Heterogeneity in the Effects of Uncertainty Shocks on Labor Market Dynamics and Extensive vs. Intensive Margins of Adjustment*

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Abstract

The real option value theory posits that non-convex adjustment costs pertaining to a firm's input are central to comprehending the consequences of increased uncertainty. This paper leverages the diversity observed at both sectoral and country levels in the degree of irreversibility associated with hiring and firing, a critical factor generating what is commonly referred to as "wait-and-see" behavior in times of heightened uncertainty. Our findings reveal two key insights. First, in alignment with the concept of second-moment shocks, uncertainty shocks predominantly influence the labor market through the extensive margin rather than the intensive margin. Second, the effects of uncertainty shocks exhibit pronounced heterogeneity across countries and industries, and the adverse employment effects (extensive margin) are amplified in a country with strict employment protection or in an industry characterized by a higher natural layoff rate, consistent with the real option theory.

Keywords: Uncertainty shocks; Irreversibility; Wait-and-see; Employment protection legislation; Natural layoff rate; Difference-in-difference

JEL codes: E24; J20; J50

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I. INTRODUCTION

The global financial crisis of 2008-09, stemming from the collapse of the U.S. housing markets in 2007, had far-reaching consequences, triggering recessions worldwide. Notably, in the United States and several other advanced economies, this crisis and its aftermath were marked by a significant surge in long-term unemployment and a protracted jobless recovery (Elsby et al., 2010; Katz, 2010). Given that this crisis unfolded amid an unprecedented level of uncertainty (Bloom, 2009; Bloom et al., 2018), it is unsurprising that a burgeoning body of literature has explored the role of uncertainty in shaping labor market dynamics.

Despite its crucial significance in fostering a comprehensive understanding of labor market dynamics, the majority of studies have primarily focused on examining the impact of uncertainty shocks on unemployment (i.e., the extensive margin only), with a predominant focus on the U.S. labor market (e.g., Caggiano et al., 2014; Choi and Loungani, 2015; Leduc and Liu, 2016; Pries, 2016; Ravn and Sterk, 2017; Schaal, 2017; Ferrara and Guérin, 2018; Kandoussi and Langot, 2022).[1] Given the substantial institutional, cultural, and compositional disparities in labor markets across different nations, it can be challenging to extrapolate the findings from these studies to other countries.

Moreover, the intensive margin might respond to uncertainty shocks differently, because convex adjustment costs in the intensive margin do not introduce a kink in costs around zero, and therefore, there is no option value associated with waiting. In light of this, we present comprehensive empirical evidence regarding the nexus between uncertainty and labor markets, utilizing an extensive international industry-level panel dataset with breakdown of total hours worked into

[1] While there are many studies on estimating the effects of uncertainty shocks using international panel data (e.g., Choi, 2017; Ozturk and Sheng, 2018; Bonciani and Ricci, 2020; Cuaresma et al., 2020), they do not focus on labor market heterogeneity. Although Netšunajev and Glass (2017) discover some heterogeneity in the labor market effects of uncertainty shocks between the United States and the euro area, they treat the euro area as an aggregate and ignore potential heterogeneity across countries within the region. Cross-country studies on the link between uncertainty and labor markets include Martínez-Matute and Urtasun (2018), but they did not exploit industry-level data as we do.

employment and average hours worked. These endeavors represent pioneering efforts in empirically testing the predictions of the real option value theory, marking our substantial contribution to the existing literature.

Diverse theoretical frameworks, ranging from considerations of risk aversion, growth options, to the Oi-Hartman-Abel effect, have been put forth to decipher the intricate relationship between uncertainty and economic activity. In our investigation, we center our focus on the real option value theory, as initially proposed by Bernanke (1983) and more recently expounded upon by Bloom (2009). We undertake empirical tests of its theoretical postulates by employing a two-pronged approach: (i) employing detailed data encompassing both the extensive and intensive margins of labor inpu and (ii) harnessing a range of country and industry-specific characteristics to serve as proxies for the degree of irreversibility in the decisions related to hiring and firing.

When firms face non-convex adjustment costs in determining their production input, due to factors such as fixed costs and the (partial) irreversibility of their decisions, they tend to hire and invest only when business conditions, encompassing productivity and demand, are notably favorable, and conversely, they fire and disinvest only when conditions are sufficiently bad. This reasoning applies equally to capital adjustment. By moving out the upper and lower thresholds for hiring and firing, heightened uncertainty extends the region of inaction, therefore, firms become more prudent in their responses to fluctuations in business conditions.

When non-convex labor adjustment costs pertain to the extensive margin, uncertainty shocks induce a decline in employment. Consequently, the "wait-and-see" behavior prevalent in labor markets becomes more prominent in countries or industries characterized by heightened irreversibility in the decisions related to hiring or firing. A parallel line of reasoning was explored by Greenland et al. (2019) in their examination of the relationship between uncertainty and exports. Their findings indicated that increases in policy uncertainty decrease both trade values and the extensive margin but do not reduce the intensive margin.

A cross-country analysis, in isolation, is unable to adequately control for the comprehensive array of confounding factors necessary to address our research question. Indeed, uncertainty itself can exhibit responses to macroeconomic variables, introducing the potential for reverse causality. To surmount these challenges, we employ a three-dimensional panel encompassing country, industry, and time dimensions, capitalizing on the heterogeneity in the degree of irreversibility in hiring and firing across sectors and nations. By extending Rajan and Zingales' (1998) difference-in-difference methodology to this panel framework, we disentangle the differential effects of uncertainty shocks on labor market dynamics contingent on country-level labor market rigidity and the industry-level propensity to adjust labor demand through the extensive margin.

We gauge labor market rigidity by employing employment protection legislation (EPL) data from the OECD. To proxy the intrinsic propensity at the industry level, which remains relatively stable over time and across countries, we utilize the natural layoff rates proposed by Bassanini et al. (2009). Our identifying assumption is that in countries where firms are subject to more stringent employment protections or in industries that heavily rely on the extensive margin (through layoffs) for labor input adjustments due to industry-specific technological and market-driven factors, a higher degree of irreversibility prevails. Such differences are translated into the relative significance of the wait-and-see channel in response to uncertainty shocks. We further employ Jordà's (2005) local projection method to trace the dynamic effects of uncertainty shocks interacting with country- and industry-specific characteristics. This approach proves particularly suited for estimating nonlinearities, including interactions between shocks and other variables of interest.

Our initial findings confirm the adverse impact on employment, a trend that aligns with recent findings within the context of the U.S. economy. Interestingly, while employment experiences a decline, average hours worked per employee does not decrease in response to uncertainty shocks. This starkly contrasts with first-moment shocks, where both margins of adjustment move in the same direction. This divergence constitutes a distinctive feature of the labor market effects associated with uncertainty shocks. Moreover, it is important to note that not all countries and industries respond to uncertainty shocks in the same manner. The negative employment effect is more pronounced in nations with stricter employment protections and in industries where firms rely more heavily on the extensive margin for adjustment. We also observe that the detrimental employment effect is notably amplified when these country and industry-specific factors interact with one another. These empirical findings consistently align with the theoretical predictions of the wait-and-see channel.

Our results are robust to a pacebo test with a first-moment shock, using an alternative measure of industry layoff rates, the exclusion of the global financial crisis, controlling for confounding factors, subsample analysis, the inclusion of other amplification channels of uncertainty shocks—especially financial constraints advocated by recent studies—, and the use of natural disasters and terrorist attacks as an instrument for uncertainty. We further investigate whether this differential effect depends on the underlying state of the economy and the sign of the shock. We find that the differential effect is stronger during recessions than expansions and for the rise of uncertainty than its resolution.

The remainder of the paper is organized as follows. Section II illustrates theoretical channels to interpret our findings. Section III describes the data used in the analysis. Section IV outlines our empirical strategy. Section V presents the main results, a battery of robustness checks, and additional exercises. Section VI concludes.

II. Wait-and-See Channel and Irreversibility

We introduce a theoretical framework to interpret our analysis of the impact of uncertainty shocks on labor markets, building on the work of Bloom (2009). Bloom's model, which incorporates time-varying uncertainty shocks, reveals that higher uncertainty prompts firms to temporarily halt both investment (and disinvestment) and hiring (and firing) due to partial irreversibility in these decisions. This aligns with the theoretical predictions stemming from real option value theory. In a related study, Schaal (2017) emphasizes the significance of time-varying micro-level uncertainty in explaining fluctuations in aggregate unemployment.

According to real option value theory, uncertainty induces caution in firms regarding both hiring and firing due to the costs associated with reversing these actions. A non-convex cost leads to an inaction region crucial for real options effects. While the net effect on employment levels is theoretically ambiguous since both hiring and firing decrease, empirical studies and calibrated quantitative models generally find a negative effect of uncertainty shocks on employment.[2] However, this effect varies depending on the degree of irreversibility, as reversible actions do not result in option loss. Thus, variations in the degree of irreversibility in hiring and firing across countries and industries can explain heterogeneity in the effect of uncertainty shocks on employment.

Additionally, to the extent that the extensive margin is typically subject to higher irreversibility than the intensive margin of labor adjustment, uncertainty shocks could have distinct effects on different margins of labor adjustment.[3] Therefore, while uncertainty shocks may reduce overall labor demand, their specific impact on labor markets hinges on the relative margin of adjustment. These insights highlight the significance of labor market policies in response to uncertainty shocks, distinct from those prompted by first-moment shocks like productivity shocks.

We explore the theoretical connection between uncertainty and irreversibility and assess whether our empirical measure of irreversibility in hiring and firing can explain the documented heterogeneity in labor market dynamics across countries and industries. Specifically, we consider

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[2] This is because more mass of firms is right-shifted due to depreciation (for capital) and attrition (for labor). See p.642 in Bloom (2009) for a detailed discussion.

[3] There might exist additional heterogeneous effects of uncertainty shocks along the extensive margin itself. For example, Lotti and Viviano (2012) consider a model with two types of workers. Those on long-term contracts are more productive but difficult to hire and fire. Workers on short-term contracts are less productive but easier to hire and fire. During periods of higher uncertainty, the ratio of short-term to long-term workers increases, as firms prefer to exploit "their current profit opportunities using less irreversible and sometimes costlier (or less efficient) inputs of production, like temporary workers, mainly in the form of employment-agency placement." Similarly, Valletta and Bengali (2013) show that firms may switch from hiring full-time to part-time employees during periods of high uncertainty because part-time employees are so flexible, as indeed happens in recessions. While this is an interesting direction of empirical research, we focus on the extensive vs. intensive margins of labor adjustment because of the limited data on the share of short-term or part-time employees consistent across countries and industries.

three types of labor adjustment costs similar to Bloom (2009): partial irreversibility C_L^P, fixed disruption costs C_L^F, and quadratic adjustment costs C_L^Q.

First, labor partial irreversibility derives from per capita hiring, training, and firing costs and is denominated as a fraction of total wages (at the standard working week). For simplicity, Bloom (2009) assumes these costs apply equally to gross hiring and gross firing of workers. Second, when new workers are added to the production process, there may be a fixed loss of output. For example, adding workers may require fixed costs of advertising, interviewing, and training. They are fixed disruption costs and denominated as a fraction of total sales. Third, convex labor adjustment costs exist due to higher costs for more rapid changes in working hours, where $C_L^Q \times L(\frac{h}{\bar{h}} - 1)^2$ are the quadratic adjustment costs; h denotes hours worked of employed workers; and $\bar{h}$ is the predetermined working hours on the contract.

As a result, a firm's total adjustment cost function can be summarized as:

$$C(\bullet) = wC_L^P(E^+ + E^-) + C_L^F I_{\{E \neq 0\}} S + C_L^Q L(\frac{h}{\bar{h}} - 1)^2, \tag{1}$$

where w is real wages, E^+ and E^- are the absolute values of positive and negative hiring, $I_{\{E \neq 0\}}$ is an indicator function, and S is real sales. The law of motion for employment is $L_t = (1 - \delta)L_{t-1} + E_t^+ - E_t^-$, where δ is the attrition rate, and total hours worked H is the product of total employment L and average hours worked h.

In equation (1), the first two terms pertain exclusively to the extensive margin of labor adjustment, while the quadratic component of the last term relates to the intensive margin of adjustment. It is crucial to emphasize that quadratic (or convex) adjustment costs do not lead to a wait-and-see response to uncertainty shocks. Supporting this notion, Varejão and Portugal (2007) offer strong micro-level evidence indicating the presence of nonconvexities in the labor adjustment process. This evidence is in line with the idea that inaction is a prevalent response, action spells are short-lived, and extreme adjustment episodes account for a significant portion of employment adjustments.

Thus, treating non-convex and convex adjustment costs the same when investigating the effect of uncertainty shocks on labor markets could be misleading. To address this gap in the literature, we introduce a comprehensive approach by considering both country and industry-level proxies for non-convex labor adjustment costs (C_L^P and C_L^F), which are crucial for understanding the relative margin of labor adjustment in response to uncertainty shocks.[4] Note that our simple theoretical framework taken from Bloom (2009) is based on a partial equilibrium approach exclusively focuses on labor demand by firms, without taking into account labor supply decisions by workers. While a general equilibrium model that incorporates both labor supply and demand decisions could provide more comprehensive theoretical predictions, our framework is particularly well-suited to the empirical analysis that includes various combinations of fixed effects. This allows us to control for various general equilibrium forces that impact employment, thereby sharpening identification.

III. Data

This section describes the data used in the empirical analysis. We take industry-level data on output and labor input from the EU KLEMS and World KLEMS databases. In particular, the breakdown of total hours worked (H) into the number of employees (L) and the average hours worked per employee (h) in KLEMS allows us to examine the effects of uncertainty shocks on both margins of labor adjustment.[5] Other databases often used in cross-country/industry analysis, such as the OECD Structural Analysis Database (STAN) or the United Nations Industrial Development

[4] We do not consider C_L^P and C_L^F separately for three reasons. First, it is difficult to separate the two components of adjustment costs in the data. Second, in his simulated model, Bloom (2009) shows that the predictions are very sensitive to the inclusion of non-convex adjustment costs but are much less sensitive to the type of non-convex adjustment costs. Third, it is logical that the expense incurred in terminating employees equates to a significant cost for forward-looking firms when it comes to making new hires.

[5] See O'Mahony and Timmer (2009) for further details on KLEMS data.

Organization (UNIDO) database, only provide information on industry-level employment, not hours worked.[6]

Our sample covers an unbalanced panel over the period 1970-2013 of 31 industries from 21 industrial countries where main variables are available (Australia, Austria, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Korea, Luxembourg, the Netherlands, Poland, Portugal, Spain, Sweden, and the United Kingdom).[7] While a few advanced economies have all the available data from 1970, most of our sample countries have available data from the 1980s (or the 1990s for a few emerging market economies). Table A.1 in the appendix summarizes the period coverage of the sample and the number of observations by country.

Measuring uncertainty. To measure uncertainty, we follow the standard approach in the literature by constructing a country-specific uncertainty measure based on stock market volatility. This measure offers the advantage of extensive availability over an extended time period and facilitates cross-country comparisons.[8] Additionally, Bloom et al. (2018) provide robust evidence that stock market volatility is closely linked to cross-sectional variations in stock prices, output, and productivity growth. Therefore, we employ stock market volatility as a proxy for the variance of underlying shocks to the economy, which aligns with the prevailing definition of uncertainty shocks in the extensive body of literature (Bloom, 2009; Christiano et al., 2014; Bloom et al., 2018; Fernández-Villaverde and Guerrón-Quintana, 2020). However, we also test the robustness of our

[6] Another advantage of KLEMS is that it covers not only manufacturing sectors but also service sectors, which are not included in STAN and UNIDO. To the extent to which the two sectors exhibit distinct patterns of labor adjustment, the analysis of service sectors provides an extra opportunity to understand the labor market dynamics in response to uncertainty shocks. However, these advantages come at some cost: the level of disaggregation of the manufacturing sector in KLEMS is coarser than STAN and UNIDO.

[7] While a more recent vintage of data conforming to the ISIC Rev. 4 (NACE Rev. 2) industry classification is available, it comes with a shorter time-series coverage, commencing from 1995. In our paper, we deliberately selected the vintage of data used to access information from earlier decades, offering a broader spectrum of labor market policy variations across countries.

[8] For example, other uncertainty measures such as consumer- or firm-level surveys are not easily comparable across countries owing to the use of different questionnaires. Cross-sectional measures such as the dispersion of firm-level profit, employment, and productivity are not always available for many countries in our sample.

findings using the World Uncertainty Index (WUI), a novel text-based measure of uncertainty recently developed by Ahir et al. (2022).

Specifically, we use the realized volatility of aggregate stock market returns from each of our sample countries as a proxy for uncertainty. Although one would prefer implied volatility over realized volatility, as the former contains forward-looking information, the difference is minor at the annual frequency we consider here. For each country, annualized realized volatility RV_t is calculated by using daily stock prices as follows: $RV_{i,t} = 100 \times \sqrt{\sum_{t=1}^{T_i} r_{i,s}^2}$, where $r_{i,s}$ are daily returns of the stock market in a country i from each trading day s.

Measuring irreversibility in labor adjustment. To gauge the degree of irreversibility in employment adjustment, we adopt the approach outlined by Basannini et al. (2009) and subsequent studies, such as Lashitew (2016) and Furceri et al. (2019). Specifically, we employ sectoral natural layoff rates to assess a firm's reliance on the extensive margin when making adjustments to its labor input. Basannini et al. (2009) utilize industry-level natural layoff rates, defined as the percentage ratio of annual layoffs to total employment in the United States, as a proxy for the inherent propensity for layoffs in the absence of EPL.[9] Our key assumption is that in industries where firms exhibit a relatively higher inclination to adjust their workforce through layoffs rather than more flexible means, labor adjustments rely more on the extensive margin. Given that adjustments through the extensive margin are typically less reversible than those through the intensive margin, the influence of the wait-and-see channel of uncertainty shocks is likely to be more pronounced in these industries.

Building on the work of Ciminelli et al. (2022), we use data from the 2014 Displaced Workers Survey (DWS), which was conducted in the context of the more comprehensive IPUMS-CPS (as detailed in Flood et al., 2018). Through this process, we compute the layoff rate to align with the

[9] Industry classifiers based on layoff rates are more appropriate than those based on the gross job turnover rate to the extent that we focus on dismissal regulations. This is because gross job turnover rates tend to be larger in expanding industries characterized by a high share of hires in total turnover and in industries that usually rely on voluntary quits rather than layoffs to adjust their human resources.

ISIC Rev. 4 industry classification, consistent with the one used in the 2017 EU KLEMS database. This results in the derivation of natural layoff rates for 31 industries. This industry-level layoff rate data constitutes a substantial expansion of the dataset initially compiled by Basannini et al. (2009), who calculated U.S. layoff rates using data from the 2004 CPS Displaced Workers Supplement for 22 industries, categorized to match the classification employed in the EU KLEMS 2007 database (ISIC Rev. 3 classification).

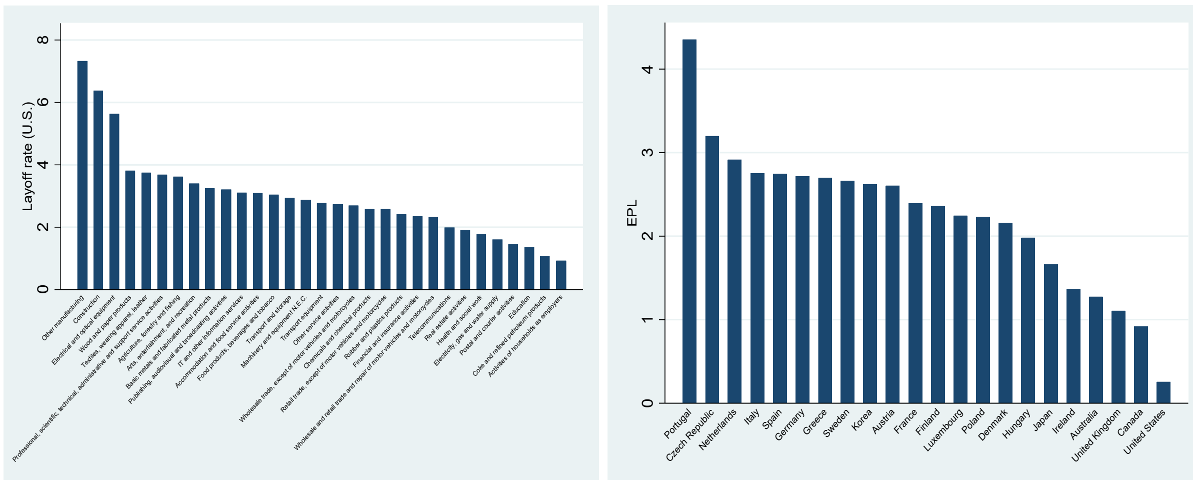
We utilize U.S. data due to the virtually non-existent EPL in the United States. In other words, the U.S. economy serves as the closest approximation to a frictionless economy where employers can freely adjust their workforce in response to operational requirements.[10] In our baseline analysis, we do not include the United States, which is a common practice in the difference-in-difference approach akin to Rajan and Zingales (1998). The rationale behind this exclusion is that if U.S. uncertainty systematically influences its industry-level layoff rates, incorporating the United States in the analysis would introduce bias to the estimation results.

The left panel in Figure 1 plots industry-level natural layoff rates. "Other manufacturing," "Construction," and "Electrical and optical equipment" are among those sectors characterized by a higher layoff rate, while "Postal and courier activities," "Education," and "Activities of households as employees" are among those sectors with the lowest layoff rate. As a robustness check, we also employ natural layoff rates using the U.K. data. Although the number of industries in which natural layoff rates are available is only 14 for the United Kingdom, the ranking of overlapping industries by layoff rates is similar between the United States and the United Kingdom, supporting our

[10] While using U.S. layoff rates can serve as a reasonable proxy for the underlying propensity for layoffs in the absence of dismissal regulations, a potential concern is that these rates may not be representative of the entire sample. In other words, U.S. layoff rates could be influenced by specific regulations or sectoral patterns. However, this issue is likely not critical within our empirical framework for two reasons, particularly given that the majority of countries in our sample are advanced economies. First, differences in natural layoff rates are more likely to reflect variations in industry-specific factors shared across countries rather than differences in countries' institutional characteristics. This is because we also account for the degree of employment protection at the country level in our robustness checks. Second, cross-country differences are expected to persist in our sample due to the slow process of growth convergence in advanced economies.

identifying assumption.[11] Table A.2 in the appendix provides further details of the natural layoff rate data.

Figure 1. Natural layoff rates and strictness of employment protection legislation



Note: Industry-level natural layoff rates are measured from the U.S. 2014 Displaced Workers Survey (DWS) and plotted in the left panel. The country-level average value of employment protection legislation is plotted in the right panel. The United States is included here as a benchmark but not included in the sample for estimation.

IV. Empirical Framework

To assess the dynamic effect of aggregate uncertainty shocks interacted with industry-level characteristics, we embed the difference-in-difference approach proposed by Rajan and Zingales (1998) into Jordà's (2005) local projection method. The local projection method simply requires estimating a series of regressions for each horizon h for each variable. The model embedded with a difference-in-difference structure is as follows:

$$Y_{i,j,t+h} - Y_{i,j,t-1} = \alpha_{i,j} + \alpha_{i,t} + \alpha_{j,t} + \beta^h C_j U_{i,t} + \textstyle\sum_{p=1}^{n} \gamma^h Z_{i,j,t-p} + \varepsilon_{i,j,t+h}, \qquad (2)$$

where $Y_{i,j,t}$ is a measure of industry-level outcomes, such as the log level of employment or average hours worked per employee; C_j measures industry-level intrinsic characteristics, such as the natural layoff rate or the degree of external financial dependence; $U_{i,t}$ denotes the identified uncertainty

[11] Spearman's rank correlation between the two measures is 0.74.

shocks. $Z_{i,j,t}$ is a set of control variables, including lags of the dependent variable $Y_{i,j,t}$, lags of the interaction variable $C_j U_{i,t}$, and their lags. $\alpha_{i,j}$, $\alpha_{i,t}$, and $\alpha_{j,t}$ are country-industry, country-year, and industry-year fixed effects, respectively.

The uncertainty shock used in the following exercises is identified by the four-variable Vector Autoregressions (VARs) estimated for each country during the sample period. The VARs include real GDP growth, CPI inflation, stock market returns, and stock market volatility. They are the minimum set of variables capturing the most important dimensions of the economy (real, nominal, and financial) and, at the same time, are consistently available for a wide sample of countries. The uncertainty shock is identified by the Cholesky ordering whereby the stock market volatility is placed in the last part of the system to purge the first-moment shock hitting the economy.

The advantages of having a three-dimensional (i countries, j industries, and t years) dataset are threefold. First, the inclusion of country-time fixed effects allows us to control for any unobserved cross-country heterogeneity in the macroeconomic shocks that affect industry-level outcomes. In a pure cross-country analysis, this would not be possible, leaving open the possibility that the impact attributed to uncertainty shocks would be due to other unobserved macroeconomic shocks. It also allows controlling for time-varying shocks at the industry level, such as industry-specific cost-push or demand shocks. The inclusion of country-industry fixed effect allows controlling for industry-specific factors, including cross-country differences in comparative advantages or the initial share of the industry in the aggregate economy.

Second, it mitigates concerns about reverse causality. While it is typically difficult to identify causal effects using time-series data at the aggregate level, it is much more likely that aggregate uncertainty affects cross-industry differences in employment or hours worked than the other way around. Since we control for country-year fixed effects, and therefore for aggregate employment, reverse causality in our set-up would imply that differences in employment across sectors influence uncertainty at the aggregate level. Moreover, our main independent variable is the interaction between the identified uncertainty shocks at the macro-level and industry-specific natural layoff rates; this makes it even less plausible that causality runs from industry-level employment growth to this composite variable.

Third, when investigating the heterogeneity in the effects of uncertainty shocks on labor markets across countries based on their labor market rigidities, the three-dimensional dataset can sharpen the identification. This is because countries differ not only in the degree of labor market rigidities but also in their industry composition. To the extent to which hiring or firing is costlier for some industries than others, and their employment share in the aggregate economy differs across countries, one cannot identify whether the observed differentials truly reflect labor market rigidities, measured by EPL. As long as industry composition varies over time, including just country-fixed effects in the regression framework using aggregate labor market variables cannot control for this confounding factor.

A remaining possible concern in estimating equation (2) with OLS is that (i) other macroeconomic variables, such as the economy-wide growth or the degree of employment protection originally used in Basannini et al. (2009), could affect industry-level outcomes when interacted with industries' layoff rates or (ii) uncertainty shocks could affect industry labor variables when interacted with other industry characteristics, such as external financial dependence used in Rajan and Zingales (1998). Our interaction effects might merely pick up the bias from omitting these composite variables to the extent to which each component of our composite variable is correlated with other factors. These issues are addressed in the sub-section of robustness checks. We further employ an LP-IV approach (Stock and Watson, 2018), embedded with exogenous instruments, such as disaster events from Baker et al. (forthcoming) or exogenous elections from Ahir et al. (2022), to mitigate remaining endogeneity concerns.

V. Empirical Findings

A. Preliminary Analysis

Aggregate effect of uncertainty shocks. To ensure the consistency of our results with previous studies, we first examine the aggregate effect of uncertainty shocks on labor markets. While the net impact of expanding the inaction region following an uncertainty shock is theoretically uncertain, Bloom (2009) demonstrates that the overall effect of such shocks on employment is negative. This negativity arises because more units are concentrated around the hiring threshold than the firing threshold in his model, influenced by labor attrition and business-conditions growth. Moreover, the variation in the job finding rate associated with hiring is shown to be more crucial than the separation rate related to firing in explaining unemployment dynamics, both over time (Hall, 2005; Shimer, 2005; Hairault et al., 2015) and across countries (Hobijn and Şahin, 2009). Subsequent studies, using U.S. data, also confirm this negative effect of uncertainty shocks on employment (Caggiano et al., 2014; Choi and Loungani, 2015; Leduc and Liu, 2016; Schaal, 2017; Mumtaz et al., 2019).

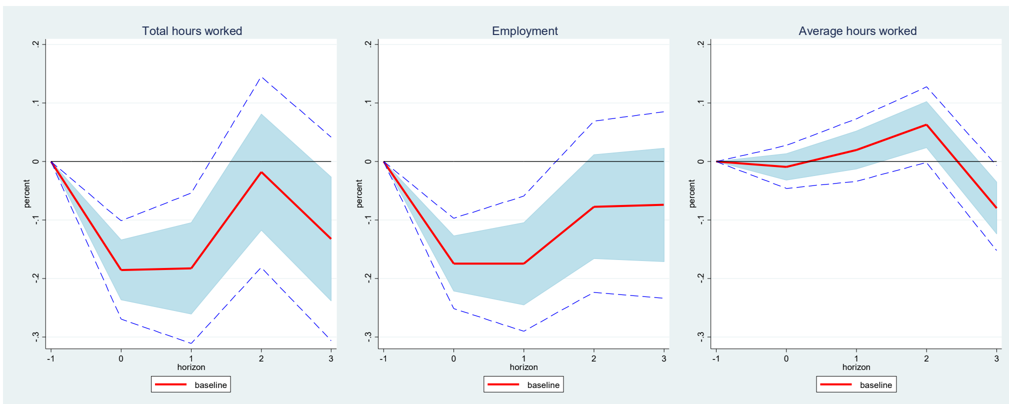
We estimate equation (3) to gauge the aggregate effect of uncertainty shocks:

$$Y_{i,j,t+h} - Y_{i,j,t-1} = \alpha_{i,j} + \alpha_{j,t} + \beta^h U_{i,t} + \textstyle\sum_{p=1}^{n} \gamma^h Z_{i,j,t-p} + \varepsilon_{i,j,t+h}, \tag{3}$$

where $Z_{i,j,t}$ is a set of control variables, including lags of the dependent variable $Y_{i,j,t}$ and lags of the main regressor. The decomposition of the response of total hours worked into employment (extensive margin) and average hours worked (intensive margin) allows us to evaluate the importance of each margin in response to the uncertainty shock.

In Figure 2, the left panel illustrates the response of total hours worked to the uncertainty shock over a four-year period following the shock, using estimated coefficients (i.e., β^h for h=0, 1, 2, and 3) with 68% and 90% confidence intervals. The middle and right panels break down this response into employment and average hours worked. As depicted in the left panel, after accounting for various fixed effects, a one standard deviation uncertainty shock leads to, on average, a 0.2 percent reduction in total hours worked on impact across various countries and industries. This effect is both economically and statistically significant, extending the observed adverse impact of uncertainty shocks on labor markets from the U.S. economy to a comprehensive dataset spanning international industry levels.

Figure 2. Aggregate effect of uncertainty shocks on labor market outcomes



Note: This graph plots the impulse response functions of labor market variables to the one standard deviation uncertainty shock by estimating equation (3). The shaded area and the dashed line denote 68% and 90% confidence intervals, respectively.

Importantly, the decline in total hours worked is primarily attributed to adjustments on the extensive margin rather than the intensive margin. Average hours worked show a nearly zero and statistically insignificant response, which is consistent with the simulation results in Bloom (2009).[12] To further contextualize these findings, we compare the impact of uncertainty shocks (i.e., second-moment shocks) with that of first-moment shocks, which are measured by a negative shock to output or the stock market.[13] The results presented in Figures A.1 and A.2 in the appendix reveal that both labor margins decrease in response to negative first-moment shocks. While both first and second-

[12] This is because quadratic costs do not introduce a kink in adjustment expenses around zero, and as a result, there is no option value associated with waiting.

[13] The identification of the stock market shock follows the same Cholesky ordering, with the output growth and stock market return variables preceding the stock market volatility variable.

moment negative shocks have adverse effects on the economy, resulting in a reduction in total hours worked, a notable difference is observed in the intensive margin of adjustment, aligning with the concept of wait-and-see behavior under uncertainty.

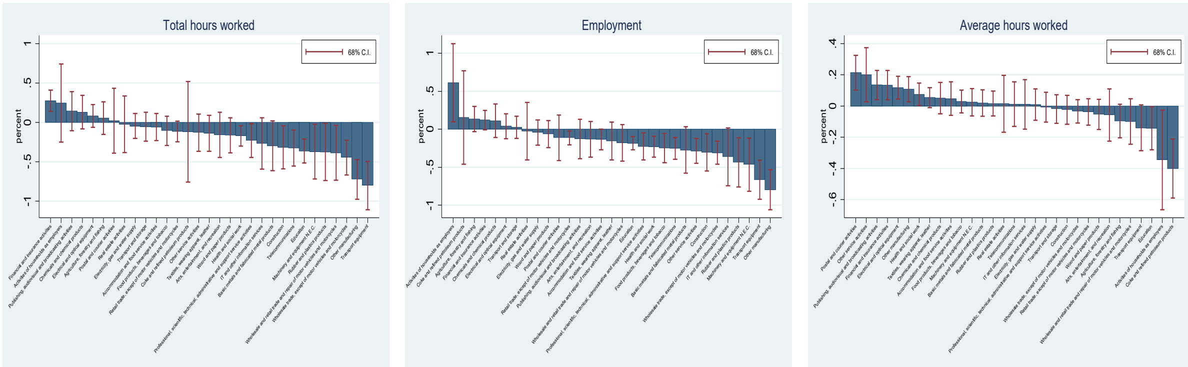
Industry-level heterogeneous effect of uncertainty shocks. We proceed to explore potential variations in the impact of uncertainty shocks on labor markets across industries. Depending on industry-specific attributes, the adverse effects of uncertainty shocks and the relative significance of adjustments through the two margins may exhibit discrepancies. This industry-level heterogeneity is crucial for a comprehensive understanding of the effects of uncertainty shocks on labor markets and for formulating relevant policy implications, an aspect often unaddressed in the existing literature. To investigate industry-level heterogeneity, we estimate equation (3) for each industry j separately, denoted as equation (4):

$$Y_{i,t+h} - Y_{i,t-1} = \alpha_i + \alpha_t + \beta^h U_{i,t} + \textstyle\sum_{p=1}^{n} \gamma^h Z_{i,t-p} + \varepsilon_{i,t+h}. \qquad (4)$$

In Figure 3, impact coefficients and their associated confidence intervals are presented for each of the 31 industries. A few interesting observations stand out. As observed in Figure 2, the variation in the response of total hours worked is primarily attributed to the extensive margin, with significant heterogeneity observed between the manufacturing and service sectors. Employment in the manufacturing sector, characterized by a higher natural layoff rate, appears particularly susceptible to uncertainty shocks, while employment in the service sector displays relatively greater resilience to the same shocks.

The responses of the intensive margin are generally centered around zero and mostly statistically insignificant, aligning with the theoretical predictions regarding uncertainty shocks (Bloom, 2009). These findings continue to support the notion of distinct margins of adjustment in response to uncertainty shocks. Notably, the correlation between the industry-level responses of employment and average hours worked is negative (-0.37) and statistically significant at the five percent level, distinguishing the effects of uncertainty shocks from those of first-moment shocks that induce a positive correlation.

Figure 3. Industry-by-industry effect of uncertainty shocks on labor market outcomes



Note: This graph plots the impact coefficient and the associated 68 percent confidence intervals for each industry by estimating equation (4).

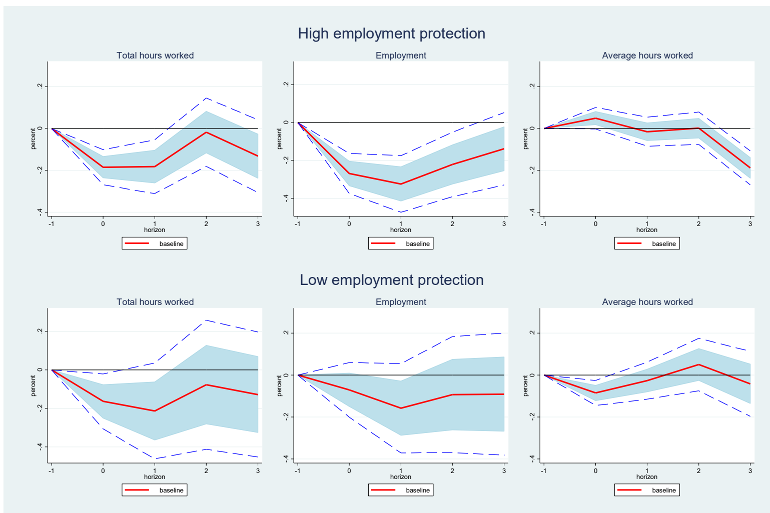
B. Investigation of Channels

The considerable heterogeneity in the labor market effects of uncertainty shocks, particularly regarding the margin of adjustment, can be explained by factors related to the irreversibility of hiring and firing. To explore these factors, we systematically examine the role of irreversibility using empirical proxies at both the country and industry levels.

Country-level labor market characteristics. Hiring and firing workers are known to be more costly for continental European firms compared to their U.S. counterparts due to more restrictive EPLs (Bentolila and Bertola, 1990; Vindigni et al., 2015). We gauge the degree of employment protection by utilizing data on the strictness of EPLs pertaining to individual and collective dismissals (regular contracts) sourced from the OECD (see the right panel in Figure 1). The presence of dismissal protections elevates firms' adjustment costs unless they are mitigated through Coasean bargaining. Consequently, firms may opt to refrain from hiring or firing workers when their short-term marginal productivity diverges from the market wage (Blanchard and Portugal, 2001; Autor et al., 2007).

Everything else equal, this institutional characteristic implies that non-convex adjustment costs C_L^P and C_L^F are higher in continental Europe, for example, so the wait-and-see channel of uncertainty shocks is likely to be stronger in these countries. To test this hypothesis, we separate the sample countries into two groups, based on the average strength of employment protection, and estimate equation (3) for each group. Figure 4 presents the estimation results. In line with the theoretical prediction, the adverse employment effects of the uncertainty shock in Figure 2 are mostly driven by countries with stricter employment protection. The response of employment in countries with weaker employment protection is not statistically significant at the 90% confidence level and barely significant after one year only at the 68% confidence level. Moreover, we continue to observe limited and statistically insignificant changes in average hours worked.

Figure 4. Effect of uncertainty shocks on labor market outcomes: role of country-level employment protection



Note: This graph plots the impulse response functions of labor market variables to the one standard deviation uncertainty shock by estimating equation (3). The shaded area and the dashed line denote 68% and 90% confidence intervals, respectively.

There are other institutional characteristics related to labor adjustment costs at the country level. Investigating the role of additional institutional characteristics helps us comprehend the underlying heterogeneity in these effects.[14] We assess the role of these three additional characteristics in shaping the response of the extensive and intensive margin to uncertainty shocks. To save space, we only plot the difference in the responses between the group of countries with more rigid labor

[14] For example, while our baseline measure only applies to dismissals of regular contracts, the regulation of temporary employment contracts also captures labor adjustment costs. Additionally, countries with higher expenditures on active labor market policies or more stringent product market regulations tend to have more inflexible labor markets.

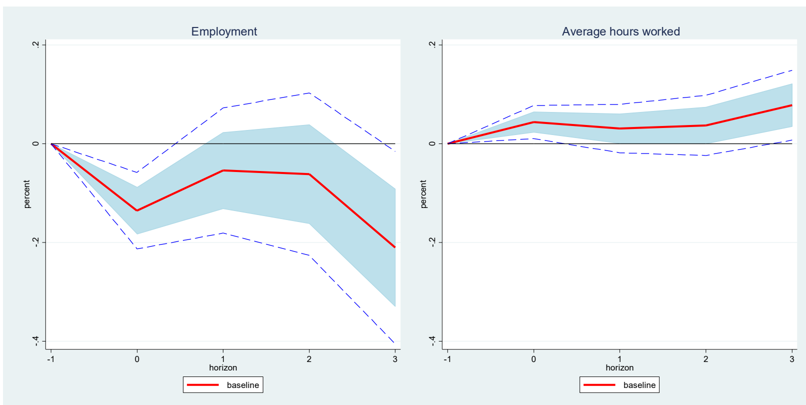
markets and those with less rigid labor markets (Figure A.3 in the appendix), not the individual responses. In sum, consistent with the case of regular employment contracts, we confirm that the adverse effect on employment is stronger in countries with more rigid labor markets, and the difference is statistically significant. In contrast, the effect on average hours worked does not display much difference, as the intensive margin is not subject to irreversibility.

Our findings bear significant policy implications. While the productivity ramifications of employment protection via misallocation have been thoroughly explored in the literature (e.g., Blanchard and Portugal, 2001; Autor et al., 2007; Lashitew, 2016; Duval et al., 2020), only a handful of studies have systematically delved into the interplay between employment protection and uncertainty shocks (Mumtaz et al., 2018). Our empirical findings demonstrate that the detrimental impact of uncertainty shocks on employment is notably pronounced in countries characterized by more rigid labor markets, a result of firms' optimal wait-and-see behavior under irreversibility.

Our results align with the theoretical framework put forth by Bentolia and Bertola (1990), illustrating that the interaction between high adjustment costs and the uncertain economic environment encountered by major European nations elucidates a pivotal facet of their employment dynamics. Moreover, our results complement recent U.S. state-level evidence from Mumtaz et al. (2018), who establish that states with right-to-work legislation exhibit a more substantial effect of uncertainty shocks on employment, and international evidence from Istrefi and Mouabbi (2018) that the impacts of interest rate uncertainty are amplified in countries with greater labor market rigidities. Given the elevated uncertainty since the global financial crisis, policymakers must be cognizant of the repercussions of stringent employment protection on labor markets.

Natural layoff rates as reliance on the extensive margin of adjustment. We now turn our attention to assessing differences in the reliance on the extensive margin of labor adjustment at the industry level and its role in shaping the effect of uncertainty shocks on labor markets. As previously mentioned, we employ the U.S. natural layoff rate and estimate the dynamic framework specified in equation (2) to uncover the distinct impact of uncertainty shocks on labor market variables over short to medium-term horizons. The availability of this measure at the industry level, rather than the country level, bolsters the identification strength, as our uncertainty shocks exhibit variation across countries and time. Compared to equation (3), equation (2) permits the inclusion of country-time fixed effects, which further alleviates concerns related to other potential confounding factors, such as unobserved macroeconomic shocks. Country-level proxies, due to their perfect multicollinearity with fixed effects, cannot achieve such robust identification.

Figure 5. Differential effect of uncertainty shocks on labor market outcomes: role of industry-level natural layoff rates



Note: Estimates are based on equation (2). The solid line denotes the differential employment (left panel) and average hours worked (right panel) effect of uncertainty shocks between industry with a high natural layoff rate (at the 75^{th} percentile of the distribution) and industry with a low natural layoff rate (at the 25^{th} percentile of the distribution) when the country-level uncertainty shock also increases from the 25^{th} percentile to the 75^{th} percentile of the distribution. The shaded area and the dashed line denote 68% and 90% confidence intervals, respectively.

In the left panel of Figure 5, we depict the differential response of employment based on the estimated coefficients. Instead of presenting the estimated coefficient itself, we illustrate the differential effect to facilitate the interpretation of the results. This differential effect corresponds to the difference in employment decline between industries with relatively high adjustment costs (at the 75th percentile of the distribution of layoff rates in the United States) and those with relatively low adjustment costs (at the 25th percentile of the distribution) when the country-level uncertainty shock increases from the 25th percentile to the 75th percentile of the distribution, equivalent to approximately a one standard deviation rise in uncertainty. On impact, this effect amounts to a

0.14 percent reduction in employment.[15] Given that the average (median) employment growth stands at 0.53 (0.59) percent, this differential effect is not only statistically significant but also economically meaningful.

The right panel in Figure 5 plots the differential response of the average hours worked to the same shock. Although the differential effect is small and mostly statistically insignificant, the sign of response (i.e., opposite to the extensive margin) is consistent with the results above using country-level employment protection as a proxy for the degree of irreversibility.

C. Sensitivity Tests

This section performs a battery of sensitivity tests to check whether the results presented above are robust to alternative specifications and remaining endogeneity concerns.

Placebo test with a first-moment shock. To address the possibility that natural layoff rates might be associated with other structural characteristics and could lead to different responses through a distinct mechanism, we conducted a placebo test. We examine whether natural layoff rates could characterize labor input responses to a first-moment shock. Specifically, we test if industries with higher natural layoff rates fire more workers in response to a negative output shock, leading to an employment decline in these industries. To the extent that heightened uncertainty often coincides with economic downturns, this would imply that the response we observed is driven by the sensitivity of employment to business cycles rather than the wait-and-see channel of uncertainty shocks.

To test this hypothesis, we repeat the same exercise but interact with the natural layoff rates with negative output shocks identified from the same VAR model. Figure A.4 in the appendix presents the results of this test. In contrast to Figure 5, there is no statistically significant differential response of employment to the negative output shock at a 90% confidence level. This suggests that

[15] We also try a specification in which natural layoff rates become a binary variable (take a value of one for the industry with layoff rates above the median and zero, otherwise). The results are qualitatively similar to the baseline.

natural layoff rates do not merely proxy the business cycle sensitivity of employment. Moreover, both the extensive and intensive margins of adjustment change in the same direction, which is in stark contrast to the case of uncertainty shocks. While the omission of this interaction variable from our baseline specification is unlikely to have a substantial impact on our estimates, we assess the robustness of our results by adding the interaction of output shocks with sectoral natural layoff rates in equation (2). The results, reported in Figure A.5, indicate that including these controls does not significantly affect our findings. These findings support our interpretation of natural layoff rates and provide further evidence for the wait-and-see channel of uncertainty shocks.

Ruling out alternative explanations. We consider the possibility that the differential decline in employment shown in Figure 5 might be attributed to higher exit rates in industries with higher natural layoff rates in response to uncertainty shocks. In such cases, firms may opt to exit the market (and therefore fire workers) instead of waiting, leading to a reduction in employment for different reasons. Given that uncertainty tends to rise during recessions, this scenario is plausible. However, it is empirically challenging to disentangle this channel from the wait-and-see channel, especially when separate hiring and firing data are not available. To address this concern, we estimate the differential effects on output using value-added and gross output, as presented in Figure A.6. Interestingly, the results show that the output of industries with higher natural layoff rates decreases less, suggesting that the more substantial decline in employment in these industries is unlikely driven by higher exit rates.

Alternative layoff rates. Our working assumption is that the distribution of sectoral layoff rates is stable over time and consistent across countries, allowing us to use U.S. natural layoff rates as proxies for natural layoff rates in other countries. To validate this assumption, Basannini et al. (2009) found that the variation in the distribution of sectoral layoff rates is primarily explained by differences across industries, and the correlation between the corresponding distributions of U.S. layoff rates is relatively stable over time. However, to further explore the robustness of our findings, we re-estimate equation (2) using industry-specific layoff rates for the United Kingdom. The OECD's dismissal procedures indicators suggest that the United Kingdom has the second to third least regulated labor market among OECD countries, making the UK sectoral layoff rates a valid alternative measure. The results obtained from this exercise are presented in Figure A.7 in the appendix and are consistent with those reported in the baseline analysis.

Manufacturing vs. service sectors. In order to assess the robustness of our results and account for potential differences between the manufacturing and service sectors, we conduct a sensitivity test by using a subsample consisting of only the manufacturing sector. Figure A.8 in the appendix demonstrates that our findings remain consistent and robust when focusing exclusively on the manufacturing sector, addressing any concerns related to differences in structural factors between the manufacturing and service sectors.

Excluding the global financial crisis. We address the concern that the inclusion of the global financial crisis might have dramatically changed the mechanism through which uncertainty shocks affect labor markets. Our measure of uncertainty reached unprecedented levels during this period, and the crisis and its aftermath were characterized by a sharp increase in the long-term unemployment rate and jobless recovery. Although our primary focus is not on the effect of uncertainty shocks on the level of employment per se, there might be a structural break in the identified interaction effect after the crisis. To examine whether this outlier event influenced our findings, we exclude the period since 2007 and repeat the analysis.[16] Figure A.9 illustrates that even after dropping the recent crisis period, our results continue to highlight the difference between extensive and intensive margins of adjustment in response to uncertainty shocks.

Controlling for additional confounding factors. We consider the possibility that our results might be biased due to the omission of other factors correlated with both natural layoff rates and uncertainty shocks. One such candidate is labor market regulations, a variable of interest in previous research. These regulations, specifically EPL, are argued to have an impact on productivity growth in industries with higher layoff rates. Omitting EPL as a potential confounding factor could

[16] We rescale the size of uncertainty shocks during the pre-crisis period for this exercise.

introduce bias into the estimates depending on its relationship with heightened uncertainty. To assess the robustness of our findings to the inclusion of EPL, we re-estimate equation (2) by introducing an interaction variable between EPL and the industry-specific layoff rate (along with its lags). Figure A.10 reveals that the effect of uncertainty shocks on sectoral employment and average hours worked remains very close to those reported in Figure 5. This suggests that our results are robust to the inclusion of EPL as an additional confounding factor.

Controlling for competing channels. In addition to the real option value channel, the interaction effect we observed in our analysis might have captured the effect of financial frictions if industries with higher layoff rates tend to be more financially constrained. Financial frictions are known to amplify the effects of uncertainty shocks by raising borrowing costs or reducing credit availability (Christiano et al., 2014; Caldara et al., 2016; Husted et al., 2020).[17] Although the low correlation between industry-level layoff rates and external financial dependence (0.04) mitigates the concern above, we assess the robustness of our findings in light of potential financial constraints. We introduce an additional interaction term (along with its lagged values) between our uncertainty measure and the degree of external financial dependence measured using the method proposed by Rajan and Zingales (1998). Figure A.12 demonstrates that the dynamic responses of employment and average hours worked remain qualitatively similar to our baseline results even after controlling for the potential influence of external financial dependence.[18]

[17] Choi et al. (2018) found that an increase in aggregate uncertainty reduces output and productivity growth more in industries that rely heavily on external finance, using a static version of the methodology employed in our paper. In their study, the mechanism was that during periods of high uncertainty, credit-constrained firms shifted their investment composition by reducing productivity-enhancing investments, such as ICT capital, which is more vulnerable to liquidity risks. To assess whether this previous finding is still applicable in our alternative empirical framework, we substituted sectoral employment with sectoral real value-added (deflated by the country-level Consumer Price Index) in our analysis. This allows us to replicate the approach of Choi et al. (2018) within our dynamic framework. The results in Figure A.11 are consistent with the static results reported in Choi et al. (2018), providing additional support for the validity of our identification strategy.

[18] We also find that the coefficients on the interaction between external finance dependence and uncertainty are never statistically significant at any time horizon in the case of employment and average hours worked. This result suggests that the financial constraint channel is a less critical factor in explaining labor market dynamics.

We further test the robustness of our findings by controlling for the extra composite variables: (i) the interaction between the industry-level elasticity of substitution between labor and capital and uncertainty shocks and (ii) the industry-level labor share and uncertainty shocks. The industry-level data on the elasticity of substitution and labor share are taken from Ciminelli et al. (2022). As shown in Figure A.13 in the appendix, our results are preserved. The additional interaction terms are not statistically significant.

Local projections with an external instrument. To address remaining concerns related to potential endogeneity in the identified uncertainty shock (e.g., rising uncertainty as an endogenous response to macroeconomic development), we employ a Local Projections Instrumental Variable (LP-IV) approach following Stock and Watson (2018).[19] This method allows us to assess the dynamic effect of uncertainty shocks while mitigating potential endogeneity issues. The instruments used in our LP-IV approach are derived from Baker et al. (forthcoming), who utilized natural disasters, terrorist attacks, and political shocks as instruments to gauge the causal impact of uncertainty shocks on real GDP growth. These instruments are considered mostly exogenous to the macroeconomy, particularly in the short run, and are scaled by the increase in media mentions of the country in the 15 days following the shock compared to the 15 days before the shock to account for event magnitude.

In our LP-IV approach, each of the scaled instruments, which vary over time and by country, interacts with industry natural layoff rates before entering the estimation. This interaction variable serves as the relevant instrument because the variables to be instrumented are themselves interaction variables (Wooldridge, 2010). We proceed with a two-stage least squares (2SLS) approach. In the first step, we regress the interaction variable of uncertainty shocks and layoff rates

[19] Of course, these factors must be correlated with U.S. industry-level layoff rates to bias our estimates within our estimation framework, given the constellation of the fixed effects. This scenario is quite implausible but not impossible. One can think of a case in which massive layoffs from a disproportionally large industry having higher natural layoff rates can drive heightened uncertainty worldwide. The Great Recession triggered by the collapse in the U.S. housing markets accompanied by massive layoffs from the construction sector could be a potential example (Shoag and Veuger, 2016).

on the instruments. In the second step, we re-estimate our original equation (2) using the exogenous component driven by the instrument, which is the fitted value from the first step.

The Olea and Pflueger effective F-statistic for the impact response (h=0) is 15.14 for employment and 15.71 for average hours worked, suggesting that our instruments can be considered relevant at the 10 percent critical value.[20] Moreover, Hansen's J statistic, which tests overidentifying restrictions, does not reject the null hypothesis that the instruments are exogenous, with p-values of 0.12 for employment and 0.26 for average hours worked. The results of this LP-IV approach, presented in Figure A.14 in the appendix, largely confirm our OLS findings in Figure 5, although the associated standard errors are wider. We still find a negative and statistically significant differential effect of uncertainty shocks on employment.[21]

Alternative measure of uncertainty and instruments. We explore an alternative measure of uncertainty and instruments to mitigate potential concerns regarding the confounding effect of financial market distress on stock market volatility. We employ the World Uncertainty Index (WUI), a text-based measure of uncertainty developed by Ahir et al. (2022). The WUI offers a consistent method for assessing domestic uncertainty across countries, utilizing country reports from the Economist Intelligence Unit. Following Ahir et al. (2022), shocks to the WUI are further instrumented using exogenous election dates, providing a natural experiment framework for studying

[20] Due to the inherent serial correlation introduced by the use of the Jordà method, we employ the Olea and Pflueger effective F-statistics and thresholds as recommended by Ramey and Zubairy (2018). While an F-statistic above 10 in the first stage is typically considered an indicator of instrument relevance, Olea and Pflueger (2013) have shown that the threshold may vary, especially when there is serial correlation in the errors.

[21] One key point to consider when interpreting the economic magnitude of the IV estimates is that these coefficients reflect a Local Average Treatment Effect (LATE; Imbens and Angrist, 1994), which captures the effect of uncertainty shocks on industry-level outcomes due to rare events only. This accounts for the larger effect sizes observed in the IV estimates compared to the OLS results.

political uncertainty's economic implications and addressing endogeneity issues. The results, presented in Figure A.15, corroborate our original instrumental variable analysis.[22]

D. Exploring Non-linearity

Expansions vs. Recessions. We have established robust evidence indicating that higher uncertainty reduces employment more in industries with greater layoff rates, while these same industries experience a relative increase in average hours worked. However, our findings may not fully account for potential heterogeneity stemming from different economic regimes, such as expansions vs. recessions. Additionally, there is substantial empirical support for the idea that the negative impact of uncertainty shocks on economic activity is more pronounced during bad times compared to good times (Caggiano et al., 2014; Jones and Enders, 2016; Pellegrino et al., 2023). To address these aspects, we apply local projections to construct impulse responses within the framework of non-linear models.

Following Auerbach and Gorodnichencko (2012a, 2012b) and Ramey and Zubairy (2018), we estimate the following equation in which the dynamic response is allowed to vary with the state of the economy:

$$Y_{i,j,t+h} - Y_{i,j,t-1} = \alpha_{i,j} + \alpha_{i,t} + \alpha_{j,t} + \beta_R^h F(z_{i,t-1}) C_j U_{i,t} + \beta_E^h (1 - F(z_{i,t-1})) C_j U_{i,t} + \sum_{p=1}^{n} \gamma^h Z_{i,j,t-p} + \varepsilon_{i,j,t}, \qquad (5)$$

with $F(z_{i,t}) = \frac{exp(-\theta z_{i,t})}{1+exp(-\theta z_{i,t})}$ and $\theta > 0$, where $z_{i,t}$ is an indicator of the state of the economy.[23]

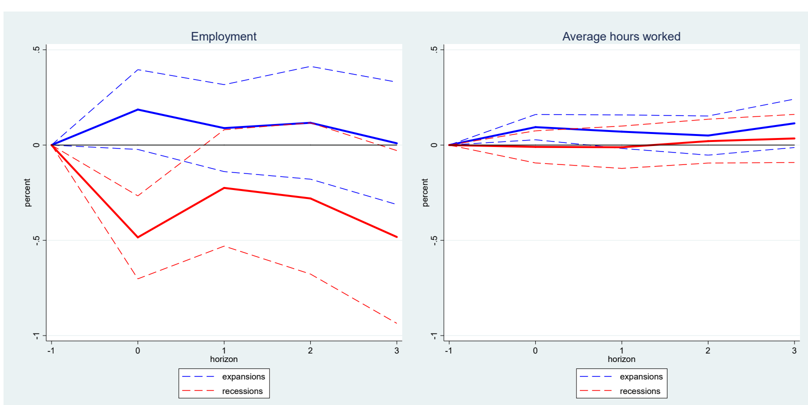
[22] The effective F-statistic of the first stage regression for the impact response (h=0) is 24.71 and 19.94 for employment and average hours worked, respectively. Hansen's J statistic testing overidentifying restrictions does not reject the null hypothesis that the instruments are exogenous (p-value of 0.36 for employment and 0.18 for average hours worked).

[23] This methodology aligns with the smooth transition autoregressive model introduced by Granger and Terävistra (1993) and offers several advantages. First, unlike a model where each dependent variable interacts with a business cycle position indicator, our approach enables a direct examination of how the impact of uncertainty shocks varies across different economic states. Second, compared with estimating structural Vector Autoregressions for each regime, our method allows the effect of uncertainty shocks to change smoothly between recessions and expansions by considering a continuum of states to compute the impulse response functions, thus making the response more stable and precise.

The indicator of the state of the economy is real GDP growth and $F(z_{i,t})$ is a smooth transition function used to estimate the differential impact of uncertainty shocks in expansions versus recessions. The parameter θ governs the speed of transition between the two regimes. We choose $\theta = 1.5$ following Auerbach and Gorodnichencko (2012a) and normalize $z_{i,t}$ accordingly, so the economy spends about 20 percent of the time in a recessionary regime. The state variable $z_{i,t}$ is lagged to alleviate the potential concern that uncertainty shocks change the regime of the economy.

The impulse responses at each horizon are estimated directly by regressing $Y_{i,j,t+h} - Y_{i,j,t-1}$ on the shock in period t and lagged values of other control variables in the Jordà method, which does not involve any iteration. The estimated parameters depend on the economy's average behavior in the historical sample between t and $t+h$, given the shock, the initial state, and the control variables. The parameter estimates on the control variables incorporate the average tendency of the economy to evolve between states. In sum, the estimates incorporate both the natural transitions and endogenous transitions from state to state that occur on average in the data (Ramey and Zubairy, 2018).

Figure 6. Differential effect of uncertainty shocks on labor market outcomes: expansions vs. recessions

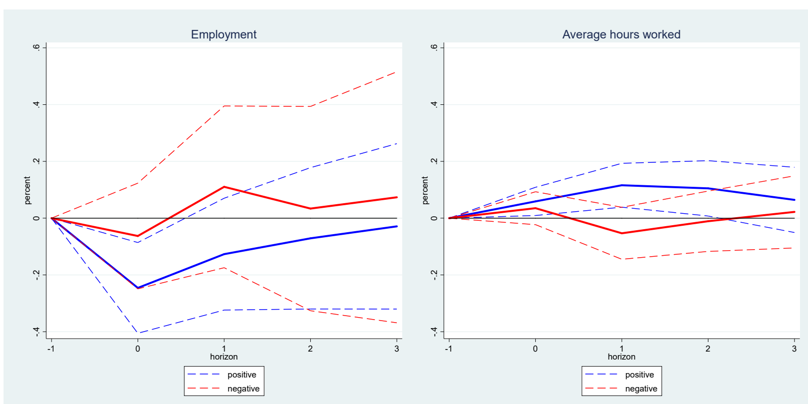


Note: Estimates are based on equation (5). The solid line denotes the differential employment (left panel) and average hours worked (right panel) effect of uncertainty shocks between industry with a high natural layoff rate (at the 75th percentile of the distribution) and industry with a low natural layoff rate (at the 25th percentile of the distribution) when the country-level uncertainty shock also increases from the 25th percentile to the 75th percentile of the distribution. The blue (red) line denotes the effect during expansions (recessions). The dashed line denotes a 90% confidence interval.

The coefficients β_E^h and β_R^h trace the dynamic response when the economy is in expansions and recessions, respectively, which are shown in Figure 6. While the differential effect on employment is statistically insignificant during expansions, it becomes larger and more statistically significant during recessions compared to the baseline result, suggesting that the wait-and-see channel of uncertainty shocks is magnified in bad times when the realization of the first-moment shock is low. This finding is consistent with the implication of concave hiring rules (i.e., firms respond more to bad shocks than good shocks) on employment (Ilut et al., 2018).

Positive vs. negative uncertainty shocks. In principle, an increase in uncertainty does not necessarily have a symmetric effect with a decrease in uncertainty. For example, using a logistic smooth transition autoregressive (LSTAR) process, Jones and Enders (2016) find that a positive shock to uncertainty has a greater effect than a negative shock and argue that the usual linear estimates for the consequences of uncertainty are underestimated in the circumstances such as the recent financial crisis.

Figure 7. Differential effect of uncertainty shocks on labor market outcomes: positive vs. negative uncertainty shocks



Note: Estimates are based on equation (6). The solid line denotes the differential employment (left panel) and average hours worked (right panel) effect of uncertainty shocks between industry with a high natural layoff rate (at the 75th percentile of the distribution) and industry with a low natural layoff rate (at the 25th percentile of the distribution) when the country-level uncertainty shock also increases from the 25th percentile to the 75th percentile of the distribution. The blue (red) line denotes the effect of positive (negative) uncertainty shocks. The dashed line denotes a 90% confidence interval.

To explore potential differences in the effects of increasing and decreasing uncertainty, we estimate the following specification:

$$Y_{i,j,t+h} - Y_{i,j,t-1} = \alpha_{i,j} + \alpha_{i,t} + \alpha_{j,t} + \beta_{+}^{h} D_{i,t} C_j U_{i,t} + \beta_{-}^{h} (1 - D_{i,t}) C_j U_{i,t} + \sum_{p=1}^{n} \gamma^h Z_{i,j,t-p} + \varepsilon_{i,j,t}, \quad (6)$$

where D is a dummy variable that takes the value of one for an increase in uncertainty and zeroes otherwise. The results obtained by estimating equation (6) are presented in Figure 7. They confirm that the differential effect on employment is larger for an increase than a decrease in uncertainty, suggesting that the real option value channel is more relevant when facing heightened uncertainty than the resolution of uncertainty.

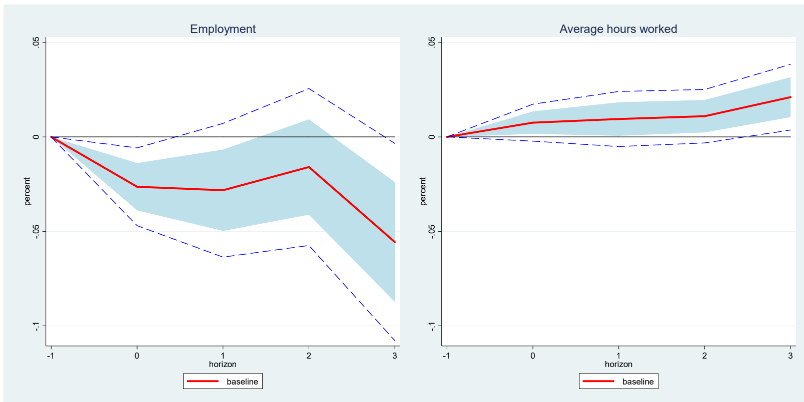
Considering both country and industry-level proxies. To further explore the potential influence of labor market regulations at the country level on the differential effect of our main interest, we examine whether countries with more rigid labor markets exhibit a larger interaction effect using our industry-level natural layoff rates. If the wait-and-see mechanism with irreversibility in hiring and firing is a crucial factor in explaining employment dynamics, the interaction effect should be more pronounced in countries with more binding constraints on the extensive labor adjustment. A related study by Lashitew (2016) suggests that the misallocation effect of stringent employment protection is more significant in industries with higher natural layoff rates.

Once again, local projections enable us to easily extend the baseline model to test an additional hypothesis. This involves including the so-called triple difference-in-difference term as follows:

$$Y_{i,j,t+h} - Y_{i,j,t-1} = \alpha_{i,j} + \alpha_{i,t} + \alpha_{j,t} + \beta^h C_j EPL_{i,t-1} U_{i,t} + \sum_{p=1}^{n} \gamma^h Z_{i,j,t-p} + \varepsilon_{i,j,t}, \quad (7)$$

where $EPL_{i,t-1}$ captures the degree of a country-specific stringency of employment protection used in the previous exercise; a vector of control variables $Z_{i,j,t}$ further includes the interaction term $C_j EPL_{i,t-1}$. Unlike the previous exercise, we use time-varying measures, not the average value, to further exploit the within-variation in EPL. This term is lagged to mitigate reverse causality concerns.

Figure 8. Differential effect of uncertainty shocks on labor market outcomes: role of country-level EPL



Note: Note: Estimates are based on equation (7). The solid line denotes the differential employment (left panel) and average hours worked (right panel) effect of uncertainty shocks between industry with a high natural layoff rate (at the 75th percentile of the distribution) and industry with a low natural layoff rate (at the 25th percentile of the distribution) when the country-level uncertainty shock also increases from the 25th percentile to the 75th percentile of the distribution while moving from low employment protection (at the 25th percentile of the distribution) to high employment protection (at the 75th percentile of the distribution) simultaneously. The shaded area and the dashed line denote 68% and 90% confidence interval, respectively.

Figure 8 presents the differential effect by tracking the coefficients on the tripple interaction term obtained from estimating equation (7). In addition to the original differential effect, we also multiply the difference in the degree of employment protections between relatively more stringent countries (the 75th percentile of the distribution) and less stringent countries (the 25th percentile of the distribution). Indeed, the differential effects we found in Figure 5 strengthen in a country with a more stringent EPL, consistent with the re-enforcing mechanism at both country and industry-levels.

VI. Conclusion

In summary, our study has delved into the impact of uncertainty shocks on labor markets, employing a comprehensive international industry-level dataset. The distinctive nature of our data, which decomposes total hours worked into employment and average hours worked, has unveiled intriguing uncertainty shock dynamics. Notably, we observe a reduction in labor input solely along the extensive margin, aligning with the predictions of real option value theory à la Bloom (2009). These dynamics stand in contrast to first-moment shocks, where both extensive and intensive margins exhibit responses in the same direction.

We have paid particular attention to assess how this effect systematically varies concerning employment protections and natural layoff rates, serving as proxies for the degree of irreversibility in employment decisions at both the national and industry levels. The adverse impact on employment is notably pronounced in situations of stringent employment protections or within industries heavily reliant on the extensive margin for labor demand adjustments. Our findings underscore the pivotal role of the channel in comprehending the labor market repercussions of uncertainty shocks, thereby offering pertinent policy implications.

Nonetheless, it is essential to acknowledge certain limitations in our findings. Foremost among these is the fact that our empirical approach, utilizing the difference-in-difference method, exclusively captures the partial equilibrium effects of uncertainty shocks. As discussed by Bloom et al. (2018), the consideration of general equilibrium effects plays an additional role in shaping the impact of uncertainty shocks on the broader economy, including labor markets. Consequently, a degree of caution is warranted when interpreting our results. Nevertheless, our study contributes robust empirical evidence that sheds light on the heterogeneous effects of uncertainty shocks on labor markets from the perspective of real option value theory, a dimension often overlooked in existing literature.

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Appendix

Table A.1. Sample coverage and the number of observations

Countries	Sample coverage	Number of observations
Australia	1970-2007	950
Austria	1985-2013	899
Canada	1976-2010	910
Czech Republic	1995-2013	583
Denmark	1979-2013	1,085
Finland	1987-2013	837
France	1975-2013	1,134
Germany	1970-2013	1,364
Greece	1995-2013	589
Hungary	1995-2013	589
Ireland	1998-2013	496
Italy	1973-2013	1,271
Japan	1970-2009	1,120
Korea	1980-2010	806
Luxembourg	1995-2013	475
Netherlands	1983-2013	949
Poland	2000-2013	434
Portugal	1995-2013	589
Spain	1972-2013	1,302
Sweden	1993-2012	579
United Kingdom	1970-2013	1,339

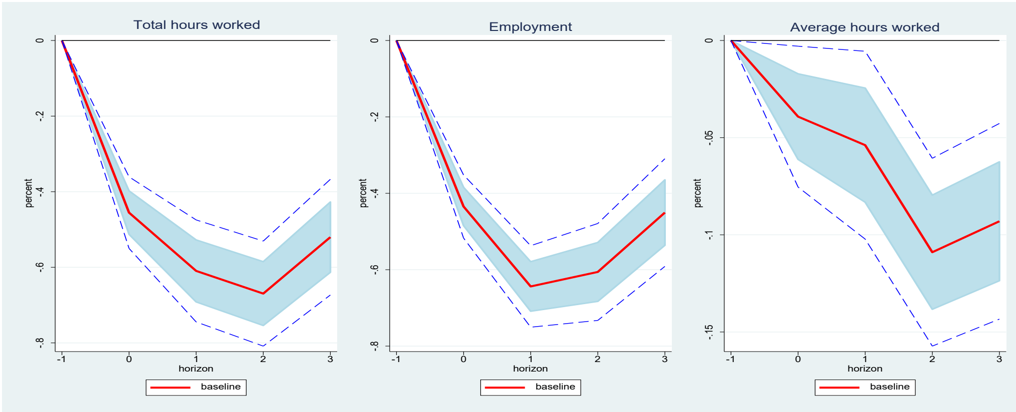
Note: The United States is dropped from the baseline analysis.

Table A.2. Industry-level layoff rates

	2011	2012	2013	Average (U.S.)	U.K.	Industry Code
Food products, beverages, and tobacco	3.04	1.99	4.07	3.04	4.17	10t12
Textiles, wearing apparel, leather	2.18	3.10	5.92	3.73	9.76	13t15
Wood and paper products	4.31	3.21	3.90	3.81	5.55	16t18
Coke and refined petroleum products	0.00	0.00	3.21	1.07	/	19
Chemicals and chemical products	3.43	2.11	2.18	2.58	4.05	20t21
Rubber and plastics products	2.82	2.22	2.17	2.41	5.48	22t23
Basic metals and fabricated metal products	2.44	3.35	3.92	3.24	5.53	24t25
Electrical and optical equipment	4.67	5.96	6.25	5.63	6.54	26t27
Machinery and equipment N.E.C.	3.04	2.39	3.16	2.86	/	28
Transport equipment	2.94	2.01	3.37	2.77	4.54	29t30
Other manufacturing	8.54	7.48	5.92	7.31	6.76	31t33
Wholesale and retail trade and repair of motor Vehicles and motorcycles	2.30	2.18	2.48	2.32	/	45
Wholesale trade, except of motor vehicles and Motorcycles	1.85	2.84	3.39	2.69	/	46
Retail trade, except of motor vehicles and Motorcycles	2.04	2.46	3.22	2.57	/	47
Transport and storage	2.48	2.92	3.41	2.94	3.55	49t52
Postal and courier activities	1.58	1.40	1.34	1.44	/	53
Publishing, audiovisual and broadcasting activities	2.70	2.56	4.36	3.21	/	58t60
Telecommunications	2.08	1.81	2.05	1.98	/	61
IT and other information services	2.47	3.14	3.69	3.10	/	62t63
Agriculture, forestry and fishing	0.00	5.20	5.62	3.61	/	A
Electricity, gas and water supply	1.15	2.21	1.43	1.59	3.56	DtE
Construction	4.51	5.63	8.98	6.37	5.86	F
Accommodation and food service activities	1.96	2.86	4.43	3.08	2.79	I
Financial and insurance activities	2.51	1.93	2.59	2.34	2.85	K
Real estate activities	1.28	1.53	2.91	1.91	/	L
Professional, scientific, technical, administrative and support service activities	2.62	3.59	4.84	3.68	/	MtN
Education	0.90	1.43	1.72	1.35	/	P
Health and social work	1.31	1.50	2.54	1.78	/	Q
Arts, entertainment, and recreation	2.06	2.81	5.33	3.40	/	R
Other service activities	1.85	2.61	3.72	2.73	/	S
Activities of households as employers	0.47	1.10	1.16	0.91	/	T

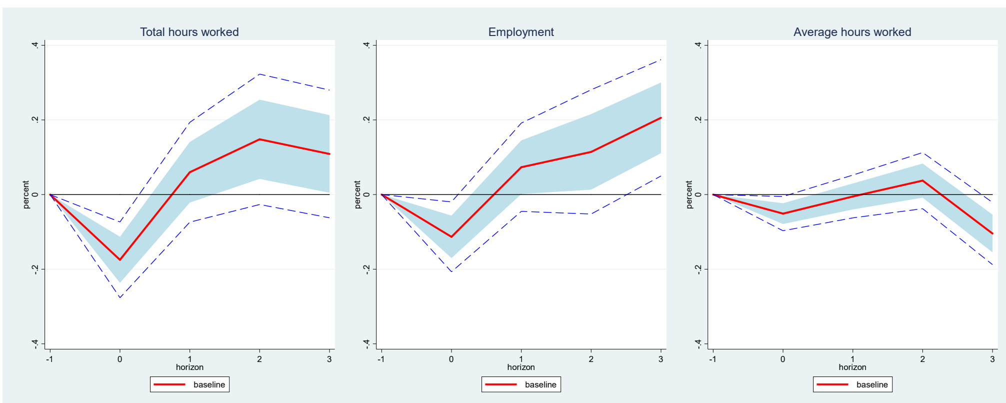
Note: The average value of U.S. layoff rates between 2011 and 2013 is used in the baseline analysis.

Figure A.1. Aggregate effect of negative output shocks on labor market outcomes



Note: This graph plots the impulse response functions of labor market variables to the one standard deviation negative first-moment shock captured by real GDP growth by estimating equation (3). The shaded area and the dashed line denote 68% and 90% confidence interval, respectively.

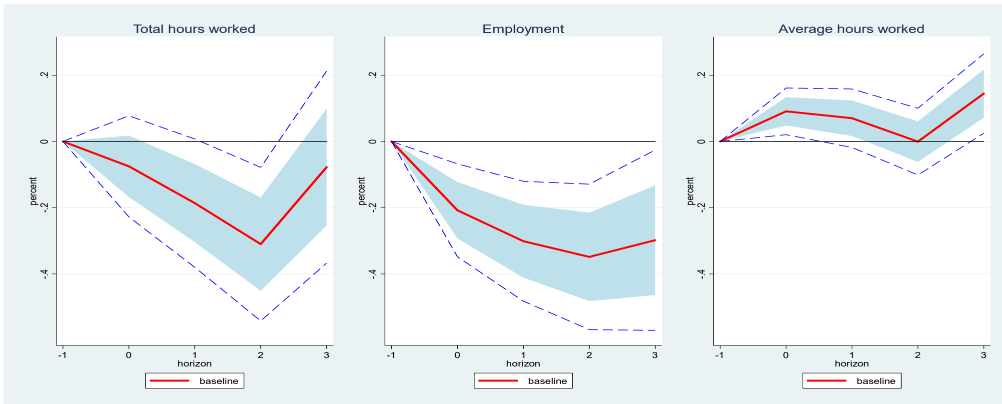
Figure A.2. Aggregate effect of the stock market shocks on labor market outcomes



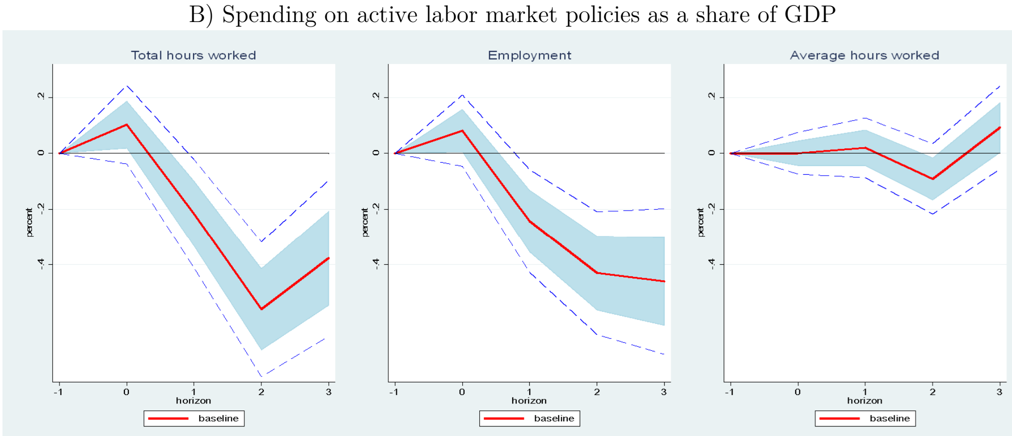
Note: This graph plots the impulse response functions of labor market variables to the one standard deviation negative first-moment shock captured by stock market returns by estimating equation (3). The shaded area and the dashed line denote 68% and 90% confidence interval, respectively.

Figure A.3. Differential effect of uncertainty shocks on labor market outcomes: role of other country-level institutional factors

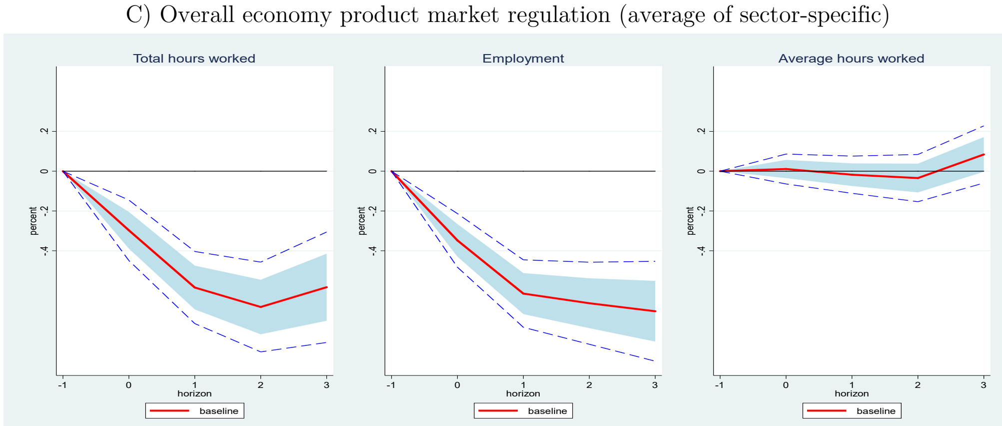
A) Regulation of temporary employment contracts



B) Spending on active labor market policies as a share of GDP

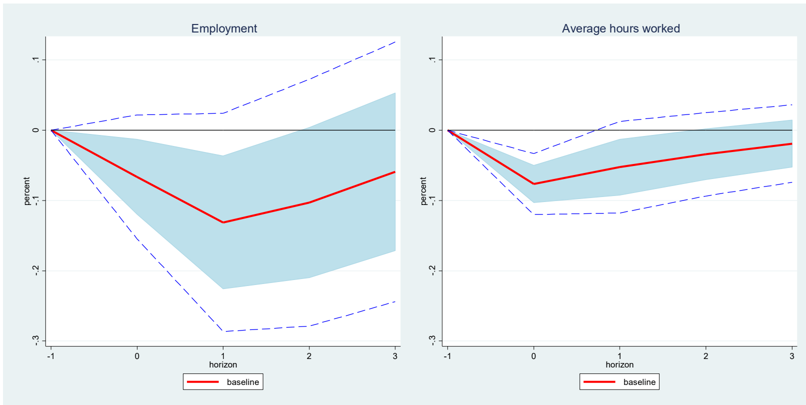


C) Overall economy product market regulation (average of sector-specific)



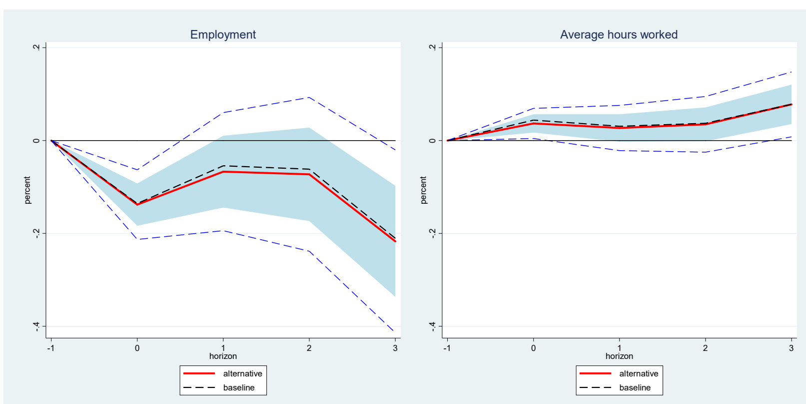
Note: This graph plots the differential impulse response functions of labor market variables between the two groups of countries depending on each institutional factor (1=high; 0=low) to the one standard deviation uncertainty shock. The shaded area and the dashed line denote 68% and 90% confidence intervals, respectively.

Figure A.4. Differential effect of negative output shocks on labor market outcomes: role of industry-level natural layoff rates



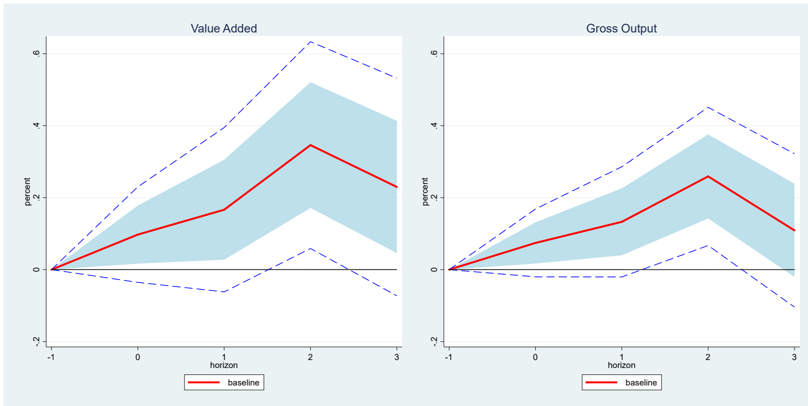
Note: Estimates are based on equation (2). The solid line denotes the differential employment (left panel) and average hours worked (right panel) effect of output shocks between industry with a high natural layoff rate (at the 75th percentile of the distribution) and industry with a low natural layoff rate (at the 25th percentile of the distribution) when the country-level output shock also increases from the 25th percentile to the 75th percentile of the distribution. The shaded area and the dashed line denote 68% and 90% confidence intervals, respectively.

Figure A.5. Differential effect of uncertainty shocks on labor market outcomes: controlling for the interaction between output shocks and the natural layoff rates



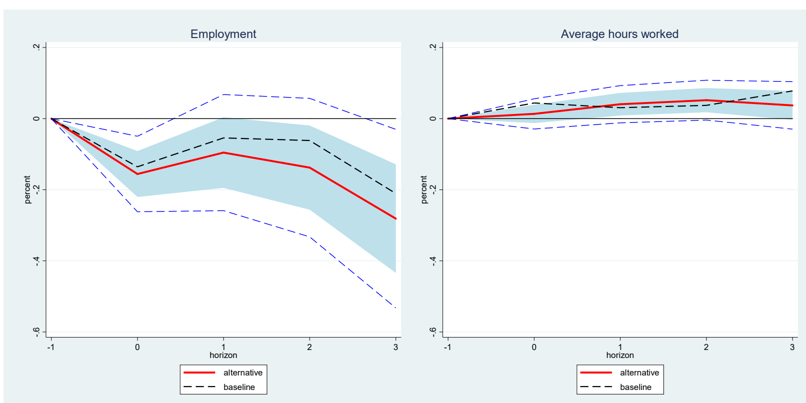
Note: Estimates are based on equation (2) while controlling for the interaction between negative output shocks and the natural layoff rates. The solid line denotes the differential employment (left panel) and average hours worked (right panel) effect of uncertainty shocks between industry with a high natural layoff rate (at the 75th percentile of the distribution) and industry with a low natural layoff rate (at the 25th percentile of the distribution) when the country-level uncertainty shock also increases from the 25th percentile to the 75th percentile of the distribution. The shaded area and the dashed line denote 68% and 90% confidence intervals, respectively.

Figure A.6. Differential effect of uncertainty shocks on output



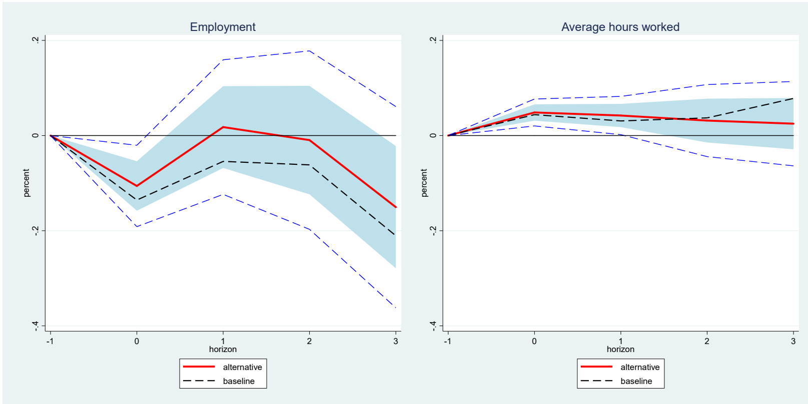
Note: Estimates are based on equation (2). The solid line denotes the differential value-added (left panel) and gross output (right panel) effect of uncertainty shocks between industry with a high natural layoff rate (at the 75$^{\text{th}}$ percentile of the distribution) and industry with a low natural layoff rate (at the 25$^{\text{th}}$ percentile of the distribution) when the country-level uncertainty shock also increases from the 25$^{\text{th}}$ percentile to the 75$^{\text{th}}$ percentile of the distribution. The shaded area and the dashed line denote 68% and 90% confidence intervals, respectively.

Figure A.7. Differential effect of uncertainty shocks on labor market outcomes: using the U.K. natural layoff rates



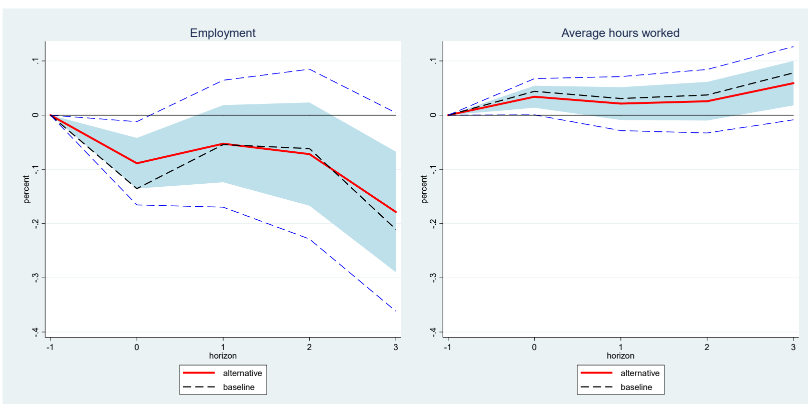
Note: Estimates are based on equation (2) using the U.K. natural layoff rates. The solid line denotes the differential employment (left panel) and average hours worked (right panel) effect of uncertainty shocks between industry with a high natural layoff rate (at the 75$^{\text{th}}$ percentile of the distribution) and industry with a low natural layoff rate (at the 25$^{\text{th}}$ percentile of the distribution) when the country-level uncertainty shock also increases from the 25$^{\text{th}}$ percentile to the 75$^{\text{th}}$ percentile of the distribution. The shaded area and the dashed line denote 68% and 90% confidence intervals, respectively. The black dashed line denotes the impulse response function obtained in the baseline analysis.

Figure A.8. Differential effect of uncertainty shocks on labor market outcomes: using the manufacturing sectors only



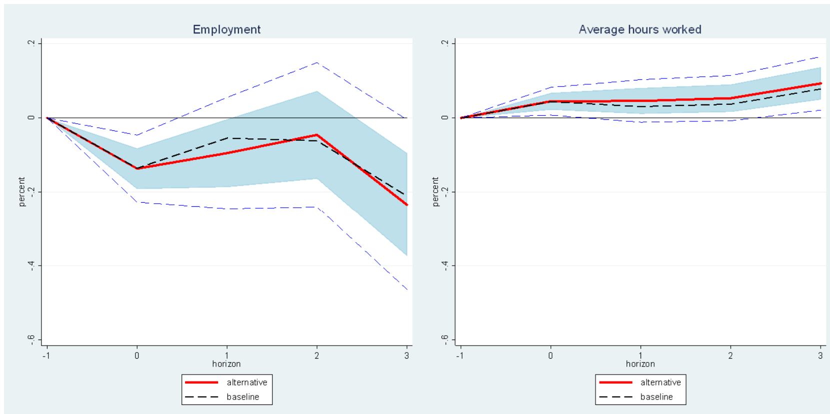
Note: Estimates are based on equation (2) using the manufacturing sectors only. The solid line denotes the differential employment (left panel) and average hours worked (right panel) effect of uncertainty shocks between industry with a high natural layoff rate (at the 75^{th} percentile of the distribution) and industry with a low natural layoff rate (at the 25^{th} percentile of the distribution) when the country-level uncertainty shock also increases from the 25^{th} percentile to the 75^{th} percentile of the distribution. The shaded area and the dashed line denote 68% and 90% confidence intervals, respectively. The black dashed line denotes the impulse response function obtained in the baseline analysis.

Figure A.9. Differential effect of uncertainty shocks on labor market outcomes: dropping the Global Financial Crisis period and its aftermath



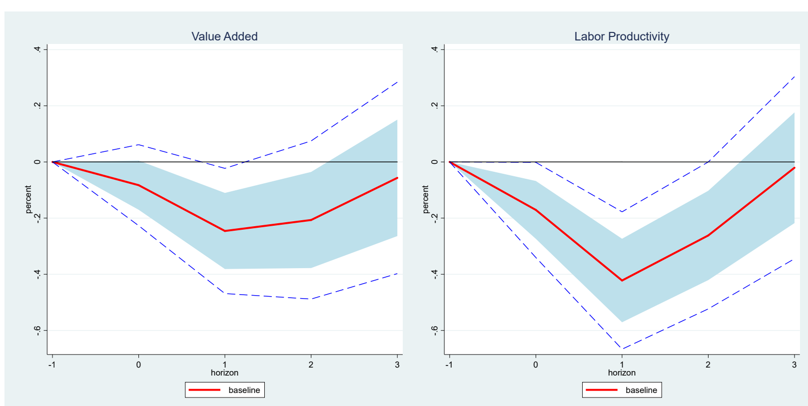
Note: Estimates are based on equation (2) using the sample period until 2007. The solid line denotes the differential employment (left panel) and average hours worked (right panel) effect of uncertainty shocks between industry with a high natural layoff rate (at the 75^{th} percentile of the distribution) and industry with a low natural layoff rate (at the 25^{th} percentile of the distribution) when the country-level uncertainty shock also increases from the 25^{th} percentile to the 75^{th} percentile of the distribution. The shaded area and the dashed line denote 68% and 90% confidence intervals, respectively. The black dashed line denotes the impulse response function obtained in the baseline analysis.

Figure A.10. Differential effect of uncertainty shocks on labor market outcomes: controlling for EPL



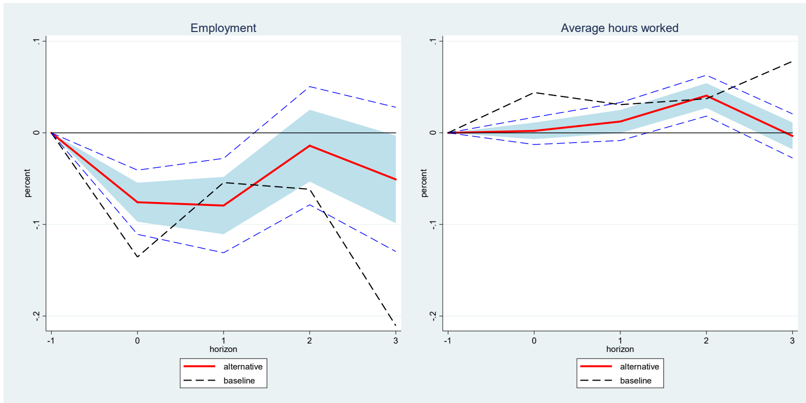
Note: Estimates are based on equation (2) while controlling for the interaction between EPL and the natural layoff rates. The solid line denotes the differential employment (left panel) and average hours worked (right panel) effect of uncertainty shocks between industry with a high natural layoff rate (at the 75^{th} percentile of the distribution) and industry with a low natural layoff rate (at the 25^{th} percentile of the distribution) when the country-level uncertainty shock also increases from the 25^{th} percentile to the 75^{th} percentile of the distribution. The shaded area and the dashed line denote 68% and 90% confidence intervals, respectively. The black dashed line denotes the impulse response function obtained in the baseline analysis.

Figure A.11. Differential effect of uncertainty shocks on real output: interacting with external financial dependence



Note: Estimates are based on equation (2) using the interaction between uncertainty shocks and external financial dependence. The solid line denotes the differential value added (left panel) and labor productivity (right panel) effect of uncertainty shocks between industry with high external financial dependence (at the 75^{th} percentile of the distribution) and industry with low external financial dependence (at the 25^{th} percentile of the distribution) when the country-level uncertainty shock also increases from the 25th percentile to the 75th percentile of the distribution. The shaded area and the dashed line denote 68% and 90% confidence intervals, respectively.

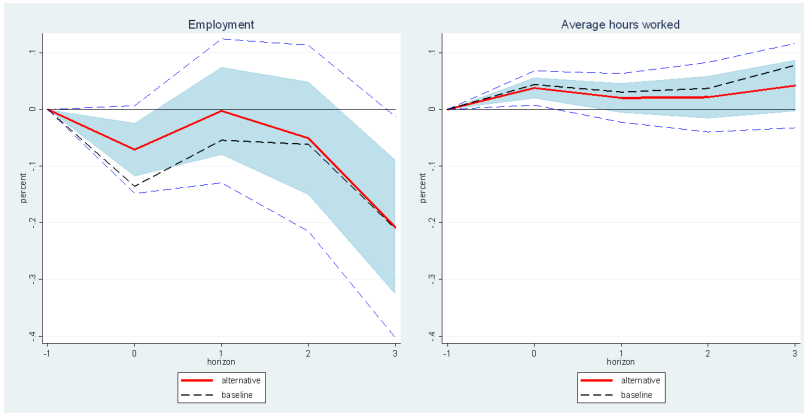
Figure A.12. Differential effect of uncertainty shocks on labor market outcomes: controlling for the interaction between uncertainty shocks and external financial dependence



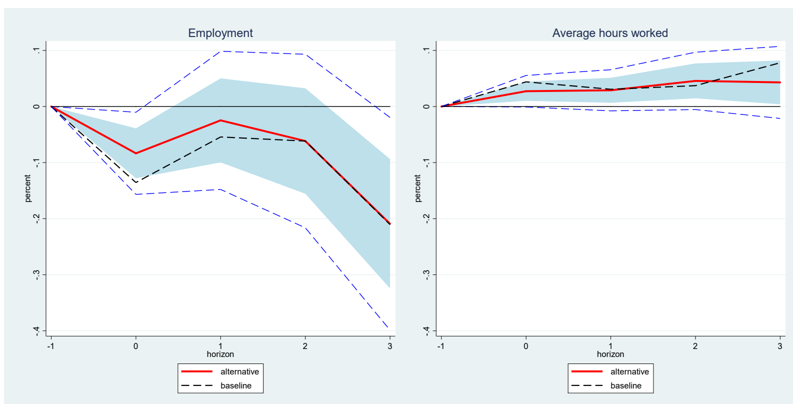
Note: Estimates are based on equation (2) while controlling for the interaction between uncertainty shocks and external financial dependence. The solid line denotes the differential employment (left panel) and average hours worked (right panel) effect of uncertainty shocks between industry with a high natural layoff rate (at the 75^{th} percentile of the distribution) and industry with a low natural layoff rate (at the 25^{th} percentile of the distribution) when the country-level uncertainty shock also increases from the 25^{th} percentile to the 75^{th} percentile of the distribution. The shaded area and the dashed line denote 68% and 90% confidence interval, respectively. The black dashed line denotes the impulse response function obtained in the baseline analysis.

Figure A.13. Differential effect of uncertainty shocks on labor market outcomes: controlling for other composite variables

A) Controlling for the elasticity of substitution between capital and labor

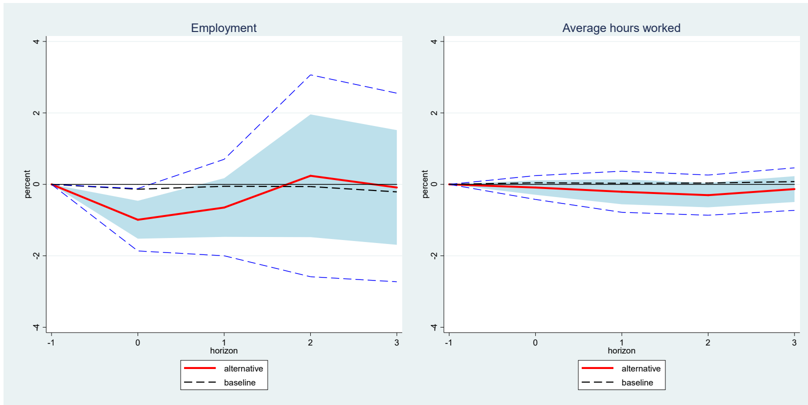


B) Controlling for labor share



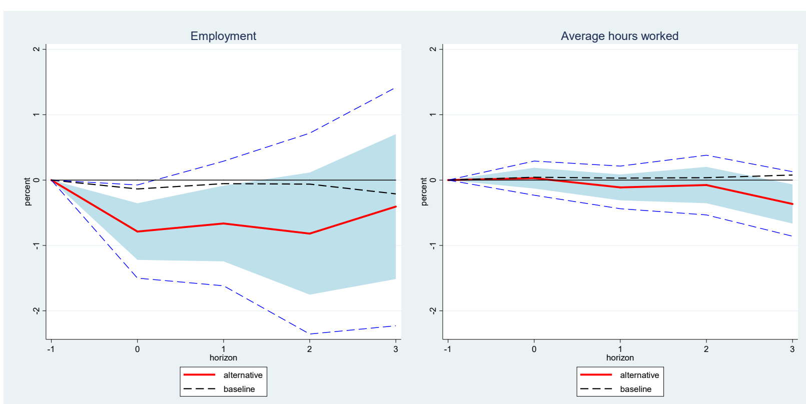
Note: Estimates are based on equation (2) while controlling for the interaction between additional industry-level variables and uncertainty shocks. The solid line denotes the differential employment (left panel) and average hours worked (right panel) effect of uncertainty shocks between industry with a high natural layoff rate (at the 75th percentile of the distribution) and industry with a low natural layoff rate (at the 25th percentile of the distribution) when the country-level uncertainty shock also increases from the 25th percentile to the 75th percentile of the distribution. The shaded area and the dashed line denote 68% and 90% confidence intervals, respectively. The black dashed line denotes the impulse response function obtained in the baseline analysis.

Figure A.14. Differential effect of uncertainty shocks on labor market outcomes: LP-IV using exogenous disaster events



Note: Estimates are based on equation (2) while instrumenting the uncertainty shock using exogenous disaster events identified from Baker et al. (forthcoming). The solid line denotes the differential employment (left panel) and average hours worked (right panel) effect of uncertainty shocks between industry with a high natural layoff rate (at the 75$^{\text{th}}$ percentile of the distribution) and industry with a low natural layoff rate (at the 25$^{\text{th}}$ percentile of the distribution) when the country-level uncertainty shock also increases from the 25$^{\text{th}}$ percentile to the 75$^{\text{th}}$ percentile of the distribution. The shaded area and the dashed line denote 68% and 90% confidence interval, respectively. The black dashed line denotes the impulse response function obtained in the baseline analysis.

Figure A.15. Differential effect of uncertainty shocks on labor market outcomes: LP-IV using the WUI and exogenous elections



Note: Estimates are based on equation (2) while instrumenting the uncertainty shock identified by the WUI using exogenous elections identified by Ahir et al. (2022). The solid line denotes the differential employment (left panel) and average hours worked (right panel) effect of uncertainty shocks between industry with a high natural layoff rate (at the 75$^{\text{th}}$ percentile of the distribution) and industry with a low natural layoff rate (at the 25$^{\text{th}}$ percentile of the distribution) when the country-level uncertainty shock also increases from the 25$^{\text{th}}$ percentile to the 75$^{\text{th}}$ percentile of the distribution. The shaded area and the dashed line denote 68% and 90% confidence intervals, respectively. The black dashed line denotes the impulse response function obtained in the baseline analysis.