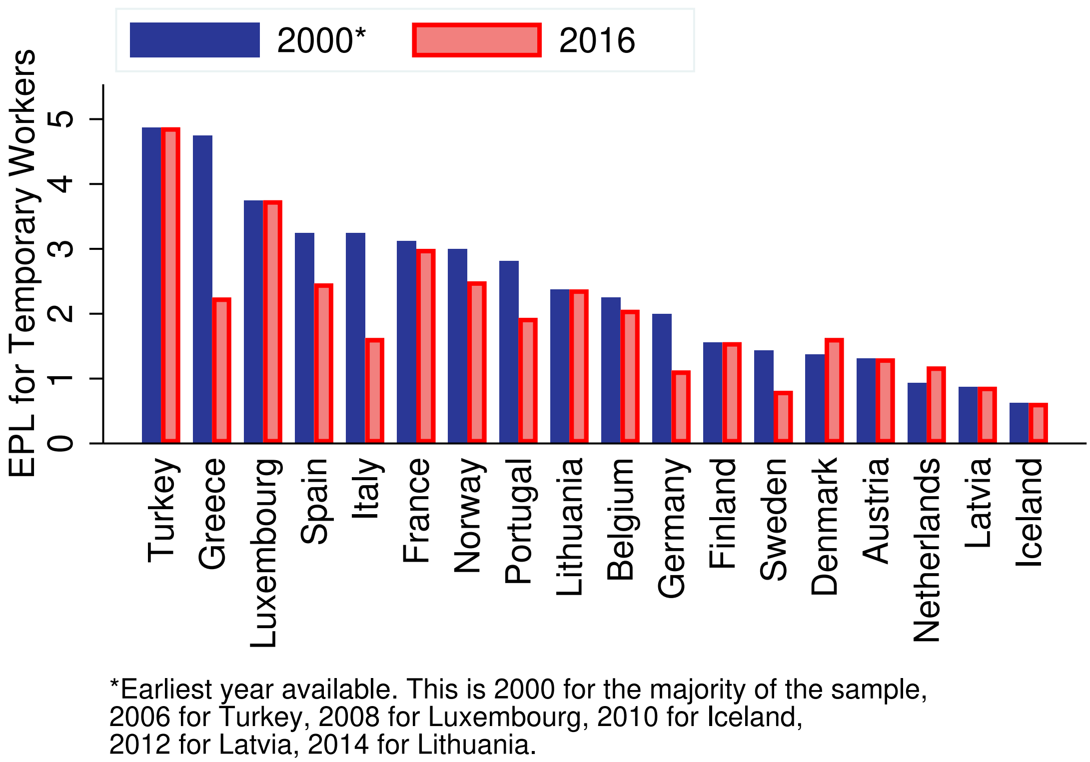


Figure A.1: EPL for temporary workers

Note: This figure shows the measure of strictness of Employment Protection Legislation (EPL) for temporary workers at the beginning and at the end of the sample period (respectively 2000 and 2016) for the sample of countries in the analysis. For the countries without data in 2000 we use the earliest data point available, as indicated in the figure. The source is the OECD Indicators of Employment Protection database.

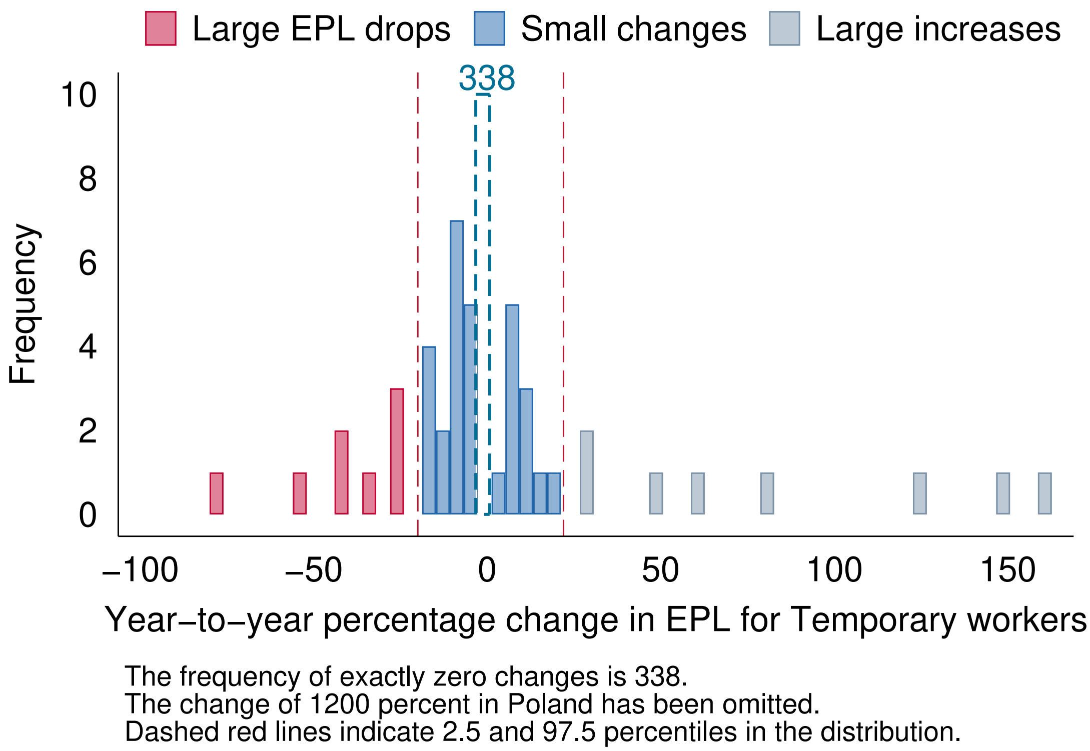


Figure A.2: Frequency distribution of percent EPL changes

Note: The figure shows the frequency of percent yearly changes in the measure of Employment Protection Legislation (EPL) for temporary workers. The frequency of exactly zero changes is represented by the dashed bar. We omitted the 12-fold increase in EPL for Poland in 2003-2004. The graph uses EPL data from 2000 to 2016 for all European countries for which they are available (not just those in the sample). The vertical dashed lines separates small changes (center) from "large EPL drops" (yearly drops in the index larger than 20% of their previous value, on the left) and "large increases" (yearly increases in the index of more than 20%, on the right). Authors' calculations from the OECD Indicators of Employment Protection database.

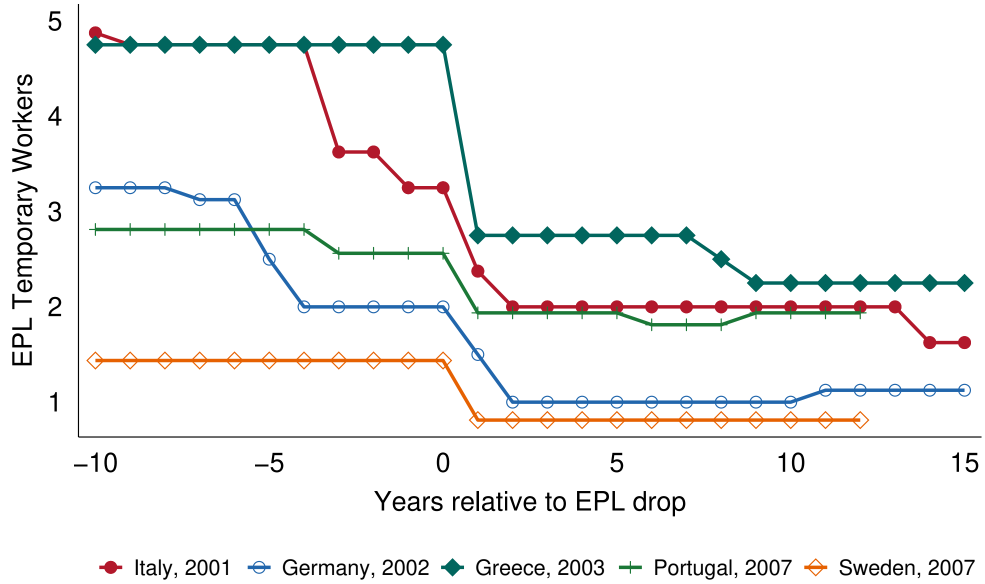


Figure A.3: EPL for temporary workers around Big EPL drop

Note: This figure shows the evolution of the index of strictness of Employment Protection Legislation (EPL) for temporary workers around the event (a large drop in this index). A drop in EPL is considered large if the measure of EPL drops by 20% or more from one year to the next. The figure shows the raw data for the five countries in our sample which experienced a large EPL drop within the sample period (2000-2016). The x-axis is expressed in relative years from the event; the date of the event for each country is indicated in the label.

Table A.3 : Reform episodes corresponding to "large EPL drops"

Country (Year)	Reform	Change in EPL index	Percent change
Italy (2001)	Expanded valid cases for the use of fixed-term contracts (law no. 368/2001).	-0.88	-26.8%
Germany (2002)	Maximum total duration of temporary work agreements was increased to 24 months, any limit to total duration lifted in 2004.	-1	-50%
Greece (2003)	Fixed-term contracts maximum renewals increased.	-2	-42.1%
Portugal (2007)	Maximum permitted assignment to temporary work agencies increased from one to two years.	-0.62	-24.2%
Sweden (2007)	Extension of maximum duration of temporary contracts increased from one to two years.	-0.63	-43.8%

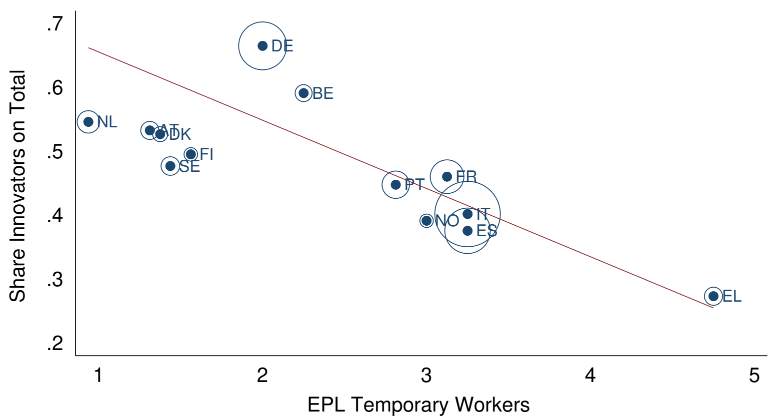
Note: this table reports the reform episodes associated to "large EPL drops" as defined in the text. The sources are OECD (2004) for Italy, Germany and Greece, and Duval et al. (2019) for Portugal and Sweden.

A.4 Descriptive Results

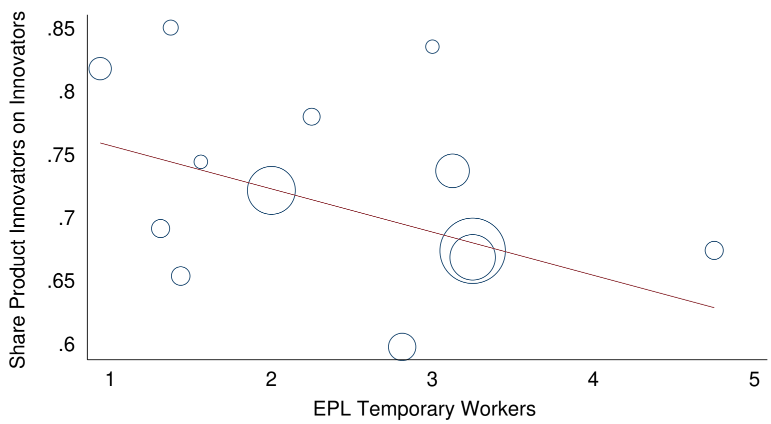
EPL and innovation in the cross-section. Figure A.4 shows how our measure of employment protection correlates with key outcome variables in the first year of our panel (2000). Panel (a) shows a strong negative correlation between employment protection for temporary workers and the share of innovative firms driven by two distinguishable clusters: the northern European countries, such as Netherlands and Germany, with a relatively low level of employment protection and a relatively high share of firms that report carrying out innovation activities; and the southern European countries, with relatively fewer innovators and a higher value for the EPL index.[34] Among firms that engage in any innovation, panels (b) and (c) show that higher employment protection for temporary workers is associated with a relatively low share of firms conducting product innovation and a relatively high share of process innovators, while the converse holds for low-EPL countries. The same patterns are present in all waves of the survey (available upon request), and in the pooled sample, as can be noted from a comparison of columns 1 through 4 with column 5 in Table 1.

[34] An exception to this geographical pattern is Norway, which appears among southern European countries both in terms of EPL and of share of innovators.

(a) Innovators



(b) Product on innovators



(c) Process on innovators

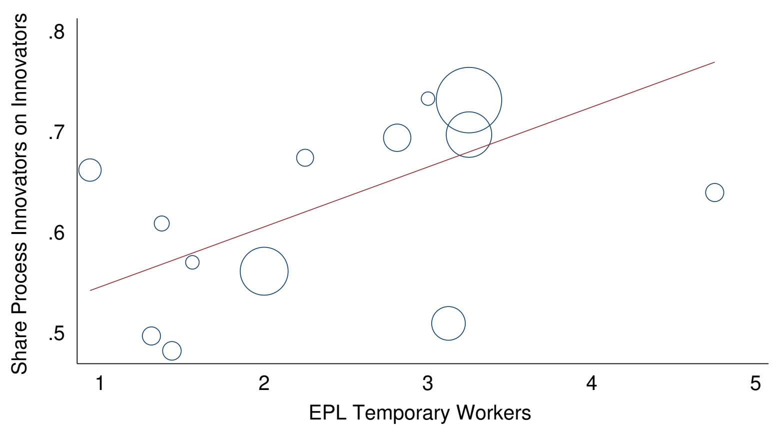


Figure A.4: Correlations between EPL for temporary workers and main CIS variables in 2000

Note: The figure shows the cross-sectional correlations between EPL Temp and the three key outcome variables from the CIS: share of firms that carry out innovation out of all respondents in panel (a), share of innovative firms that engage in product innovation in panel (b), and share of innovative firms that engage in process innovation in panel (c). Data are for the manufacturing sector in the first year of our sample (2000). Observations are weighted by the number of respondent firms in each country.

B Additional Results and Robustness

B.1 Additional Controls

In this appendix, we discuss the addition of flexible covariate-specific time trends to our baseline specification (2), in order to assess the robustness of our findings to the inclusion of further control variables. Namely, we include interactions of year dummies with a set of covariates taken at their value in 2000 (before any of the treatments took place). The covariates we include are (the data sources are detailed in Appendix A.1):

- *Labor market features* in 2000: EPL for individual dismissals; EPL for collective dismissals; EPL for regular workers (weighted average of EPL for individual and collective dismissals); collective bargaining coverage; trade union density; spending on unemployment benefits (% of GDP); spending on active labor market policies (% of GDP); total spending on labor market policies (sum of unemployment benefits and active labor market policies); labor share for the manufacturing sector.

- *Macroeconomic conditions and trade openness* in 2000: Average yearly GDP growth between 1998 and 2000; trade (imports + exports) with Euro area countries (as of 2001)[35] as a share of GDP; trade with accession countries (meaning countries that joined the EU between 2004 and 2013)[36] as a share of GDP.

- *Sectoral composition* in 2000: average potential for automation, constructed as an employment-weighted average (using 2000 employment levels) of the average robot penetration for detailed manufacturing sectors in the US for 2004 (Acemoglu and Restrepo, 2020a);[37] task offshoring at the broad industry level (Autor and Dorn, 2013); average capital-labor ratio for the manufacturing sector.

These controls are not available for all countries in year 2000: Tables B.2 and B.4 indicate the coverage for each variable. Since the sample size does not allow us to include all the covariates at the same time, we proceed as follows.

First, we select a subset of summary variables to include in the diff-in-diff specification (2), chosen to maximize the spectrum of areas and the number of countries covered, while preserving enough degrees of freedom to reliably estimate the parameters of interest. These results are presented in the main text in Table 4.

[35]Euro area countries as of 2001 were: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain.

[36]The countries that joined the European Union between 2004 and 2013 are: Bulgaria, Croatia, Cyprus, Czechia, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia, Slovenia.

[37]We chose to use the US APR to avoid any endogeneity issues with the European measure. We choose 2004 as our reference year, as it is the earliest year reported by Acemoglu and Restrepo (2020b) that features non-negligible robot penetration in most of the sectors according to the IFR classification.

Second, we present results for all and additional variables individually. Results are reported in Tables B.1 and B.3 .

Results

Table B.1 reports the coefficients on the dummies "short run" (≤ 5 years after treatment) and long run (> 5) resulting from the estimation of our diff-in-diff specification (2) with covariate-specific trends for the macro (GDP and trade) and the sectoral composition (automation potential, task offshoring, capital-labor ratio) variables, one by one. Analogously, Table B.3 reports the coefficient estimates when controlling for labor market conditions. The outcome of interest is the ratio of process to product innovation, our main summary measure. In the tables, we indicate the controls included in each specification, and report the number of clusters together with model and residual degrees of freedom. These statistics reveal that the inclusion of interacted controls naturally results in substantial degree of freedom reductions, as well as a sample restrictions due to data availability (we report variable availability for each country in Tables B.2 and B.4). Therefore, we report 90% wild-bootstrap confidence interval to assess the significance of our estimates. All the coefficient estimates remain negative, 10% significant, and generally quantitatively close to the main coefficient estimates.

Table B.1 : Difference-in-differences results for the ratio of process to product innovators, Macro, Trade and Sectoral composition controls

	(1)	(2)	(3)	(4)	(5)	(6)
Short Run	0.031	-0.027	0.019	-0.025	0.010	0.063
	(0.089)	(0.111)	(0.104)	(0.100)	(0.122)	(0.110)
	[−0.248, 0.368]	[−0.339, 0.193]	[−0.343, 0.226]	[−0.223, 0.158]	[−0.283, 0.226]	[−0.399, 0.283]
Long Run	-0.177	-0.267	-0.244	-0.214	-0.188	-0.249
	(0.081)	(0.066)	(0.066)	(0.074)	(0.078)	(0.082)
	[−0.376, −0.029]	[−0.369, −0.107]	[−0.346, −0.103]	[−0.330, −0.039]	[−0.355, 0.001]	[−0.363, −0.019]
Constant	0.807	0.798	0.874	0.783	0.816	0.773
	(0.044)	(0.036)	(0.138)	(0.056)	(0.061)	(0.038)
GDP Growth (av. two years)	3					
Trade with Euro Area		3				
Trade with Accession Countries			3			
Automation potential				3		
Task offshoring					3	
Capital-Labor Ratio						3
Observations	119	119	119	114	114	79
Number of Clusters	18	18	18	17	17	10
Number of Firms	2298051	2298051	2298051	2099149	2099149	1922666
DoF Residual	85	85	85	81	81	53
DoF Model	33	33	33	32	32	25

Note: The dependent variable in all columns is the ratio of process to product innovators. All specifications are weighted by the number of respondent firms and include country and time fixed-effects. Cluster-robust standard errors in parentheses; wild-boostrap 90% confidence intervals in brackets. This table displays the estimates for our baseline diff-in-diff specification controlling for interactions of year dummies with the listed variables. See text for a description and sources for the control variables. “DoF Residual” and “DoF Model” denote the degrees of freedom of the residuals and the model respectively.

Table B.2 : Variable availability for Macro, Trade, and Sectoral composition controls

Country	All controls	GDP Growth (av. two years)	Trade with Euro Area	Trade with Accession Countries	Automation potential	Task offshoring	Capital-Labor Ratio
Austria	3	3	3	3	3	3	3
Belgium	3	3	3	3	3	3	3
Germany	3	3	3	3	3	3	3
Denmark	3	3	3	3	3	3	3
Greece		3	3	3	3	3	
Spain	3	3	3	3	3	3	3
Finland	3	3	3	3	3	3	3
France	3	3	3	3	3	3	3
Iceland		3	3	3	3	3	
Italy	3	3	3	3	3	3	3
Lithuania		3	3	3	3	3	
Luxembourg		3	3	3	3	3	
Latvia		3	3	3	3	3	
Netherlands	3	3	3	3	3	3	3
Norway		3	3	3	3	3	
Portugal		3	3	3	3	3	
Sweden	3	3	3	3	3	3	3
Turkey		3	3	3			

Note: This table displays the availability for each variable and country in the benchmark year 2000. “All controls” denotes the joint availability of all the variables in the subsequent columns.

Table B.3 : Labor Market controls, one by one

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Short Run	-0.120	0.023	0.030	-0.037	-0.026	-0.034	0.105	0.019	0.057
	(0.107)	(0.130)	(0.137)	(0.099)	(0.089)	(0.090)	(0.089)	(0.155)	(0.088)
	[−0.351, 0.113]	[−0.332, 0.233]	[−0.323, 0.284]	[−0.273, 0.155]	[−0.213, 0.156]	[−0.203, 0.154]	[−0.129, 0.290]	[−0.401, 0.250]	[−0.250, 0.325]
Long Run	-0.225	-0.218	-0.159	-0.235	-0.194	-0.209	-0.092	-0.254	-0.238
	(0.059)	(0.056)	(0.062)	(0.074)	(0.084)	(0.080)	(0.064)	(0.048)	(0.077)
	[−0.323, −0.092]	[−0.332, −0.115]	[−0.296, −0.063]	[−0.348, −0.058]	[−0.329, 0.046]	[−0.336, −0.005]	[−0.229, −0.001]	[−0.329, −0.148]	[−0.348, −0.011]
Constant	0.772	0.792	0.806	0.762	0.798	0.783	0.769	0.791	0.777
	(0.036)	(0.043)	(0.048)	(0.062)	(0.055)	(0.058)	(0.041)	(0.038)	(0.050)
EPL collective	3								
EPL regular		3							
EPL total			3						
Active LMP spending				3					
Unemployment spending					3				
Total LMP spending						3			
CB coverage							3		
Trade union Density								3	
Labor Share									3
Observations	106	106	106	101	106	101	90	95	103
Number of Clusters	14	14	14	13	14	13	13	13	15
Number of Firms	2283908	2283908	2283908	2085006	2086551	2085006	1719133	2149570	2071147
DoF Residual	76	76	76	72	76	72	61	66	72
DoF Model	29	29	29	28	29	28	28	28	30

Note: Cluster-robust standard errors in parentheses; wild-boostrap 90% confidence intervals in brackets. All specifications are weighted by the number of respondent firms and include country and time fixed-effects. This table displays the estimates for our baseline diff-in-diff specification controlling for interactions of year dummies with the listed variables. See text for a description and sources for the control variables. “DoF Residual” and “DoF Model” denote the degrees of freedom of the residuals and the model respectively.

Table B.4 : Labor Market controls, variable availability

Country	All controls	EPL collective	EPL regular	EPL total	Active LMP spending	Unemployment spending	Total LMP spending	CB coverage	Trade union Density	Labor Share
Austria	3	3	3	3	3	3	3	3	3	3
Belgium	3	3	3	3	3	3	3	3	3	3
Germany	3	3	3	3	3	3	3	3	3	3
Denmark	3	3	3	3	3	3	3	3	3	3
Greece		3	3	3	3	3	3	3		3
Spain		3	3	3	3	3	3		3	3
Finland	3	3	3	3	3	3	3	3	3	3
France		3	3	3	3	3	3		3	3
Iceland								3	3	
Italy	3	3	3	3	3	3	3	3	3	3
Lithuania										3
Luxembourg						3		3		3
Latvia										3
Netherlands	3	3	3	3	3	3	3	3	3	3
Norway		3	3	3	3	3	3		3	
Portugal		3	3	3	3	3	3	3		3
Sweden	3	3	3	3	3	3	3	3	3	3
Turkey		3	3	3				3	3	

Note: This table displays the availability for each variable and country in the benchmark year 2000. “All controls” denotes the joint availability of all the variables in the subsequent columns.

B.2 Sectoral Composition

In our baseline analysis, we are unable to account for compositional shifts across detailed manufacturing subsectors. CIS data does not provide us with disaggregated data for the 2000 wave, which constitutes the pre-period for Italy and Germany. In this appendix, we gauge the role of sectoral shifts in the observed increase in product innovators and decrease in process-only innovators, using data on employment and value added by subsectors of manufacturing from EUKLEMS (Stehrer et al., 2019; Adarov and Stehrer, 2019) to conduct three analyses. First, we estimate directly whether the large drops in EPL were followed by a substantial sectoral reallocation, using our static specification with sector shares as the outcome variable, and find little evidence of substantial reallocation. Second, we include the shares in 2000 for the three sectors with significant changes as controls in specification (2), and this does not alter our coefficient estimates significantly. Third, we employ the estimated coefficients from the first exercise to provide some back-of-the-envelope estimates of the effect of changes in sectoral composition on reallocation of innovation activity. Our results suggest that the small sectoral shifts that followed large EPL drops can only account for a fraction of the changes in innovation activity that we report in the main text.

Changes in manufacturing composition. EUKLEMS provides data on employment and value added for twelve subsectors of manufacturing, for the entire period of analysis and all countries in our main sample except Iceland, Norway and Turkey. These subsectors correspond to groupings of 1 to 3 different level 2 NACE rev. 2 codes (e.g. “Food”' groups codes 10, 11 and 12, corresponding to food, beverages and tobacco products manufacturing, respectively).

For each subsector, we run specification (2), where the outcome variable is in turn the fraction of employment or value added in the subsector over the manufacturing total.

Figure B.1 displays the results for the share of employment (top panel), and value added (bottom panel). Qualitatively, the two panels report similar estimates, though value added estimates appear more volatile. Most coefficients are statistically indistinguishable from zero, and point estimates are relatively small for the only three sectors with significant coefficient estimates in at least one of the two specifications (Chemical-Pharmaceutical, Electronics, and Transport equipment). Overall, these results suggest that large EPL drops were not associated with large shifts in the sectoral composition of manufacturing.

Controlling for initial sector shares. For the three sectors with significant coefficient estimates in the previous exercise, we take their share in manufacturing in the year 2000 and interact it with yearly dummies. We include these as controls in specification (2), and display the results in Table B.5 . Both when including them one-by-one and all together the coefficient estimates remain close to the baseline and significant.

Contribution of sectoral changes to the reallocation of innovation activity. We use the estimates of changes in sectoral composition following a drop in EPL discussed above to compute the contribution of sectoral composition to the observed reallocation of innovation activity.

We proceed in two steps. First, we compute the sectoral shares in manufacturing following a drop in EPL by summing initial shares and the estimated changes presented in Figure B.1. Second, we use these shares as weights to average the shares of product and process innovators across manufacturing subsectors. The resulting measures allow us to compute the changes in process and product innovation arising from sectoral shifts that followed our event.

Due to data availability, we are forced to make two assumptions to measure the quantities needed for this exercise. First, we proxy employment and value added shares in CIS data by the share of firms active in each manufacturing subsector.[38] Second, we use the share of process and product innovators for each subsector in 2000 from available CIS microdata as our estimate for the corresponding measure in aggregate data.

We provide two sets of calculations, corresponding to different assumptions on the type of innovation conducted by the firms entering and exiting each sector.

First, we assume that firms that enter and exit each subsector are representative of the average firm in that subsector. That is, their probability of conducting each type of innovation equals the average share of innovators in that innovation activity and subsector. The results are summarized in the top panel of Table B.6 . Under this assumption, the implied change in the share of product or process innovators and in their ratio is between 0.1 and 0.4 pp in absolute value (sometimes even with the "wrong" sign), tiny compared to our estimates that range from 5 to 25 pp in absolute value, regardless of whether we use all estimated sectoral shifts (columns 1 and 2) or we restrict to the three sectors with significant estimates (columns 3 and 4). Columns 5 and 6 report the results of this exercise when we use confidence interval bounds instead of point estimates for changes in sectoral composition. For each subsector, we choose the confidence interval's bound that maximizes the change in the outcomes of interest, in the same direction as our baseline estimates. In this sense, columns 5 and 6 report the results that take to the extreme the possible contribution of sectoral changes to the reallocation of innovation activity. Even in this scenario, the implied decrease in the ratio

[38] There is no value added and employment is only available in very broad bins.

of process to product innovation is no greater than 2.2 pp, more than ten times smaller than our estimated effect of 25.1 pp.

Second, we restrict our attention to significant sectoral shifts and we assume that all the firms that exit are process innovators only and all the firms that enter are product innovators only. We use this extreme assumption to provide an upper bound of the effects of sectoral shifts on our baseline results. The results from this exercise are reported in the lower panel of Table B.6 . Point estimates from the value added specification in column 4 (which reports more extreme shifts than the employment specification) imply an increase in the fraction of product innovators of 1.8 pp (compared to our estimate of 9.7 pp) and a decrease in the process to product ratio of 7.7 pp (our estimate is 25.1 pp). Even using confidence interval boundaries as discussed above (column 6), the implied increase in the fraction of product innovators is only about a third of our baseline, and the implied decrease on the process to product ratio is less than 60% of our estimate.

Taken together, these pieces of evidence suggest that changes in sectoral composition following big EPL drops are unlikely to be the main driver of the observed changes in innovation activity.

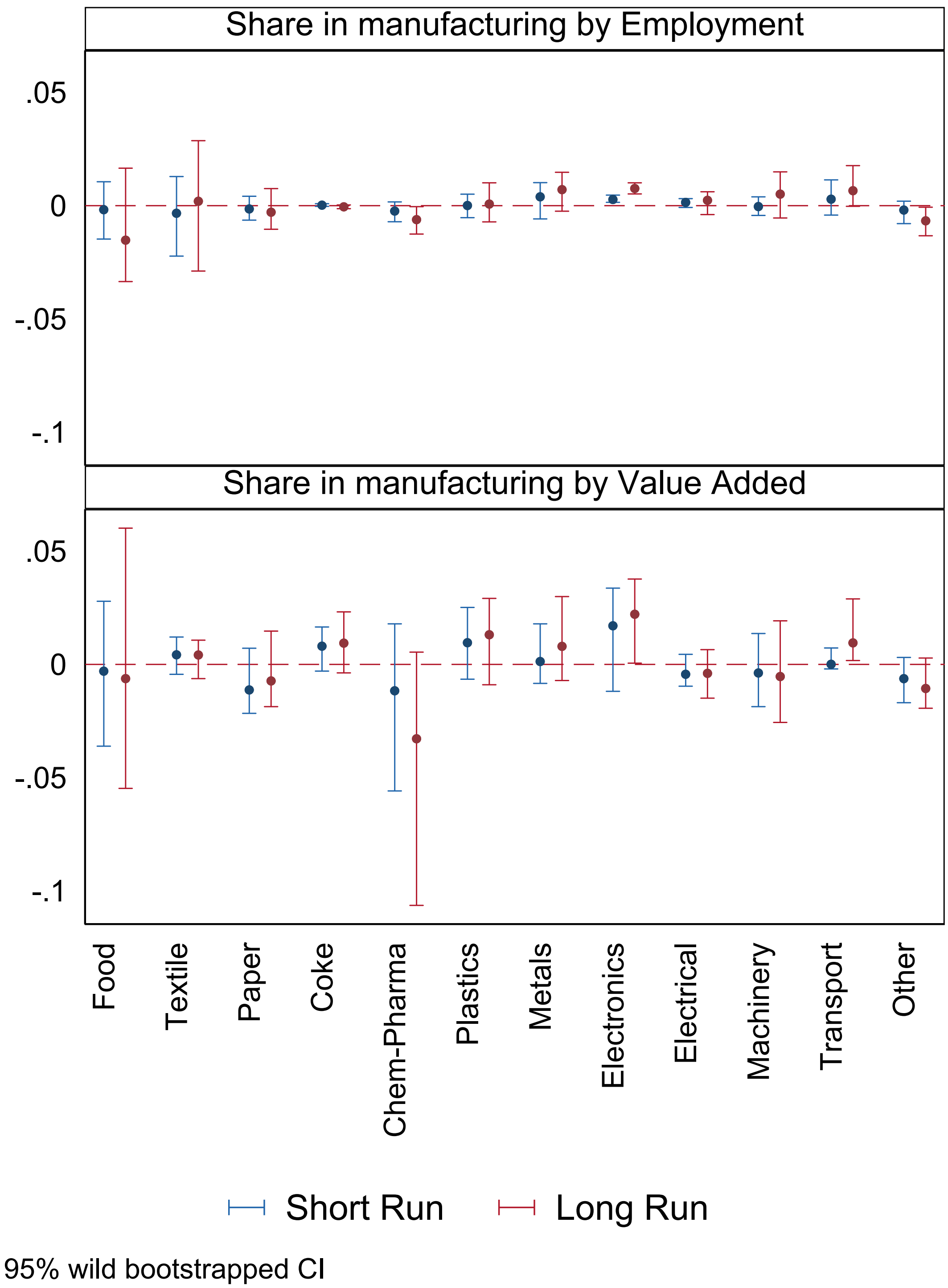


Figure B.1: Diff-in-diff results for sectors' share in manufacturing

Note: For each of the subsectors in manufacturing, we estimate specification (2) using as outcome variable the subsector's share of manufacturing employment (upper panel) or value added (lower panel). The figure shows the coefficients on the "short run" (blue, on the left) and "long run" (red, on the right) dummies, and the corresponding wild-bootstrap 95% confidence intervals.

Table B.5 : Difference-in-differences results for the ratio of process to product innovators, including sectoral composition controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Short Run	-0.081	-0.016	-0.042	-0.017	-0.033	-0.048	-0.017
	(0.131)	(0.116)	(0.113)	(0.083)	(0.117)	(0.107)	(0.084)
	[−0.392, 0.306]	[−0.291, 0.185]	[−0.324, 0.186]	[−0.193, 0.139]	[−0.310, 0.179]	[−0.321, 0.144]	[−0.236, 0.157]
Long Run	-0.306	-0.218	-0.245	-0.246	-0.233	-0.251	-0.255
	(0.068)	(0.078)	(0.078)	(0.067)	(0.077)	(0.074)	(0.062)
	[−0.406, −0.030]	[−0.370, −0.013]	[−0.365, −0.077]	[−0.345, −0.051]	[−0.382, −0.060]	[−0.359, −0.060]	[−0.340, −0.066]
Constant	0.670	0.774	0.786	0.762	0.761	0.781	0.762
	(0.066)	(0.062)	(0.043)	(0.052)	(0.060)	(0.039)	(0.045)
Chem-Pharma emp. share	3	3					
Electronics emp. share	3		3				
Transport emp. share	3			3			
Chem-Pharma VA share	3				3		
Electronics VA share	3					3	
Transport VA share	3						3
Observations	98	103	98	98	103	98	98
Number of Clusters	14	15	14	14	15	14	14
Number of Firms	2069602	2071147	2069602	2069602	2071147	2069602	2069602
DoF Residual	33	72	68	68	72	68	68
DoF Model	64	30	29	29	30	29	29

Note: The dependent variable in all columns is the ratio of process to product innovators. All specifications are weighted by the number of respondent firms and include country and time fixed-effects. Cluster-robust standard errors in parentheses; wild-boostrap 90% confidence intervals in brackets. This table displays the estimates for our baseline diff-in-diff specification controlling for interactions of year dummies with the listed variables. “DoF Residual” and “DoF Model” denote the degrees of freedom of the residuals and the model respectively.

Table B.6 : Changes in innovation activity implied by sectoral reallocation (in pp)

	Changes implied by sectoral reallocation						Estimated changes	
	All sectors Point estimates		Only sectors w. significant changes Point estimates		Only sectors w. significant changes CI bounds			
	EMP (1)	VA (2)	EMP (3)	VA (4)	EMP (5)	VA (6)	Coeff. (7)	[95% CI] (7)
	Panel A: representative firms							
Share Innovators on Total	0.2	-0.1	0.0	-0.2	0.0	-1.5	6.1	[-2.3, 12.2]
Share Process Innovators on Innovators	-0.1	-0.2	-0.1	-0.2	-0.1	0.2	-5.1	[-16.4, 4.7]
Share Product Innovators on Innovators	0.2	-0.3	0.1	-0.2	0.1	-1.6	9.7	[0.5, 17.2]
Process to Product Ratio	-0.4	0.1	-0.3	0.0	-0.2	2.2	-25.1	[-35.3, -7.4]
	Panel B: entries (exits) are product (process) innovators							
Share Innovators on Total			1.3	3.0	2.7	6.5	6.1	[-2.3, 12.2]
Share Process Innovators on Innovators			-2.0	-4.3	-3.8	-8.3	-5.1	[-16.4, 4.7]
Share Product Innovators on Innovators			0.9	1.8	1.6	3.4	9.7	[0.5, 17.2]
Process to Product Ratio			-3.8	-7.7	-6.9	-14.6	-25.1	[-35.3, -7.4]

Note: The table shows the long-run changes in innovation activity implied by sectoral reallocation within manufacturing. These back-of-the-envelope calculations use the share of (product/process) innovators in the year 2000 by subsector from the CIS microdata, to which we apply the estimated long-run changes from Figure B.1. Columns 1, 3, and 5 use the estimated coefficients and confidence intervals from the employment specification (top panel of Figure B.1), while columns 2, 4, and 6 from the value added specification (bottom panel). Columns 1 and 2 use estimated coefficients for all sectors, while columns 3 through 6 focus on the sectors for which we estimate a significant coefficient in at least one of the specifications (Chemical-Pharmaceutical, Electronics, and Transport equipment) and assume no change in the other sectors. Columns 3 and 4 use the point estimates, while columns 5 and 6 the value within the confidence interval generating the largest change in the direction of our baseline estimates (lower bound for Chem-Pharma, upper bounds for Electronics and Transport). Panel A assumes that firms that enter and exit sectors are representative of the sector, i.e. they have the same likelihood to be process/product innovators as the general sector in 2000. Panel B assumes that all the firms that exit from Chem-Pharma are process innovators only and all the firms that enter in Electronics and Transport are product innovators only. Column 7 reports the estimates and confidence intervals from our main specification (from Table 3) for reference.

B.3 Treatment Effect Heterogeneity

In what follows, we focus on the ratio of process innovators to product innovators, a measure that neatly summarizes the reallocation across different innovation activities, and that fully characterizes the equilibrium of the model.

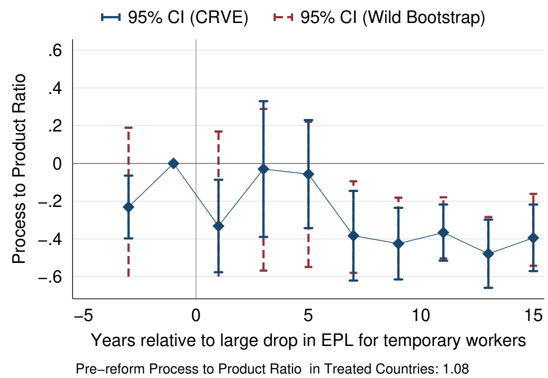
Figure B.2 shows that that the effect of weakening EPL on the process-product innovators ratio is strongest for small firms (10-49 employees), and decreases with size. In particular, our point estimates reveal a sizable and persistent reduction of more than 35% of the pre-period average for small firms. By contrast, medium-sized firms (50-250 employees) only see a 20% decline in the process-product innovators ratio, which is not significant in the long-run. Large firms (250+ employees) see no significant changes in this measure. These findings are consistent with larger firms being less affected by the rigidity of individual employment relation, as they have access to collective dismissals that significantly reduce the costs and burdens on firing firms.[39] Another possible explanation for this heterogeneity stems from the fact that we can only measure the extensive margin of innovation. Larger firms are more likely to have the resources to pursue different types of innovation, so the effects of a reform would predominantly occur along the intensive margin.

Due to the aggregate nature of our data, we are unable to observe changes in individual firm sizes. It is therefore possible that our baseline findings are driven by a general increase in firm size, which is negatively correlated with the process/product innovation ratio. However, Figure B.2 shows that both medium and small firms reduce their efforts in process innovation relative to product innovation, suggesting that this size channel is unlikely to be the sole driver of our results.

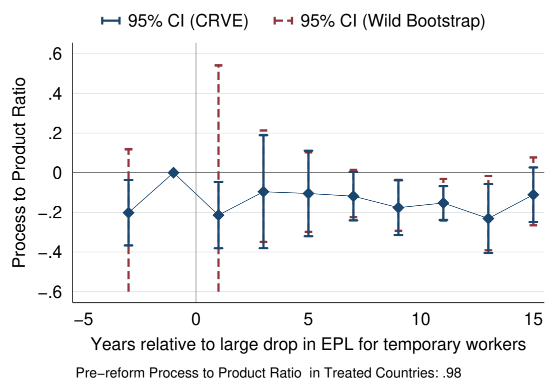
The other two heterogeneity results group treated countries by initial starting EPL (Figure B.3) and size of the drop in EPL (Figure B.4). In the first exercise, we split countries by their initial EPL level, so that we compare high(low)-EPL treated countries to high(low)-EPL control countries. In the second exercise, we split treated countries according to whether the size of the drop is high or low relative to the rest of the treated group, and compare them to all control countries. We then run separate regressions for each of these four groups. Partitioning restricts the size of the treatment group, so the reported coefficients should be interpreted with caution, and are estimated more imprecisely. With this caveat in mind, Figure B.3 suggests that labor market reforms have a sizable and significant effect on innovative activities only when starting EPL is high. Figure B.4 highlights that, in our treatment group, only the relatively large EPL reductions—more drastic reforms—induce a reallocation of innovation.

[39]For a comprehensive review on collective dismissals, see Aleksynska and Muller (2020).

(a) Less than 50 employees



(b) Between 50 and 250 employees



(c) More than 250 employees

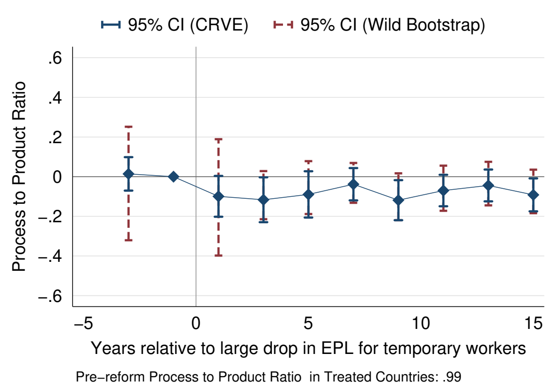


Figure B.2: Treatment heterogeneity by firm size: process to product innovators ratio.

Note: The panels in the figure plot the coefficients κ_e from regression (1). The outcome is the ratio of process innovators to product innovators. The treatment is a big drop in EPL for temporary workers. See note to Figure 3 for details. Panel (a) restricts the sample to firms with 10-49 employees at the time of the survey, panel (b) to firms with 50 to 249 employees, panel (c) to firms with more than 250 employees.

(a) High starting EPL

(b) Low starting EPL

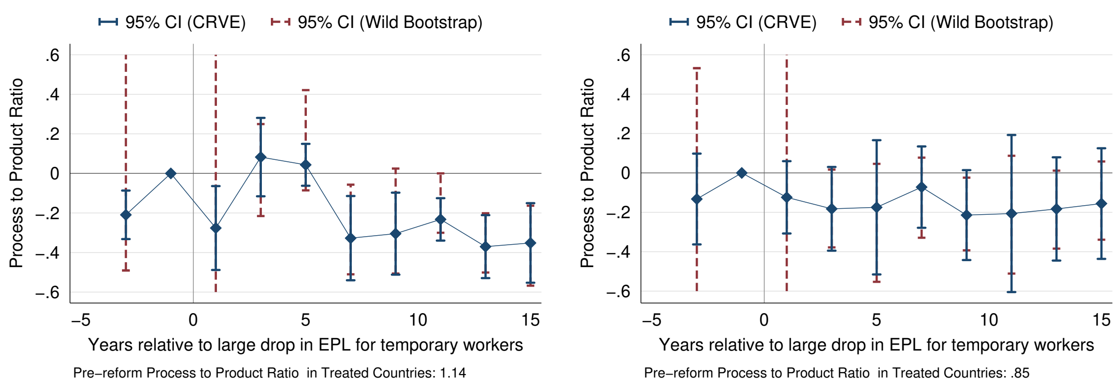


Figure B.3: Treatment heterogeneity by starting EPL level

Note: The panels in the figure plot the coefficients κ_e from regression (1). The outcome is the ratio of process innovators to product innovators. The treatment is a big drop in EPL for temporary workers. See note to Figure 3 for details. Both panels only use countries for which data on EPL for temporary workers is available for the year 2000 (all except for Turkey, Luxembourg, Iceland, Latvia, Lithuania). Panel (a) restricts the sample to countries with EPL for temporary workers in 2000 above median, while panel (b) below median. Thus the countries in panel (a) are Greece (EPL Temp in 2000: 4.75), Italy (3.25), Portugal (2.81) as treated and Spain (3.25), France (3.13), Norway (3), Belgium (2.25) as controls. Countries in panel (b) are Germany (2), Sweden (1.44) as treated, and Finland (1.56), Denmark (1.38), Austria (1.31), Netherlands (0.94) as controls.

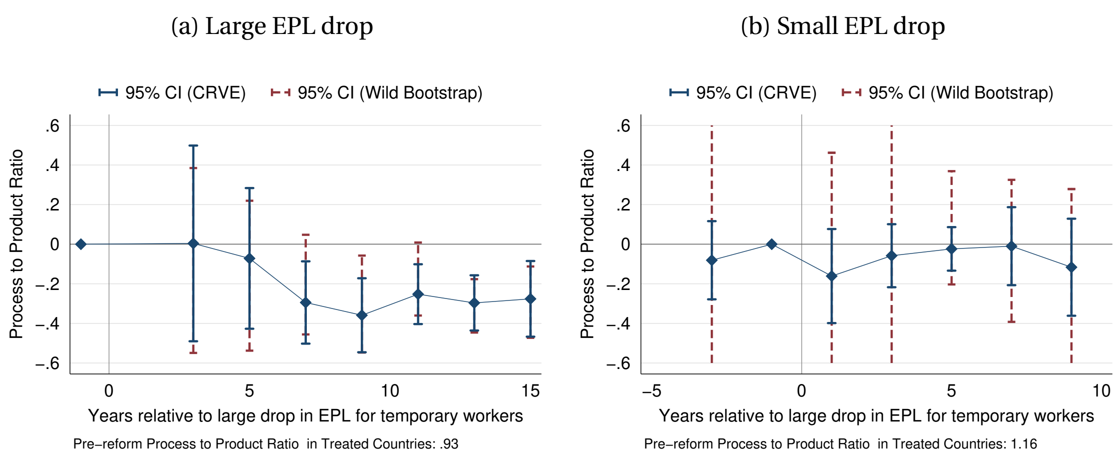


Figure B.4: Treatment heterogeneity by size of EPL drop

Note: The panels in the figure plot the coefficients κ_e from regression (1). The outcome is the ratio of process innovators to product innovators. The treatment is a big drop in EPL for temporary workers. See note to Figure 3 for details. Both panels drop countries for which we have some missing observations (Greece, Denmark, Iceland, Latvia, Turkey), but otherwise keep all the control countries. Panel (a) restricts the sample to treated countries where the big drop in EPL is relatively large (Germany, -1.25, and Italy, -1, between 2000 and 2004) while panel (b) to treated countries where the drop in EPL is relatively small (Portugal and Sweden, both -0.63 between 2006 and 2008).

B.4 Different Samples

We modify the baseline sample in two types of robustness exercises. First, we expand the sample of firms to include all sectors (in addition to manufacturing). As shown in Figure B.5, all our results carry over, and are of the same absolute and percentage magnitudes as in our baseline.

Second, we limit the sample to two panels of eleven countries each, balanced around the time of the event. Indeed, Table B.7 shows that we do not observe the same periods around the treatment date for the entire group of treated countries. Motivated by these patterns, we analyze separately the Germany-Italy and the Portugal-Sweden episodes in Figures B.6 and B.7. While the results are qualitatively unaffected by this partition, we can see that the event-study coefficients for the Portugal-Sweden episode are small and non-significant, while those for Italy and Germany are large and statistically significant for the same outcomes as the general results. To understand this result, note that this partition of the sample actually corresponds to the heterogeneity presented in Figure B.4: Germany and Italy were subject to a sizable reduction in EPL, while Portugal and Sweden passed less radical reforms, as is apparent from Figure A.3.

Table B.7 : Observations for treated countries relative to treatment

Relative Year	Germany	Greece	Italy	Portugal	Sweden	Total
-7	0	0	0	1	1	2
-3	0	1	0	1	1	3
-1	1	0	1	1	1	4
1	0	1	0	1	1	3
3	1	1	1	1	1	5
5	1	0	1	1	1	4
7	1	0	1	1	1	4
9	1	1	1	1	1	5
11	1	1	1	0	0	3
13	1	1	1	0	0	3
15	1	0	1	0	0	2
Total	8	6	8	8	8	38

Note: This table reports the years in which we have observations for each of the treated countries relative to the year of the event (big drop in EPL).

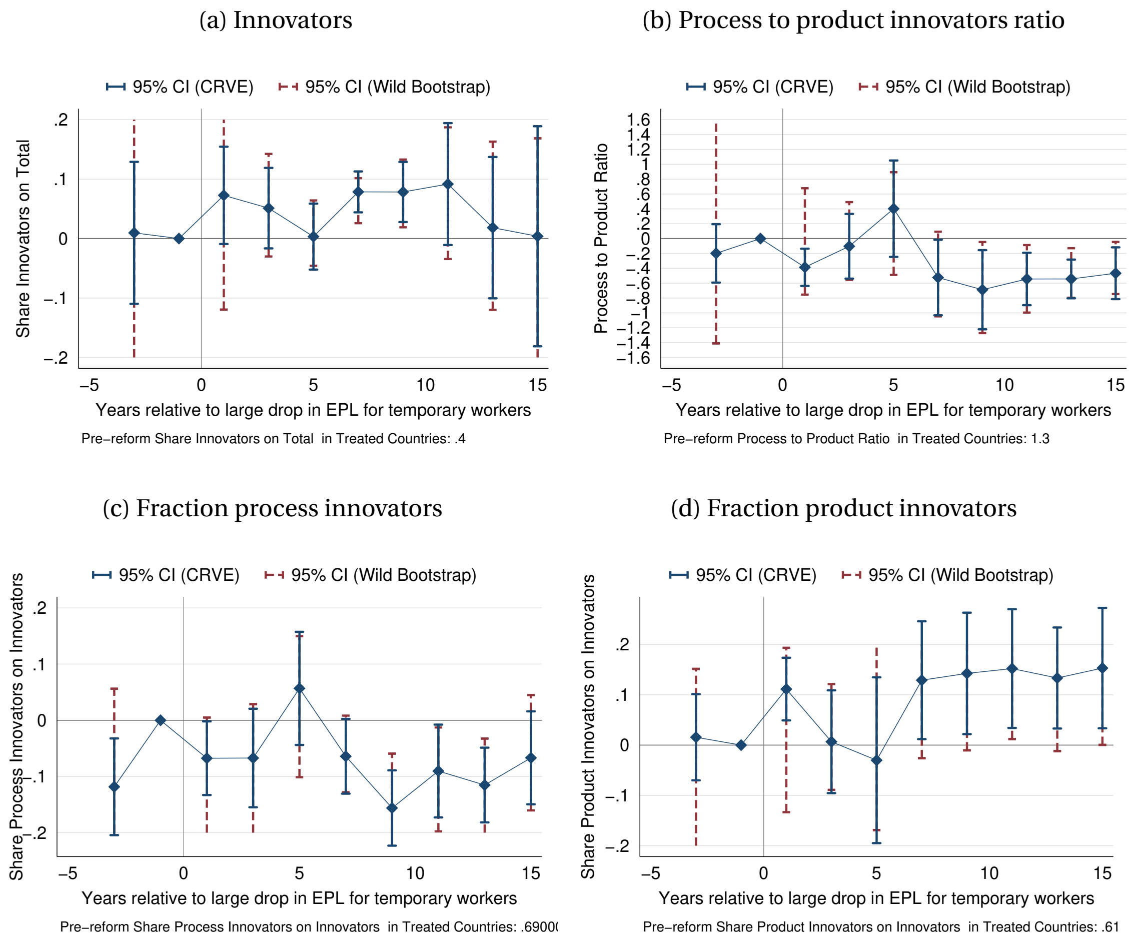
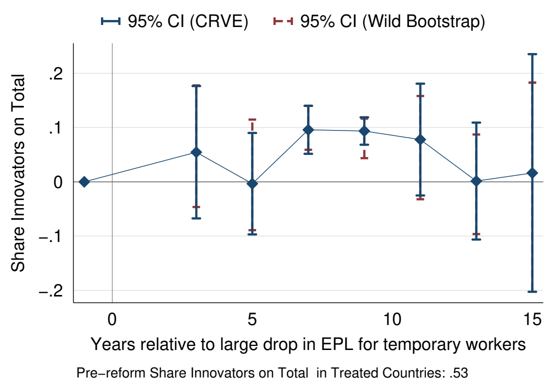


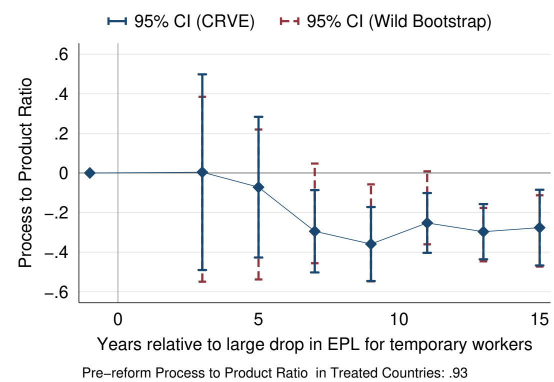
Figure B.5: Robustness to using all sectors

Note: The panels in the figure plot the coefficients κ_e from regression (1), except that country and time fixed effects are replaced by country-by-sector and time-by-sector fixed effects. The sample includes all sectors available. The treatment is a big drop in EPL for temporary workers. See note to Figure 3 for details.

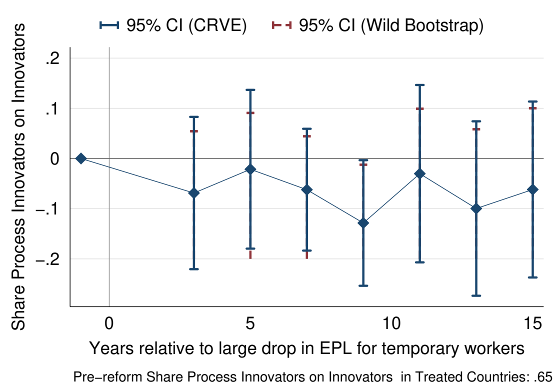
(a) Innovators



(b) Process to product innovators ratio



(c) Fraction process innovators



(d) Fraction product innovators

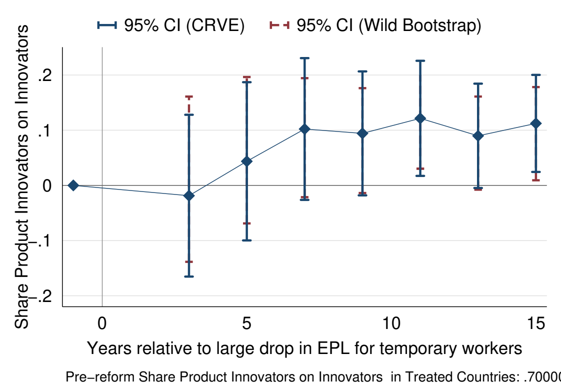
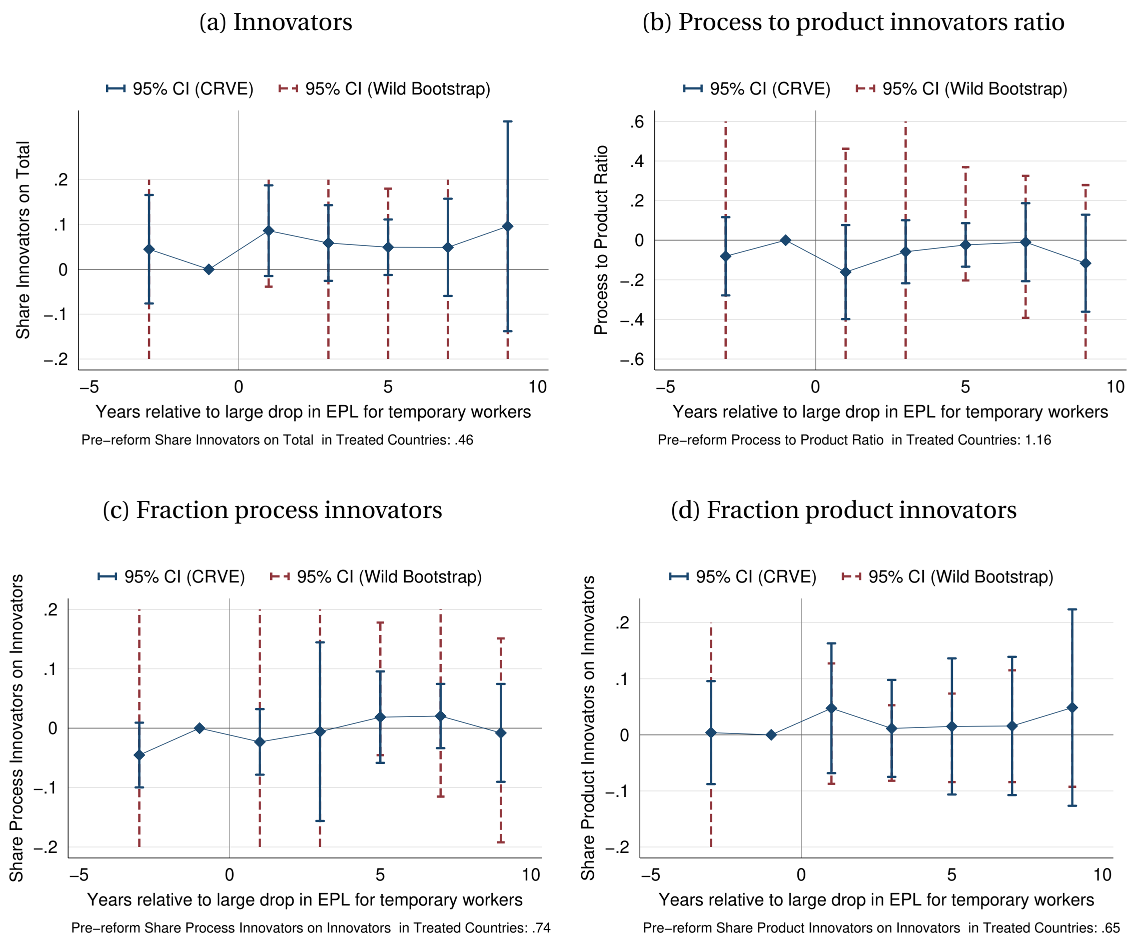


Figure B.6: Robustness to balancing the panel. Germany and Italy as treated countries.

Note: The panels in the figure plot the coefficients κ_e from regression (1). The treatment is a big drop in EPL for temporary workers. See note to Figure 3 for details. The sample is restricted to treated countries that we observe in year -1 and then in all odd years from 3 to 15 relative to the treatment year (Italy and Germany). See Table B.7 for availability of observations for the treated countries. These correspond to the countries that experience a large EPL drop (see note to Figure B.4). Among the control countries, we restrict to those that we observe for all eight waves (i.e. we drop Denmark, Turkey, Latvia and Iceland).



(a) Innovators

(b) Process to product innovators ratio

(c) Fraction process innovators

(d) Fraction product innovators

Figure B.7: Robustness to balancing the panel. Portugal and Sweden as treated countries.

Note: The panels in the figure plot the coefficients κ_e from regression (1). The treatment is a big drop in EPL for temporary workers. See note to Figure 3 for details. The sample is restricted to treated countries that we observe in year -7 and then in all odd years from -3 to 9 relative to the treatment year (Portugal and Sweden). See Table B.7 for availability of observations for the treated countries. These correspond to the countries that experience a small EPL drop (see note to Figure B.4). Among the control countries, we restrict to those that we observe for all eight waves (i.e. we drop Denmark, Turkey, Latvia and Iceland).

B.5 EPL for Regular Workers

In this appendix, we verify the robustness of our results to controlling for employment protection for regular workers, and discuss the alternative use of EPL for regular workers (individual and collective dismissals) to define treatment. We perform two sets of exercises. First, we run our main specification, which uses a drop in EPL temp for the definition of treatment, dropping countries that experience a large drop in EPL for regular workers over the sample period (Table B.9) or controlling flexibly for event-time dummies around drops in regular EPL (Table B.10). Second, we run our event-study regression using as event in turn a drop in EPL for regular workers (Figure B.8(a)) and any EPL drop (Figure B.8(b)).

Variable Construction

In the main analysis, the measure of employment protection we use (EPL Temp) is the index of "Strictness of hiring regulation for workers on temporary contracts". In the robustness exercises, the index of Employment Protection Legislation for regular workers (henceforth, EPL Total) we use is the index of "Strictness of dismissal regulation for workers on regular contracts (both individual and collective dismissals)". More details can be found in Appendix A.1.

For both EPL Temp and EPL Total, we select as the threshold for "large drops" the 2.5 percentile in the distribution of yearly percentage changes across European countries in the sample period, 2000 to 2016. For EPL Temp, this corresponds to a drop of 20%, while for EPL Total the corresponding figure is a drop of 10%. After excluding countries that experience a large increase in EPL Temp during the sample period (as explained in the sample selection, Section 1.3), we are left with five countries treated according to each of these measures. The countries and the corresponding year of large EPL drop are summarized in Table B.8 . For countries in which the event fell in an even year, we assigned the previous odd year as treatment, in order to conform to the biannual nature of the CIS data. In the main analysis (EPL Temp), this only affects Germany, which experienced a large drop in EPL in 2002 but to which we assign 2001 as the year of treatment. For EPL Total, this shifts the treatment for Greece and Spain.

For positive changes, we utilize a symmetric approach: we use the same threshold in absolute value (a yearly percentage change of 20% for EPL Temp and of 10% for EPL Total) and identify as large positive changes yearly percentage changes greater than that amount. For EPL Temp, this corresponds to the 97.5 percentile in the distribution of yearly percentage changes. As explained in the main body of the paper, these changes belong to countries that we drop from our main specification. By contrast, no change in EPL Total meets the criterion to be identified as large positive change, reflecting the fact that during the sample period changes in EPL for regular workers were rare, small, and relatively large ones were aimed at liberalizing the market rather than constraining it further.

Changes in EPL

In the main text, we argued that EPL for regular workers was mostly stable in Europe during the sample period - the changes were few and small on average. Indeed, when considering the distribution of yearly percentage changes, the mean is 0.5% and the standard deviation is 2.4 pp, while the corresponding figures for the EPL for temporary workers are 4% and 65.5 pp.

Results

In order to show that our results are not driven by underlying changes in EPL for regular workers, we run the diff-in-diff specification (2) excluding the five countries that experienced a large drop in EPL for regular workers during the sample period. These countries are Italy, Greece, and Portugal (treated), and Spain and Denmark (control). The estimated coefficients are reported in Table B.9 . We also run an alternative specification in which, rather than excluding the countries that experienced a large drop in EPL Total, we include as controls event-time dummies relative to the drop in EPL Total, which allows us to flexibly control for the evolution of the outcomes of interest around this alternative treatment. The estimated coefficients are reported in Table B.10 . As can be noted by comparing these tables with Table 3 in the main text, estimates are largely unaffected, both in their magnitude and in their significance.

Figure B.8 reports the coefficients on the relative-time dummies from specification (1), using the ratio of process to product innovation as outcome. In panel (a) treatment is a large drop in EPL Total, while in panel (b) the treatment year is defined as the earlier between the year of drop in EPL Temp and the year of drop of EPL Total. In panel (a) we see no movement in the process to product innovation ratio around a drop in EPL Total. Note that this is almost identical to panel (b) in Figure B.4, where we had restricted the treated countries to those that had experienced a relatively smaller drop in EPL Temp. We interpret this evidence as suggesting that even relatively large drops in EPL Total were not large enough to trigger the reallocation of innovation activity from process to product innovation observed following the (much larger) drops in EPL Temp. Accordingly, panel (b) shows that, when using both measures, the evolution of the outcome of interest mirrors that of the main specification.

Table B.8 : Big EPL drop events

Country	Year drop in EPL Temp	Year drop in EPL Total
Germany	2001	.
Denmark	.	2005
Greece	2003	2009
Spain	.	2011
Italy	2001	2015
Portugal	2007	2011
Sweden	2007	.

Note: Year of large EPL drop by country. A negative change in EPL is considered large if it is in the bottom 2.5% in the distribution of yearly changes in the sample period; this corresponds to negative changes larger than 20% in absolute value for EPL Temp and than 10% for EPL Total. In order to conform to the biannual nature of the CIS data, for countries in which the drop took place in an even year, we assigned the previous odd year.

Table B.9 : Main results excluding countries with big drops in EPL Total

	(1) Share Innovators on Total	(2) Share Product Innovators on Innovators	(3) Share Process Innovators on Innovators	(4) Process to Product Ratio
Short Run	0.056	0.039	-0.094	-0.179
	(0.042)	(0.029)	(0.058)	(0.103)
	[−0.020, 0.160]	[−0.009, 0.125]	[−0.247, 0.097]	[−0.488, 0.006]
Long Run	-0.029	0.013	-0.129	-0.204
	(0.029)	(0.022)	(0.059)	(0.090)
	[−0.115, 0.034]	[−0.029, 0.071]	[−0.236, 0.018]	[−0.359, 0.024]
Constant	0.523	0.771	0.633	0.813
	(0.019)	(0.019)	(0.048)	(0.064)
N	82	82	82	82
Number of Clusters	13	13	13	13
Number of Firms	1193721	1193721	1193721	1193721

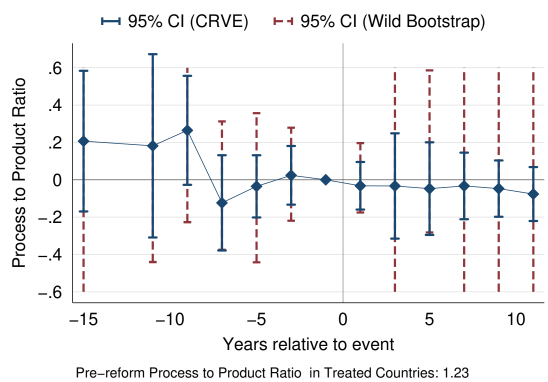
Note: This table reports the estimated coefficients of the diff-in-diff specification (2). Relative to the main specifcation, here we drop countries experiencing large drops in EPL Total during the sample period (Italy, Greece, Portugal, Spain and Denmark). Treated countries are Germany and Sweden.

Table B.10 : Main results controlling for big drops in EPL Total

	(1) Share Innovators on Total	(2) Share Product Innovators on Innovators	(3) Share Process Innovators on Innovators	(4) Process to Product Ratio
Short Run	0.058	0.072	-0.011	-0.133
	(0.028)	(0.049)	(0.061)	(0.132)
	[−0.013, 0.111]	[−0.219, 0.191]	[−0.137, 0.092]	[−0.457, 0.324]
Long Run	0.047	0.094	-0.044	-0.256
	(0.042)	(0.047)	(0.068)	(0.113)
	[−0.059, 0.131]	[−0.048, 0.186]	[−0.164, 0.089]	[−0.459, 0.011]
Constant	0.561	0.841	0.664	0.705
	(0.025)	(0.042)	(0.042)	(0.069)
N	119	119	119	119
Number of Clusters	18	18	18	18
Number of Firms	2298051	2298051	2298051	2298051

Note: This table reports the estimated coefficients of the diff-in-diff specification (2) including as controls flexible event-time dummies around a large drop in EPL Total.

(a) Event is drop in EPL for regular workers



(b) Event is earliest drop in EPL, either of EPL for temporary or for regular workers

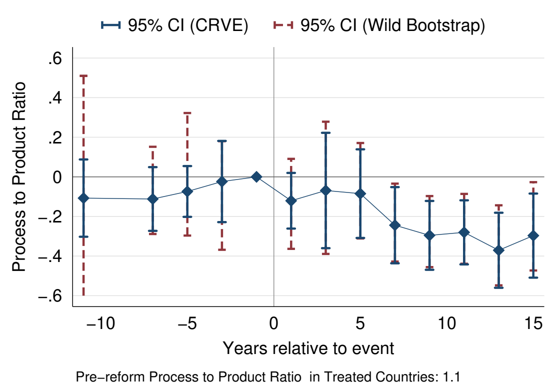


Figure B.8: Event study coefficients for alternative definitions of treatment

Note: The panels in the figure plot the coefficients κ_e from regression (1). The outcome is the ratio of process innovators to product innovators. See note to Figure 3 for details. In panel (a) the treatment is a large drop in EPL for regular workers. In panel (b) the treatment is the first year a country experiences a large EPL drop, either of EPL Temp or of EPL Total.

C Alternative Estimation Strategies

C.1 Interaction-Weighted Event Study

In this appendix, we estimate interaction-weighted (IW) event-study coefficients, and compute their standard errors using the procedure in Sun and Abraham (2021). The estimator is constructed via the following steps:

1. Estimate the saturated interaction model:

$$Y_{it} = \alpha_i + \delta_t + \sum_{e \neq -1} \kappa_{e,c} \times \mathbb{1}\{\text{Cohort} = c\}_i \times \mathbb{1}\{t - (\text{Event Year})_i = e\} \times \mathbb{1}\{\text{Treated}\}_i + \varepsilon_{it}, \tag{3}$$

   with the same notation as in the main text, and where $\mathbb{1}\{\text{Cohort} = c\}_i$ is a dummy for whether country i belongs to treatment cohort $c \in \mathscr{C}$, the set of all treated cohorts. In this context, the estimated coefficients $\hat{\kappa}_{e,c}$ are cohort-average treatment-on-the-treated (CATT) effects for relative event time e. In our application, we assign a different cohort to each country to examine country-specific effects. We verify that this procedure results in the same IW estimator and standard errors as assigning a different cohort depending on the treatment year $(\text{Event Year})_i$.

2. Estimate the system of auxiliary regressions:

$$\{\text{Cohort} = c\}_i = \sum_{e \neq -1} \xi_{e,c} \mathbb{1}\{t - (\text{Event Year})_i = e\} \times \mathbb{1}\{\text{Treated}\}_i + \upsilon_{it}, \ \forall c \in \mathscr{C}. \tag{4}$$

   These regressions return an estimate for the share of observations from cohort c that are treated at event time e, $\hat{\xi}_{e,c}$, along with the variance-covariance matrix of the system, needed to compute the standard errors.

3. Finally, obtain the IW estimator for each event period by averaging the coefficients from (3) using the shares in (4):

$$\hat{\beta}_e^{IW} = \sum_{c \in \mathscr{C}} \hat{\xi}_{e,c} \hat{\kappa}_{e,c}. \tag{5}$$

We compute the standard errors for the estimator at each event time e following Proposition 6 in Sun and Abraham (2021).

Results

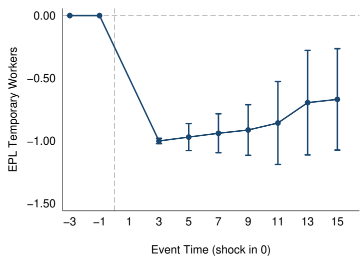
The resulting estimates allow us to rule out the presence of significant pre-trends for all variables of interest. Further, we are able to analyze the effects of a reduction in

EPL strictness for the various countries separately. In the bottom panel of the following figures, we plot the coefficients $\hat{\beta}_e^{IW}$. In each figure, the five upper panels report the coefficients $\hat{\kappa}_{e,c}$ for each country c, together with cluster-robust standard errors. The identification for the estimated effects comes from a comparison of each of the treated countries with never-treated, as well as yet-to-be-treated, countries.

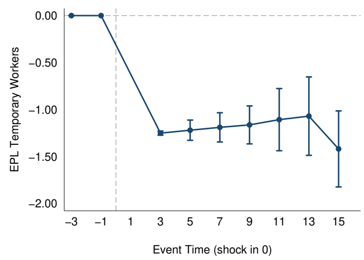
Overall, we find that all the main results presented in the text are robust to this estimation procedure. In particular, Figure C.4 confirms that the share of product innovators increases following a big drop in EPL, leading to an overall reduction in the process/product ratio in Figure 4. Similarly, the share of firms conducting only process innovation falls (Figure C.6). The country-specific effects underlying the IW estimator also highlight that overall treatment effects are driven by changes in Germany, Italy and Portugal, which are also the countries where the share of temporary workers rose significantly after the labor market reforms (Figure C.2), suggesting that the reforms relaxed a previously binding constraint. These same countries see a significant reduction in the process/product ratio, as displayed in Figure 4. We interpret these findings as indicating that the effects of the labor market reforms studied in this paper were mediated by an increase in the take-up of more flexible temporary contracts.

Figure C.1: EPL Temp: country-specific coefficients and IW estimator

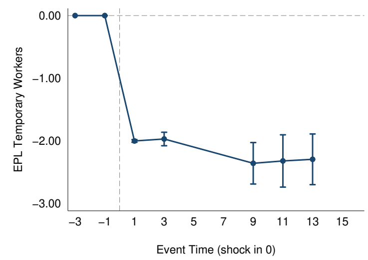
(a) Germany



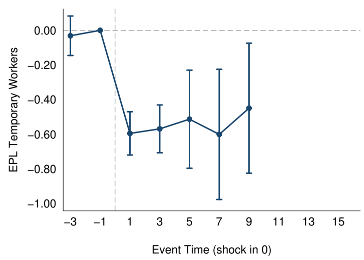
(b) Italy



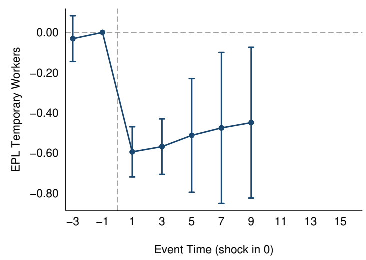
(c) Greece



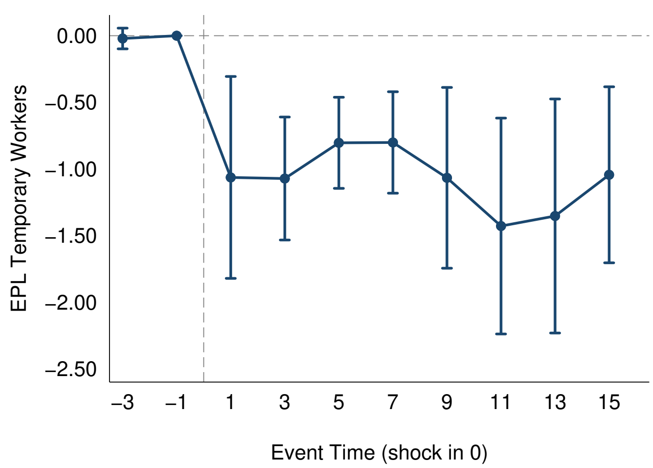
(d) Portugal



(e) Sweden



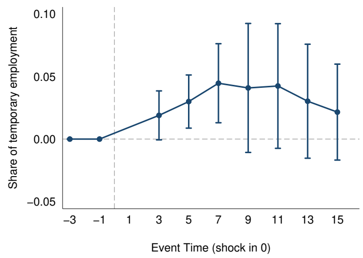
(f) IW estimator



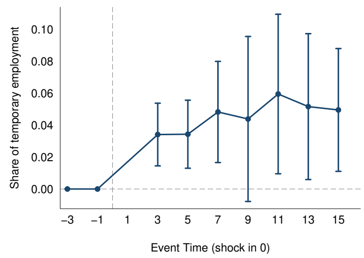
Note: Panels (a) to (e) report country-specific event-study coefficients, $\kappa_{e,c}$, from Equation (3) . Panel (f) displays the interaction-weighted event-study coefficients obtained from their aggregation, $\hat{\beta}_e^{IW}$, from Equations (4) and (5) . Panels (a) to (e) report cluster-robust standard errors, while panel (f) reports IW standard errors constructed following Proposition 6 in Sun and Abraham (2021). See main text for the dependent variable definition.

Figure C.2: Share Temp: country-specific coefficients and IW estimator

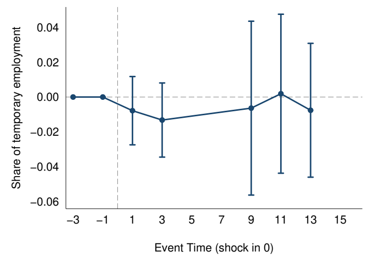
(a) Germany



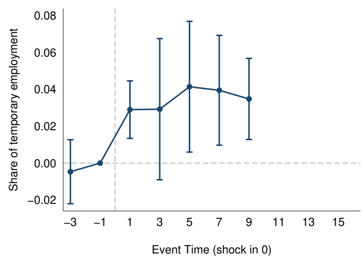
(b) Italy



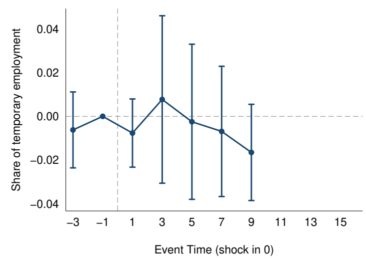
(c) Greece



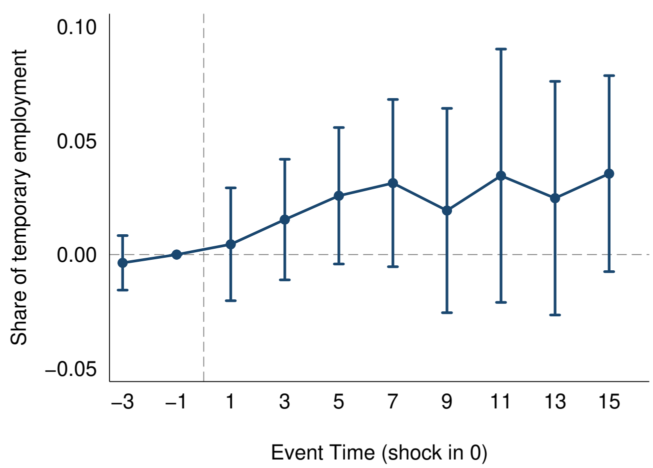
(d) Portugal



(e) Sweden



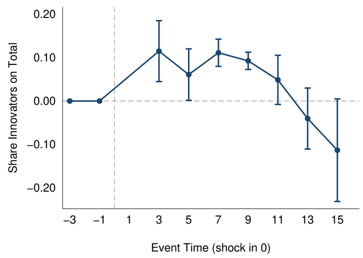
(f) IW estimator



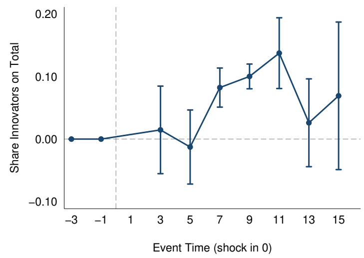
Note: Panels (a) to (e) report country-specific event-study coefficients, $\kappa_{e,c}$, from Equation (3) . Panel (f) displays the interaction-weighted event-study coefficients obtained from their aggregation, $\hat{\beta}_e^{IW}$, from Equations (4) and (5) . Panels (a) to (e) report cluster-robust standard errors, while panel (f) reports IW standard errors constructed following Proposition 6 in Sun and Abraham (2021). See main text for the dependent variable definition.

Figure C.3: Innovators on Total: country-specific coefficients and IW estimator

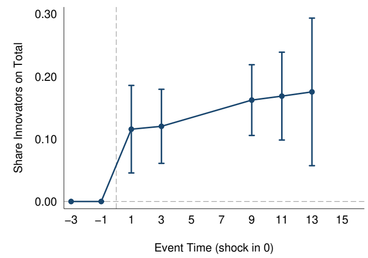
(a) Germany



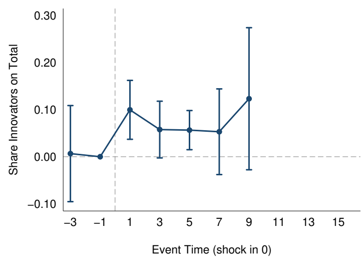
(b) Italy



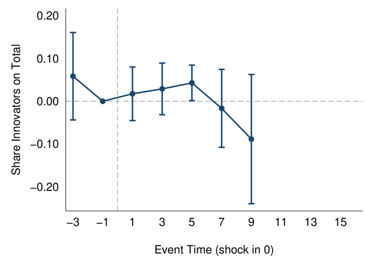
(c) Greece



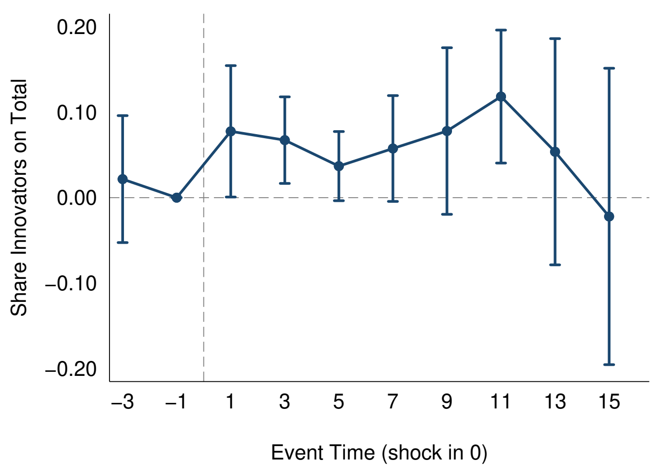
(d) Portugal



(e) Sweden

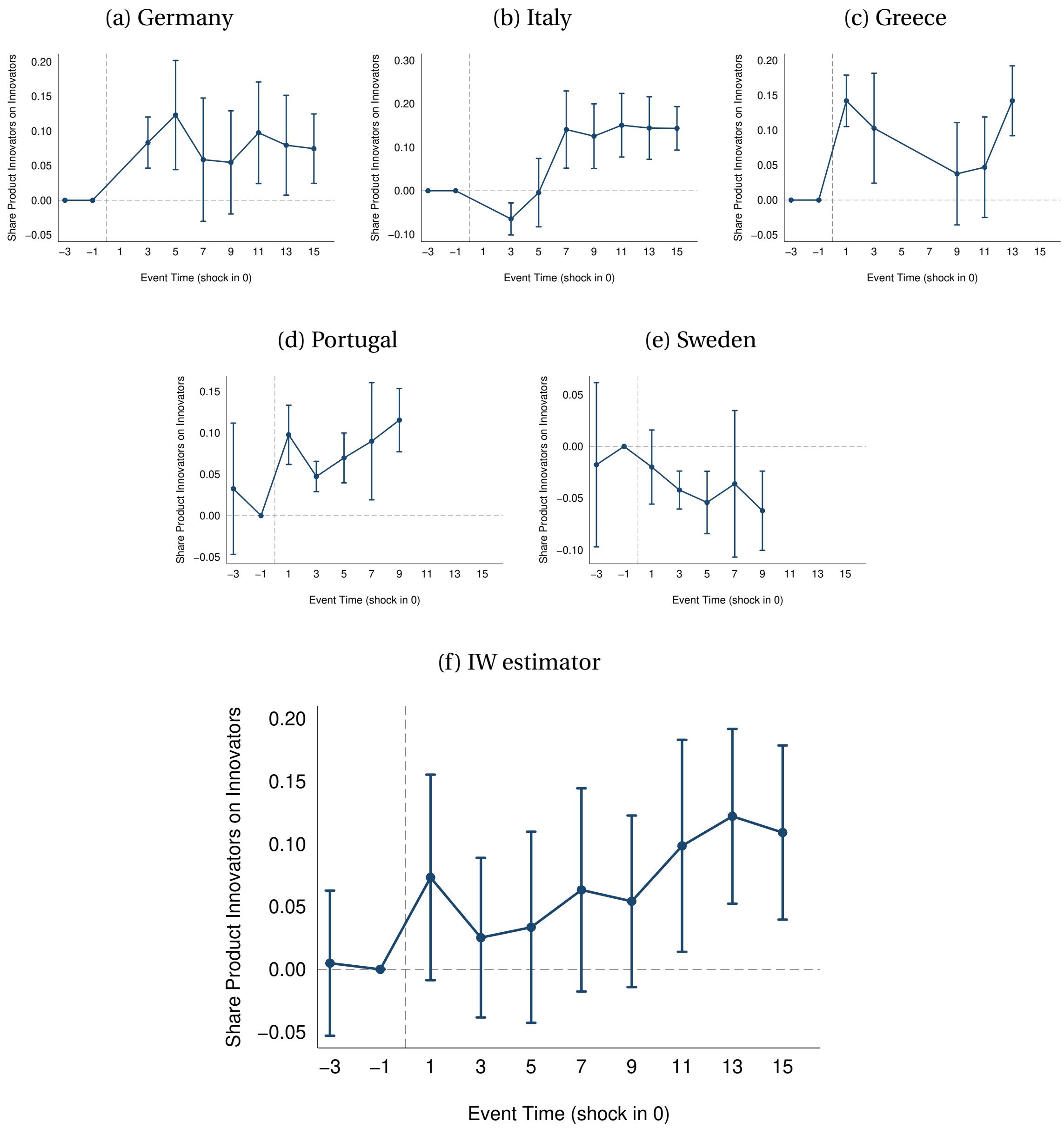


(f) IW estimator



Note: Panels (a) to (e) report country-specific event-study coefficients, $\kappa_{e,c}$, from Equation (3) . Panel (f) displays the interaction-weighted event-study coefficients obtained from their aggregation, $\hat{\beta}_e^{IW}$, from Equations (4) and (5) . Panels (a) to (e) report cluster-robust standard errors, while panel (f) reports IW standard errors constructed following Proposition 6 in Sun and Abraham (2021). See main text for the dependent variable definition.

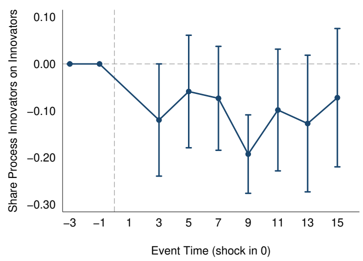
Figure C.4: Product Innovators on Innovators: country-specific coefficients and IW estimator



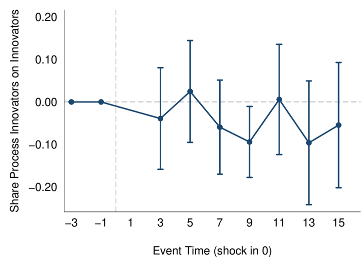
Note: Panels (a) to (e) report country-specific event-study coefficients, $\kappa_{e,c}$, from Equation (3) . Panel (f) displays the interaction-weighted event-study coefficients obtained from their aggregation, $\hat{\beta}_e^{IW}$, from Equations (4) and (5) . Panels (a) to (e) report cluster-robust standard errors, while panel (f) reports IW standard errors constructed following Proposition 6 in Sun and Abraham (2021). See main text for the dependent variable definition.

Figure C.5: Process Innovators on Innovators: country-specific coefficients and IW estimator

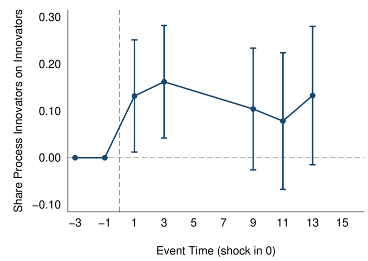
(a) Germany



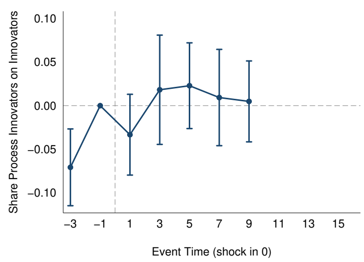
(b) Italy



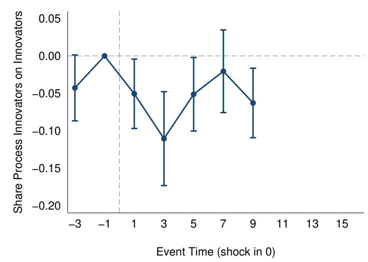
(c) Greece



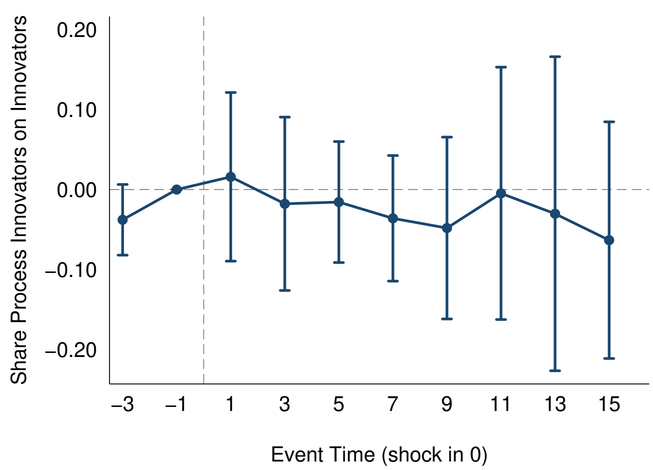
(d) Portugal



(e) Sweden



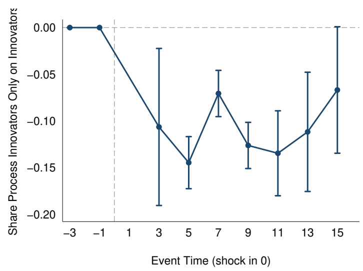
(f) IW estimator



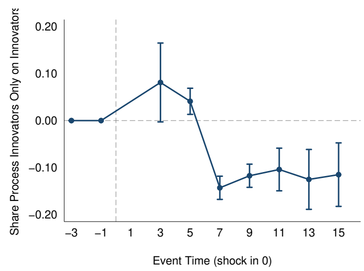
Note: Panels (a) to (e) report country-specific event-study coefficients, $\kappa_{e,c}$, from Equation (3) . Panel (f) displays the interaction-weighted event-study coefficients obtained from their aggregation, $\hat{\beta}_e^{IW}$, from Equations (4) and (5) . Panels (a) to (e) report cluster-robust standard errors, while panel (f) reports IW standard errors constructed following Proposition 6 in Sun and Abraham (2021). See main text for the dependent variable definition.

Figure C.6: Process Only on Innovators: country-specific coefficients and IW estimator

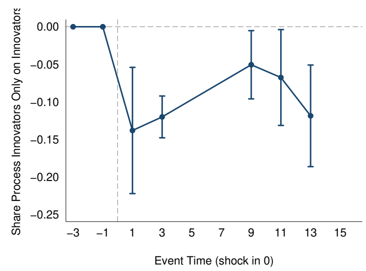
(a) Germany



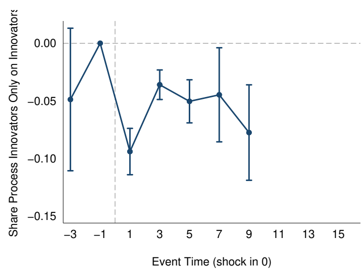
(b) Italy



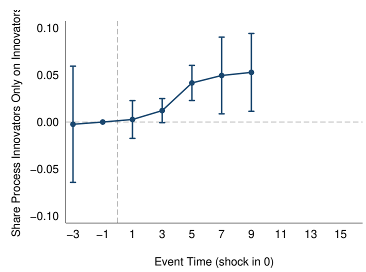
(c) Greece



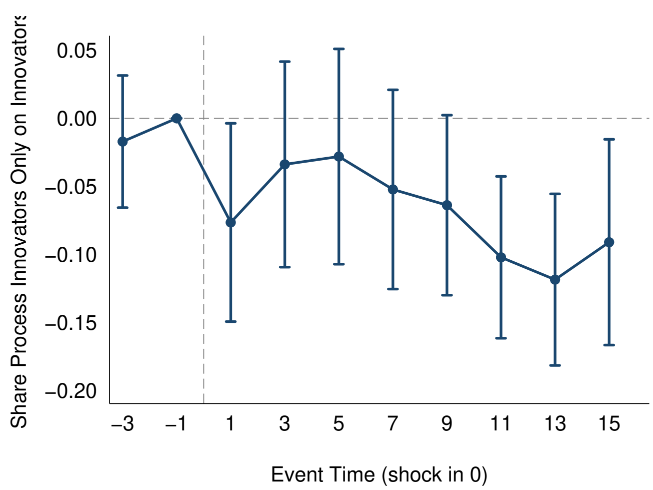
(d) Portugal



(e) Sweden



(f) IW estimator



Note: Panels (a) to (e) report country-specific event-study coefficients, $\kappa_{e,c}$, from Equation (3) . Panel (f) displays the interaction-weighted event-study coefficients obtained from their aggregation, $\hat{\beta}_e^{IW}$, from Equations (4) and (5) . Panels (a) to (e) report cluster-robust standard errors, while panel (f) reports IW standard errors constructed following Proposition 6 in Sun and Abraham (2021). See main text for the dependent variable definition.

C.2 Permutation Tests

In what follows, we use randomization inference to test the significance of our results. We conduct permutation experiments reassigning treatment status and/or year relative to treatment in the following way: (1) across periods within treated countries (within); (2) across countries preserving the treatment periods (between); (3) across both countries and periods.

We run the diff-in-diff specification (2) and focus on the "long run" coefficient. Specifically, we check whether the distribution of long run treatment effects t-statistics is centered around 0. In particular, if the distribution resulting from (1) is non-centered, baseline treatment effects stem partly from permanent heterogeneity across countries. That is, random assignment across countries is not satisfied. If the distribution resulting from (2) is non-centered, baseline treatment effects stem from differences in the time path of variables. That is, random assignment over time is not satisfied. The distribution from (3) provides a way to compute an overall randomization p-value.

Our main references are: Kennedy (1995) for residualization and general concept; Rothstein (2010) for the placebo test idea; Hsiang and Jina (2014) for the implementation; MacKinnon and Webb (2020) for using t-stat for p-values instead of coefficients.

Methodology

Our main specification (Equation (2) in the main text) can be written compactly as

$$Y_{it} = \alpha_i + \delta_t + \beta_{SR} \cdot D_{it}^{SR} + \beta_{LR} \cdot D_{it}^{LR} + \varepsilon_{ct},$$

where Y_{it} is the outcome of interest, α_i, δ_t are country- and time-effects, and D_{it}^{SR}, D_{it}^{LR} are dummies denoting treatment in the short run (equal to 1 if the country is treated and the years from treatment are between 0 and 5) and the long run (equal to 1 after 5 years from treatment). We conduct randomization inference on the coefficient β_{LR} to assess the potential bias generated by non-random assignment of the treatment across countries or time periods, as well as to generate alternative p-values for our estimates.

Using the Frisch-Waugh-Lowell theorem, we can rewrite our specification as:

$$\tilde{Y}_{it} = \beta_{LR} \cdot \tilde{D}_{it}^{LR} + \varepsilon_{it},$$

where, for $X \in \{Y, D^{LR}\}$, the notation $\tilde{X}$ indicates the residuals from regressing X on α_i, δ_t and D_{it}^{SR}.

We then apply the randomization scheme (4) in Kennedy (1995), which consists in reassigning $\tilde{D}_{it}^{LR}$ randomly N times (sampling uniformly without replacement), and computing the ensuing distribution of estimates $\hat{\beta}_n,\ n \in \{1,\ldots,N\}$, and of the corresponding t-statistics. We can use this distribution of t-statistics to obtain a p-value for the null hypothesis that the $\hat{\beta}_{LR}$ coefficient estimated from the original assignment is equal to 0. Crucially, under the null hypothesis we assume that the errors are exchangeable, that is, any permutation of true errors ε_{it} has the same distribution. In this case, the test delivers exact significance values.

In panel data, we have three ways of permuting the observations, which yield to different sets of coefficient estimates:

1. Permuting *within* countries, where we shuffle the time indexes, t, while keeping countries i fixed. In this case, the null hypothesis is that residuals are exchangeable over time within countries. Thus, the treated countries stay the same, but the treatment periods are shuffled. We call the estimated coefficients from this procedure $\hat{\beta}^w$, where w stands for *within*;

2. Permuting *between* countries, where we shuffle the i indexes, while keeping t fixed. In this case, the null hypothesis is that residuals are exchangeable across countries within time periods. We call the estimated coefficients from this procedure $\hat{\beta}^b$, where b stands for *between*;

3. Permuting both periods and countries, where it indexes are shuffled. We call the estimated coefficients from this procedure $\hat{\beta}^t$, where t stands for *total*.

These three schemes are used by Hsiang and Jina (2014), from which we also borrow parts of the randomization code. The corresponding t-statistics for the three coefficients are denoted by $\hat{T}^w$, $\hat{T}^b$, $\hat{T}^t$. Following MacKinnon and Webb (2020), and given a value for the t-statistic in the original sample, $\hat{T}$, we compute p-values:

$$p^j = \frac{1}{N}\sum_{n=1}^{N} \mathbf{1}\left\{|\hat{T}_n^j| > |\hat{T}|\right\}, \quad j \in \{w, b, t\}.$$

And use them to assess the significance of estimated coefficients.

The distributions of estimated t-statistics and coefficients can also inform us about the failure of random assignment along various dimensions. A non-centered distribution of coefficients resulting from *within* randomization points to the fact that country differences drive the estimated coefficients (if time is randomly assigned, treatment is just a country indicator). A similar result for *between* randomization points to the fact that estimated treatment effects are driven by time trends independent of treatment (if countries are randomly assigned, treatment is a period indicator).

Results

For each scheme, we report the randomization p-value computed as above, as well as the average of the distribution of the estimated long-run coefficients across all permutations. For all outcomes, the average of estimated coefficients is very close to 0, and at least one order of magnitude smaller than estimated coefficients in the original sample. We obtain p-values below 10% for all randomization schemes when the share of temporary workers is the dependent variable, and below 2% when the share of process innovators only and the ratio of process innovators to product innovators are the dependent variables.

The estimated coefficients from our baseline specification can be interpreted as causal if we have both random assignment of treatment across countries (so that treated countries can be compared to never-treated) and between time periods within each country (so that treated countries can be compared to yet-to-be-treated countries). The randomization schemes that we employ act along these two dimensions separately. The "within" scheme randomizes time periods among treated countries, while the "between" scheme randomizes treatment across all countries but keeps the time fixed. This allows us to provide suggestive evidence in favor, or against, these random assignment hypotheses. In the Figures reported below, we depict the distribution of t-statistics for the coefficients estimated according to each randomization scheme. All distributions have their mean and mode around 0. The "between" scheme produces more skewed distributions. This result can be rationalized by recalling that treated countries constitute a sizable share of the overall sample, so many permutation estimate a non-zero treatment effects due to the inclusion of countries with true non-zero treatment effect in the permutation sample. Also recall that we produce these p-values by reassigning *residualized* treatment dummies, which are different from 0 in most cases. Thus, actually-treated countries often receive non-zero values for the treatment.

Overall, our findings depose against the presence of systematic bias, as evidenced by the centered coefficient distributions, and confirm the significance of our baseline results.

Table C.1 : Baseline estimates and randomization test results, full sample

	(1) Innovators on Total	(2) Product on Innovators	(3) Process on Innovators	(4) Process Only on Innovators	(5) Process on Product	(6) Share Temp. Workers	(7) EPL Temp. Workers
Short Run	0.033	0.019	-0.007	-0.005	-0.013	0.024	-0.917
	(0.028)	(0.023)	(0.023)	(0.023)	(0.055)	(0.000)	(0.086)
	[0.027]	[0.046]	[0.041]	[0.051]	[0.111]	[0.008]	[0.149]
	[−0.027, 0.121]	[−0.092, 0.149]	[−0.135, 0.067]	[−0.204, 0.112]	[−0.407, 0.226]	[−0.002, 0.044]	[−1.273, −0.632]
Long Run	0.061	0.097	-0.051	-0.090	-0.251	0.037	-0.883
	(0.030)	(0.025)	(0.024)	(0.024)	(0.057)	(0.000)	(0.091)
	[0.033]	[0.039]	[0.045]	[0.022]	[0.059]	[0.016]	[0.205]
	[−0.030, 0.118]	[−0.001, 0.172]	[−0.168, 0.046]	[−0.144, −0.041]	[−0.350, −0.070]	[0.002, 0.086]	[−1.337, −0.419]
N	119	119	119	119	119	211984889	119
Within p-value	0.1416	0.0487	0.3186	0.0027	0.0054	0.0558	0.0040
Between p-value	0.2081	0.1138	0.2001	0.0050	0.0162	0.0333	0.0016
Total p-value	0.1744	0.0941	0.3625	0.0118	0.0163	0.0754	0.0090
Within mean coefficient	-0.0002	-0.0003	-0.0002	-0.0002	0.0001	-0.0000	-0.0007
Between mean coefficient	0.0013	0.0011	-0.0004	-0.0008	-0.0022	0.0001	-0.0083
Total mean coefficient	0.0002	0.0005	-0.0003	-0.0007	-0.0014	0.0000	-0.0007

Note: parentheses denote OLS standard errors; brackets denote cluster-robust standard errors and wild-boostrap 95% confidence interval. Within, between and total "p-values" denote the p-value for the two-sided randomization test corresponding to the "Long Run" coefficient. The p-value is obtained as the share of absolute value of the t-statistic that are more extreme than the original sample across 10000 permutations. "Within" permutes time within clusters; "Between" permutes cluster assignment; "Total" permutes both time and cluster assignment. "Mean Coefficients" report the average of the estimated "Long Run" coefficients across the 10000 permutations for each randomization scheme.

Figure C.7: Share Temporary Workers

(a) Within Randomization | (b) Between Randomization | (c) Total Randomization

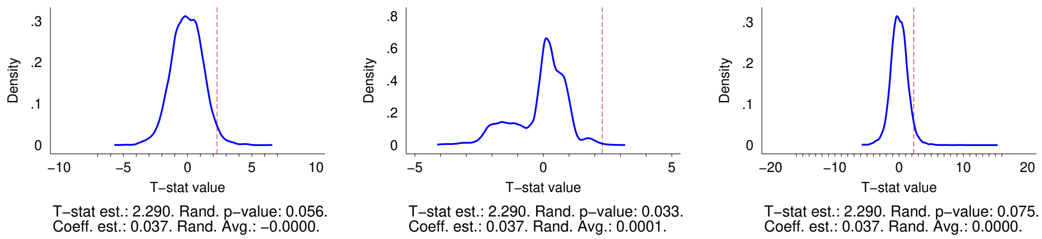


Figure C.8: EPL Temporary Workers

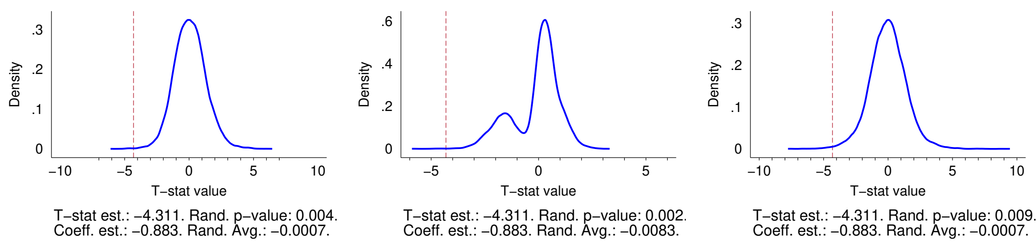


Figure C.9: Innovators on Total

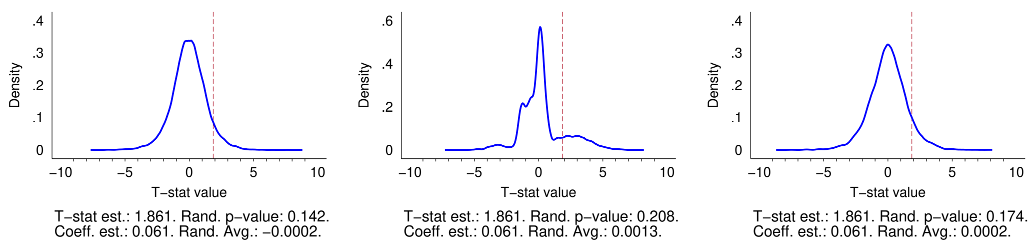


Figure C.10: Product on Innovators

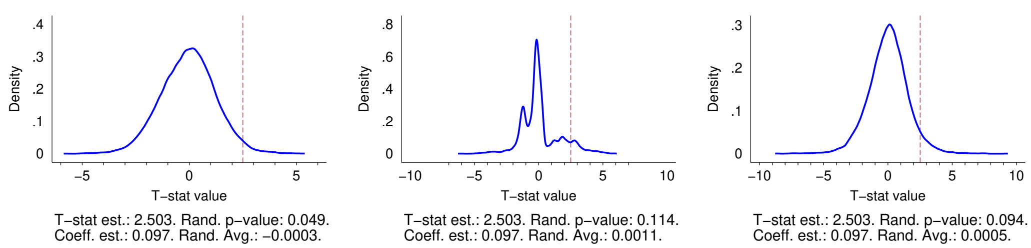
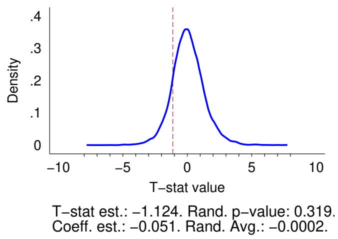
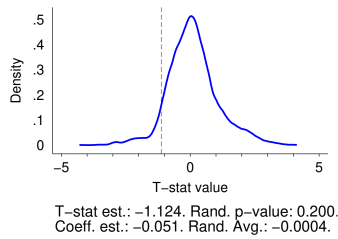


Figure C.11: Process on Innovators

(a) Within Randomization



(b) Between Randomization



(c) Total Randomization

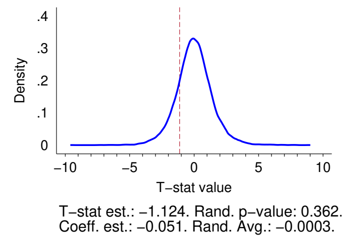
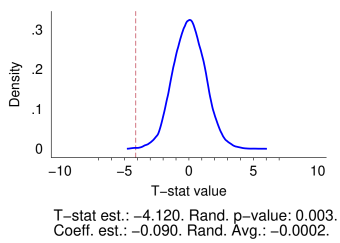
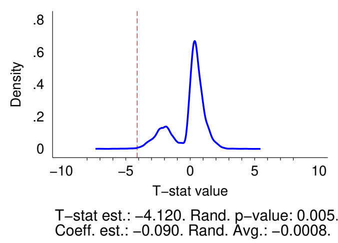
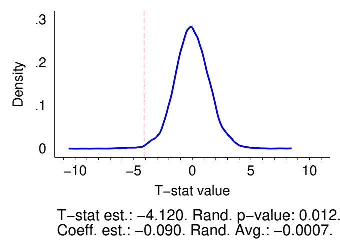


Figure C.12: Process Only on Innovators







D Theory Appendix

Proposition 1. *The operating profit function and its partial derivatives with respect to q, Γ are continuous in z.*

Proof. The profit function reads

$$\Pi(z,L) = \begin{cases} zqA(u+\Gamma)^{\theta}(L)^{\theta} - w(1+u)L & z \geq \hat{z} \\ (1-\theta)\,zqA\left(\frac{\theta zqA}{w}\right)^{\frac{\theta}{1-\theta}} + (\Gamma-1)\,wL & \bar{z} < z < \hat{z} \\ zqA(\Gamma L)^{\theta} - wL & z \leq \bar{z} \end{cases}$$

Using the definitions:

$$\bar{z}(L) = [\Gamma L]^{1-\theta}\frac{w}{\theta qA}, \hat{z}(L) = [(u+\Gamma)\,L]^{1-\theta}\frac{w}{\theta qA},$$

profits can be rewritten as:

$$\Pi(z,L) = \begin{cases} \frac{z}{\hat{z}}wL\frac{(u+\Gamma)}{\theta} - wL(1+u) & z \geq \hat{z} \\ (1-\theta)\left(\frac{z}{\bar{z}}\right)^{\frac{1}{1-\theta}}\frac{w\Gamma L}{\theta} + (\Gamma-1)\,wL & \bar{z} < z < \hat{z} \, . \\ \frac{z}{\bar{z}}\frac{wL\Gamma}{\theta} - wL & z \leq \bar{z} \end{cases}$$

We can then easily verify continuity in z, as:

$$\begin{aligned} \lim_{z\uparrow\hat{z}}\Pi(z,L) &= (1-\theta)\left(\frac{\hat{z}}{\bar{z}}\right)^{\frac{1}{1-\theta}}\frac{w\Gamma L}{\theta} + (\Gamma-1)\,wL \\ &= wL\frac{(u+\Gamma)}{\theta} - wL(1+u) \\ &= \frac{\hat{z}}{\hat{z}}wL\frac{(u+\Gamma)}{\theta} - wL(1+u) \\ &= \lim_{z\downarrow\hat{z}}\Pi(z,L) \end{aligned}$$

Similarly:

$$\begin{aligned}\lim_{z\downarrow\bar{z}}\Pi(z,L) &= (1-\theta)\left(\frac{\bar{z}}{\bar{z}}\right)^{\frac{1}{1-\theta}}\frac{w\Gamma L}{\theta}+(\Gamma-1)\,wL\\ &= \frac{\Gamma L w}{\theta}-wL\\ &= \lim_{z\uparrow\bar{z}}\Pi(z,L)\end{aligned}$$

Now note that:

$$\begin{aligned}&\frac{\partial\bar{z}}{\partial\Gamma}=(1-\theta)\,\frac{\bar{z}}{\Gamma},\ \frac{\partial\left[\frac{\Gamma L}{\bar{z}}\right]}{\partial\Gamma}=\frac{\theta}{\bar{z}}\\ &\frac{\partial\bar{z}}{\partial q}=-\frac{\bar{z}}{q}\end{aligned}$$

and analogous expressions for $\hat{z}$, replacing ΓL with $(u+\Gamma)\,L$. Thus, we obtain the partial derivative of the profit function wrt to Γ :

$$\frac{\partial\Pi}{\partial\Gamma}(z,L)=\begin{cases}\frac{z}{\hat{z}}wL & z\geq\hat{z}\\ wL & \bar{z}<z<\hat{z}\\ \frac{z}{\bar{z}}wL & z\leq\bar{z}\end{cases}$$

which is continuous as trivially:

$$wL=\frac{\hat{z}}{\hat{z}}wL=\frac{\bar{z}}{\bar{z}}wL.$$

and similarly,

$$\frac{\bar{z}}{\bar{z}}wL=\frac{\partial\Pi}{\partial\Gamma}(\bar{z},L)$$

Finally, the partial derivative of the profit function wrt to q reads:

$$\frac{\partial\Pi}{\partial q}(z,L)=\begin{cases}\frac{z}{\hat{z}}wL\frac{(u+\Gamma)}{q\theta} & z\geq\hat{z}\\ \left(\frac{z}{\bar{z}}\right)^{\frac{1}{1-\theta}}\frac{w\Gamma L}{q\theta} & \bar{z}<z<\hat{z}\\ \frac{z}{\bar{z}}\frac{wL\Gamma}{q\theta} & z\leq\bar{z}\end{cases}$$

Continuity follows readily from the definitions of $\bar{z}, \hat{z}$, whereby:

$$\left(\frac{\hat{z}}{\bar{z}}\right)^{\frac{1}{1-\theta}} = \frac{(u+\Gamma)\,L}{\Gamma L}.$$

□

Proposition 2. *Given $\bar{u}, \bar{u}'$, with $\bar{u}' > \bar{u}$, the associated optimal technology choices $\left(q^{*\prime}, \Gamma^{*\prime}\right)$, $\left(q^{*}, \Gamma^{*}\right)$, satisfy:*

$$\frac{q^{*\prime}}{\Gamma^{*\prime}} \geq \frac{q^{*}}{\Gamma^{*}}.$$

That is, the ratio of product to process innovation increases weakly when restrictions on temporary work are relaxed.

Proof. The firm's problem in period 1 reads:

$$\max_{(q,\Gamma):G(q,\Gamma)=0} \mathbb{E}_z \Pi^{*(}\left(q,\Gamma;u\right) \equiv \mathbb{E}_z \Pi\left(q,\Gamma,L^{*};u\right),$$

Now consider the analogous problem:

$$\max_{(q,\tilde{\Gamma}):G(q,\tilde{\Gamma})=0} \mathbb{E}_z \Pi^{*(}\left(q,\tilde{\Gamma};u\right),$$

with $\tilde{\Gamma} = -\Gamma$. Note that the problem above satisfies the (Edlin and Shannon, 1998) definition of regular problem with a binding constraint. Indeed:

$$\mathbb{E}_z \Pi^{*}_{q}(q,\Gamma,u) = wL^{*}\frac{(u+\Gamma)}{\hat{z}q\theta}\int_{\hat{z}}^{\infty} z\mathrm{d}F(z) + \frac{w\Gamma L^{*}}{\bar{z}^{\frac{1}{1-\theta}}q\theta}\int_{\bar{z}}^{\hat{z}} z^{\frac{1}{1-\theta}}\mathrm{d}F(z) + \\ + \frac{w\Gamma L^{*}}{\bar{z}q\theta}\int_{\bar{z}}^{\hat{z}} z^{\frac{1}{1-\theta}}\mathrm{d}F(z) > 0, \quad \forall\left(q,\Gamma,u\right) \in \left[q_0,\bar{q}\right] \times \left[\Gamma_0,\bar{\Gamma}\right] \times (0,\infty)$$

Which implies that $\mathbb{E}_z \Pi\left(q,\Gamma,L^{*};u\right)$ has path-connected level sets. Furthermore, by our assumption that the innovation possibility frontier defined by $G\left(q,\Gamma\right) = 0$ is continuous, differentiable and strictly concave immediately implies that $G_q\left(q,\Gamma\right) > 0$ for all $\left(q,\Gamma\right)$ such that $G\left(q,\Gamma\right) = 0$. Further:

$$\mathbb{E}_z \Pi^{*}_{\tilde{\Gamma}}(q,\Gamma,u) = -\mathbb{E}_z \Pi^{*}_{\Gamma}(q,\Gamma,u) = -\frac{wL^{*}}{\hat{z}}\int_{\hat{z}}^{\infty} z\mathrm{d}F(z) - wL^{*}\int_{\bar{z}}^{\hat{z}}\mathrm{d}F(z) + -\frac{wL^{*}}{\bar{z}}\int_{0}^{\bar{z}} z\mathrm{d}F(z) < 0, \quad \forall\left(q,\Gamma,u\right) \in \left[q_0\right.$$

Now note that, by continuity of the profit function's partial derivatives:

$$\mathbb{E}_z \Pi^{*}_{\tilde{\Gamma}u}(q,\Gamma,u) = \frac{(1-\theta)}{u-\tilde{\Gamma}}\frac{wL^{*}}{\hat{z}}\int_{\hat{z}}^{\infty} z\mathrm{d}F(z) > 0$$

$$\mathbb{E}_z\Pi^*_{qu}(q,\Gamma,u) = \frac{wL^*}{\hat{z}q}\int_{\hat{z}}^{\infty} z\mathrm{d}F(z) > 0$$

thus:

$$\frac{\mathbb{E}_z\Pi^*_q(q,\tilde{\Gamma},u)}{\left|\mathbb{E}_z\Pi^*_{\tilde{\Gamma}}(q,\tilde{\Gamma},u)\right|}$$

is increasing in u, since $\Pi^*_{\tilde{\Gamma}}(q,\tilde{\Gamma},u) < 0$. By (Edlin and Shannon, 1998) Strict Monotonicity Theorem 2, given an interior solution $\left(q^*,\tilde{\Gamma}^*\right)$, we have $q^{*\prime} > q^*, \tilde{\Gamma}^{*\prime} > \tilde{\Gamma}$, immediately giving:

$$\frac{q^{*\prime}}{\Gamma^{*\prime}} > \frac{q^*}{\Gamma^*}.$$

It is immediate to see that this inequality is weak if we consider corner solution at the initial value $\bar{u}$. Indeed, if $q^* = \bar{q}$, the constraint set does not allow a further increase in q, and since profits are strictly increasing in Γ for all q, u, the firm will never set $\Gamma' < \Gamma$ if q is fixed. Similarly, if the firm is only engaging in process innovation, $\Gamma^* = \bar{\Gamma}$, we can only conclude that the above inequality holds strictly only if $\bar{u}'$ is large enough that:

$$\frac{\mathbb{E}_z\Pi_\Gamma\left(q_0,\bar{\Gamma};\bar{u}'\right)}{\mathbb{E}_z\Pi_q\left(q_0,\bar{\Gamma};\bar{u}'\right)} > \frac{G_\Gamma\left(q_0,\bar{\Gamma}\right)}{G_q\left(q_0,\bar{\Gamma}\right)}.$$

□

Proposition 3. *Product quality, q, is strongly temporary-labor-complementing, while process technology, Γ, is strongly temporary-labor-replacing. Moreover, instantaneous revenues:*

$$py = zqA\left(T+\Gamma L\right)^\theta,$$

have increasing differences in $(T,(q,-\Gamma))$.

Proof. Consider the marginal revenue product of temporary labor:

$$MR_T = \frac{\partial p_i q_i}{\partial T} = \frac{\partial\left[zqA\left(T+\Gamma L\right)^\theta\right]}{\partial T} = \theta zqA\left(T+\Gamma L\right)^{\theta-1}$$

Now, we have:

$$\frac{\partial MR_T}{\partial q} = \theta zA\left(T+\Gamma L\right)^{\theta-1} > 0, \quad \forall T$$

while

$$\frac{\partial MR_T}{\partial \Gamma} = \theta\left(\theta-1\right)zqA\left(T+\Gamma L\right)^{\theta-2}L < 0, \quad \forall T.$$

More formally, we can show that output has increasing differences in $(T,(q,-\Gamma))$. For any $q' > q, \Gamma' < \Gamma$, $T' > T$, we have

$$zq'A\left(T' + \Gamma' L\right)^{\theta} - zq'A\left(T + \Gamma' L\right)^{\theta} \geq zqA\left(T' + \Gamma L\right)^{\theta} - zqA(T + \Gamma L)^{\theta}.$$

Note that:

$$\begin{aligned} zq'A\left(T' + \Gamma' L\right)^{\theta} - zq'A\left(T + \Gamma' L\right)^{\theta} &\geq zqA\left(T' + \Gamma' L\right)^{\theta} - zqA\left(T + \Gamma' L\right)^{\theta} \\ &\geq zqA\left(T' + \Gamma L\right)^{\theta} - zqA(T + \Gamma L)^{\theta} \end{aligned}$$

by the concavity of the production function. □