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Universitätsstr. 150, 44801 Bochum, Germany

Technische Universität Dortmund, Department of Economic and Social Sciences
Vogelpothsweg 87, 44227 Dortmund, Germany

Universität Duisburg-Essen, Department of Economics
Universitätsstr. 12, 45117 Essen, Germany

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Svetlana Rujin[1]

What Are the Effects of Technology Shocks on International Labor Markets?

Abstract

How do international labor markets respond to a technology shock and what is the main transmission channel across countries with different labor market institutions? To answer these questions, I identify technology shocks using the approach of Galí (1999) and decompose the responses of total hours worked into movements along the extensive and the intensive margins. Overall, my analysis shows that technology shocks have a negative effect on total hours. This effect is stronger in countries with flexible labor markets, where the adjustment takes place along both margins. In contrast, the responses of total hours are smaller in countries with strict labor market legislation, where labor adjustment takes place along the intensive margin. These differences can be linked to the strictness of institutions that target quantity and price adjustments in the labor market.

JEL Classification: O40, O57, E32, C32

Keywords: Technology shocks; labor markets; business cycle fluctuations; structural identification

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1 Introduction

How do international labor markets react to a technology shock and what is the main transmission channel in countries with different labor market institutions (henceforth LMIs)? While early studies focus on aggregate labor market effects of technology shocks (total hours worked), recent literature considers in more detail the forces behind these fluctuations along the extensive (employment) and intensive (hours per worker) margins.[1] However, due to the limited availability of internationally harmonized measures of hours worked, cross-country studies limit their attention to the extensive margin as a summary measure of labor input (Galí, 1999, 2004; Dupaigne and Fève, 2009).[2]

Abstracting, however, from the intensive margin when assessing the impact of shocks may have significant implications for the analysis. This is particularly relevant for labor markets with high adjustment costs on employment, which are associated with an increasing degree of substitution toward the intensive margin that is not subject to these costs.[3] Consequently, the interaction between shocks and LMIs is important for explaining cross-country patterns in the adjustment of labor input to these shocks.[4] Yet, international evidence on how the two margins respond to a technology shock and which role LMIs play in explaining these findings is scarce.

This paper provides novel evidence on the composition of labor market effects of technology shocks along the extensive and intensive margins for the G7 countries. To this end, I use international database of quarterly labor input measures constructed by Ohanian and Raffo (2012). Furthermore, I examine the role of LMIs in shaping the transmission of technology shocks along the two margins. To the best of my knowledge, this is the first empirical study on the composition of labor market effects of technology shocks that adopts an international perspective on a country-by-country basis.

Specifically, I identify for each country technology shocks using structural vector autoregressions (SVARs) with long-run restrictions, as proposed by Galí (1999). Following the two-step approach put forward by Fève and Guay (2009, 2010), I estimate the responses of labor input to these shocks. To assess the relevance of these results, I calculate the relative importance of technology shocks for labor market volatility. Finally, I follow Gnocchi, Lagerborg, and Pappa (2015) and explore the link between international LMIs and the responses of labor input variables to a technology shock by computing Spearman rank correlations.

Numerous studies document large differences in terms of both the volatility of total hours worked relative to output and the relative volatility of extensive and intensive margins across countries. In particular, countries with larger fluctuations in the extensive margin compared

[1] See, for example, Michelacci and Lopez-Salido (2007), Canova, Lopez-Salido, and Michelacci (2013), Braun, Bock, and DiCecio (2009).

[2] Using annual data, Galí (2005) provides international evidence on the responses of hours worked to a technology shock. Further relevant studies are summarized in Table B.1 in the Appendix.

[3] Llosa, Ohanian, Raffo, and Rogerson (2015) and Galí and van Rens (2017) show that if firms can respond to shocks by adjusting hours per worker when it is costlier to adjust employment, then omitting the intensive margin from the analysis results in severely underestimated response of employment to shocks.

[4] This issue is stressed by Blanchard and Wolfers (2000), Hornstein, Krusell, and Violante (2007), Veracierto (2008), Abbritti and Weber (2010).

to the intensive margin (like the U.S. and Canada) have larger fluctuations in total hours worked compared to the European countries.[5] To explain these differences, studies explore the link between LMIs and labor market volatilities. Abbritti and Weber (2010), Rumler and Scharler (2011), and Gnocchi et al. (2015) document that LMIs constraining quantity and price adjustments are most important for shaping cyclical fluctuations in labor input.[6]

While the literature investigating the relationship between institutions and labor market performance is vast, far less attention has been paid to the implications of LMIs for technology-induced fluctuations in labor input.[7] A closely related study is Hornstein et al. (2007) that, however, focuses on investment-specific technology shocks and looks at the data through the lens of a model with labor market frictions.

The main results of this paper are as follows. First, I provide robust evidence of a short-run decline in total hours worked following a technology shock in the G7 countries. Moreover, this effect is more pronounced in countries with flexible labor markets; for example, I find the largest drop in total hours worked for the U.S.

Second, there is cross-country heterogeneity in the responses of the two margins to a technology shock. While flexible labor markets (the U.S., Canada, and the U.K.) adjust along both margins following a technology shock, the rigid European labor markets rely heavily on the intensive margin to accommodate this shock. The forecast error variance decomposition supports these findings and shows that higher labor market rigidity is associated with a lower volatility of employment and a higher volatility of hours per worker following a technology shock. This results in a subdued responsiveness of aggregate labor input to this shocks.

Finally, cross-country heterogeneities in labor market effects of technology shocks can be linked to differences in the strictness of LMIs. In particular, LMIs affect labor market outcomes of technology shocks largely along the extensive margin, evidenced by a significantly negative correlation of the efficiency and flexibility of the labor market with the short-run response of the extensive margin to a technology shock and a significantly positive correlation with the contribution of technology shocks to fluctuations along this margin.

The results on the adjustments along the two margins are consistent with Canova et al. (2013), who find that technology shocks affect the U.S. labor market to a large extent along the extensive margin. Specifically, technology shocks are associated with a wave of layoffs that leads to high unemployment. Using Galí (1999)'s approach, Michelacci and Lopez-Salido

[5] Cross-country stylized facts underlying the evolution of labor input along the two margins can be found in Galí (2005), Merkl and Wesselbaum (2011), Blundell, Bozio, and Laroque (2011, 2013), Ohanian and Raffo (2012), Gnocchi et al. (2015), Galí and van Rens (2017).

[6] Moreover, Canova et al. (2013) discuss that one needs to treat the unconditional evidence on the link between labor input volatility and labor market characteristics with caution as country-specific shocks driving labor input volatility are quite different across countries. In addition, Blanchard and Wolfers (2000) and Abbritti and Weber (2010) find substantial difference in the response of unemployment to shocks under different constellations of labor market policies.

[7] For example, studies examining how LMIs affect labor market outcomes are: Blanchard and Wolfers (2000), Veracierto (2008), Fang and Rogerson (2009), Abbritti and Weber (2010), Gehrke, Lechthaler, and Merkl (2018). Some studies have analyzed the effects of LMIs on inflation or business cycle volatility: Thomas and Zanetti (2009), Blanchard and Galí (2010), Campolmi and Faia (2011), Gnocchi et al. (2015), Bachmann and Felder (2018).

(2007), Barnichon (2010), and Balleer (2012) obtain similar results for the U.S. In contrast, Ravn and Simonelli (2007) show that the U.S. total hours worked, employment, and vacancies increase gradually over time in response to a technology shock. However, evidence on the cross-country differences in labor market effects of technology shocks remains limited. For example, Hornstein et al. (2007) use data for an average of 15 European countries and show that labor markets in the U.S. and Europe respond differently to a technology shock. Finally, the results on the link between international labor market effects of technology shocks and LMIs are in line with the evidence in Hornstein et al. (2007), who find that institutional aspects can account for the diverging dynamics along the two margins across countries.

This paper is structured as follows: Section 2 presents international labor market characteristics. Section 3 describes the empirical framework. Section 4 presents the baseline results and Section 5 shows the robustness checks. Section 6 concludes the analysis.

2 International labor market characteristics

2.1 The data

I use the 2017 vintage of international quarterly labor input measures constructed by Ohanian and Raffo (henceforth OR-dataset) covering the period 1970:1–2016:4 unless otherwise indicated.[8] The countries included in the analysis are: Australia, Austria, Canada, Finland, France, Germany, Ireland, Italy, Japan, Norway, Korea, Sweden (from 1974:1), the U.K. (from 1971:1), and the U.S. I exclude Spain from the analysis due to the late starting date of hours series in the first quarter of 1995. This study focuses on the the G7 countries: Canada, France, Germany, Italy, Japan, the U.K., and the U.S. I present and discuss the results for these countries in the main text and report the outcomes for the remaining countries in the Appendix.

Labor input measures are total hours worked, employment (the extensive margin), and hours per worker (the intensive margin). To control for the low frequency movement in labor input induced by demographic shifts (as discussed in Christiano, Eichenbaum, and Vigfusson, 2003, 2004; Galí and Rabanal, 2005; Francis and Ramey, 2009), I normalize labor input measures by population aged 15 to 64 (Figure B.1 illustrates the series). Labor productivity is computed as the ratio between real gross domestic product (GDP) and total hours worked.[9] Throughout the analysis, I specify the variables introduced above in log first differences.[10]

To explore international labor market institutions, I use indicators that account for policies influencing both quantities and price adjustments. These indicators relate to: (i) policies influencing job and worker flows (strictness of employment protection, hiring and firing practices,

[8]Data source: `http://andrearaffo.com/araffo/Research.html`. For details see Ohanian and Raffo (2012).

[9]Due to lack of data availability, international evidence on the effects of technology shocks in Galí (1999) and Dupaigne and Fève (2009) is obtained using an employment-based productivity measure. Galí (2005) discusses the potential problems associated with its use.

[10]Table B.2 in the Appendix reports the results of the unit root tests. Galí (2005), Francis and Ramey (2005) and Ramey (2016) provide evidence supporting this specification. The results using an alternative transformation of labor input measures are provided in Section 5.

redundancy costs in weeks of salary), (ii) wage setting practices (flexibility of wage determination, coordination of wage-setting, government intervention in wage bargaining), and (iii) policies accounting for the union power (union density rate, union coverage rate, centralization of wage bargaining). Finally, I use an indicator reflecting the overall efficiency and flexibility of the labor market. The data are from the Global Competitiveness Index (GCI) Historical Dataset published by World Economic Forum (WEF), the database on Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts (ICTWSS) (Visser, 2016), and the OECD as well as the CEP-OECD institutions dataset (Nickell, 2006). All definitions are provided in Table A.1 in the Appendix.

2.2 Labor market fluctuations over the business cycle

Fluctuations in labor input exhibit considerable differences across advanced economies. For example, Fang and Rogerson (2009) and Bick, Brüggemann, and Fuchs-Schündeln (2019b) document that hours worked in France, Germany, and Italy display substantial differences relative to the U.S. (see Figure B.1). Furthermore, Galí (2005) documents that while the U.S. and Canada display an upward trend in total hours worked, the opposite holds for the remaining G7 countries. To understand the composition of the fluctuations in total hours worked across countries, I decompose them into fluctuations along the intensive and extensive margins.

Table 1 summarizes cyclical statistics on international labor markets using correlation and volatility measures.[11] Panel (a) shows that labor productivity is strongly procyclical with respect to output across the G7 countries, with an average correlation of about 0.70. Higher correlations (about 0.80) are reported for the U.K. and Germany. In contrast, for the U.S. and Canada, the correlations are smaller (about 0.50).

Panel (b) documents the results for labor input measures. Overall, there are qualitative similarities in the patterns of these statistics across countries. First, labor input is strongly procyclical with respect to output and strongly countercyclical with respect to labor productivity. Second, the correlations of the extensive margin with output are almost as high as the corresponding correlations for total hours worked and are higher than the correlations of the intensive margin with output for many countries. Finally, the opposite holds when I use labor productivity as the cyclical indicator. The correlations between the intensive margin and labor productivity are twice as high as the corresponding correlations for the extensive margin for all countries, except for the U.S., where the two margins correlate equally with labor productivity.

Yet, there is considerable variation in the magnitudes of these correlations across countries. While total hours worked are highly synchronized with output fluctuations in the U.S., Canada, and Germany (correlations are around 0.60), a lower degree of synchronization is found for the

[11]It has to be acknowledged that potential errors in the measurement of hours worked result in spurious correlations due to the "division bias". Borjas (1980) shows that division of earnings by hours worked to get the wage rate leads to the downward bias in the estimate of the wage elasticity if hours are measured with error. Furthermore, Bick, Brüggemann, and Fuchs-Schündeln (2019a) find that revisions of the hours worked per employed series between different data releases have substantial consequences for the measurement of hours worked based on the OECD and Conference Board's Total Economy Database (TED) data.

Table 1: **Business cycle statistics**

		U.S.	Canada	U.K.	Japan	France	Germany	Italy	Avg. (G7)	Avg. (EA)
		a. Correlations of labor productivity with output								
Labor productivity	Δy	0.53**	0.51**	0.78**	0.73**	0.72**	0.76**	0.65**	0.67	0.71
		b. Correlations of labor input variables with output and productivity, respectively								
Total hours worked	Δy	0.63**	0.62**	0.38**	0.17*	0.43**	0.55**	0.48**	0.46	0.48
	Δz	-0.33**	-0.38**	-0.28**	-0.56**	-0.42**	-0.20**	-0.38**	-0.36	-0.33
Employment	Δy	0.57**	0.63**	0.35**	0.16*	0.61**	0.41**	0.46**	0.45	0.49
	Δz	-0.26**	-0.20**	-0.16*	-0.23**	0.07	-0.11	-0.16*	-0.15	-0.07
Hours per worker	Δy	0.44**	0.28**	0.24**	0.07	0.21**	0.45**	0.26**	0.28	0.31
	Δz	-0.26**	-0.40**	-0.27**	-0.58**	-0.55**	-0.21**	-0.44**	-0.39	-0.40
		c. Volatility of labor input variables relative to output and productivity, respectively								
Total hours worked	Δy	0.90	0.95	0.66	0.83	0.84	0.72	0.83	0.82	0.80
	Δz	1.09	1.12	0.68	0.70	0.85	0.85	0.88	0.88	0.86
Employment	Δy	0.58	0.71	0.44	0.37	0.51	0.42	0.51	0.50	0.48
	Δz	0.71	0.83	0.46	0.31	0.51	0.50	0.54	0.55	0.51
Hours per worker	Δy	0.57	0.61	0.44	0.73	0.77	0.63	0.59	0.62	0.66
	Δz	0.69	0.72	0.45	0.61	0.77	0.74	0.62	0.66	0.71
		d. Relative volatility of the extensive to the intensive margin								
Ratio		1.03	1.17	1.01	0.50	0.66	0.67	0.86	0.84	0.72

Notes: This table reports correlations of labor productivity (Δz) with output (Δy) in panel (a); and labor input measures with output and labor productivity, respectively, in panel (b). All variables are in log first differences. Statistical significance at 5 (1) percent level is indicated by * (**). Panel (c) reports the ratios of standard deviations of labor input measures to the standard deviation of output and labor productivity, respectively. Panel (d) reports the ratios of the standard deviation of the extensive margin (employment) to the standard deviation of the intensive margin (hours per worker), based on statistics from (c). The averages for the euro area (EA) country grouping were computed using statistics for France, Germany, and Italy. Sample period is 1970:1–2016:4 (U.K.: 1971:1–2016:4). Business cycle statistics for the remaining OECD countries are reported in Table B.3 in the Appendix. Data source: Ohanian and Raffo (2012).

U.K., France, and Italy (correlations range from 0.38 to 0.48). Regarding the two margins, the highest correlations of the extensive margin with output are reported for the U.S., Canada, and France, with a coefficient of about 0.60. For the U.K., Germany, and Italy, these correlations lie between 0.35 and 0.46. Further, the intensive margin is highly correlated with output in the U.S. (0.44) and Germany (0.45), and less so in other countries.

When I use labor productivity as cyclical indicator, the correlations of total hours worked range from -0.56 in Japan to -0.20 in Germany. Furthermore, while the intensive margin is the key driver of the countercyclical movement in total hours worked in France and Germany, the opposite holds for the remaining countries. For Japan I report the lowest correlations of labor input variables with output and the highest correlations (in absolute terms) of these variables with labor productivity across the G7 countries.

Panel (c) reports the ratios of the standard deviations of labor input to the standard deviation of output and labor productivity, respectively. Overall, total hours worked are less volatile with respect to both measures. Only in the U.S. and Canada, total hours worked are as volatile as output and have a greater volatility with respect to labor productivity. Furthermore, the intensive margin is, on average, more volatile than the extensive margin. However, the results in panel (d) indicate that while in the U.K., the U.S., and Canada, the volatility of the extensive margin is equal to or greater than that of the intensive margin, the opposite applies to the euro area countries and Japan. Thus, given the relative importance of fluctuations in hours per worker over the business cycle for many countries, abstracting from the intensive margin necessarily eliminates a key feature of labor market adjustment (Llosa et al., 2015).

In sum, there are quantitatively important differences along the two margins in the G7 countries. Fang and Rogerson (2009) find that, on average, differences in employment and hours per worker are of roughly equal importance in accounting for differences in total work between European economies and the U.S. Bick et al. (2019b) examine the sources of these differences and find that cross-country variation in the educational composition accounts for a significant share of the observed Europe-U.S. hours gap through its effect on employment. They further emphasize the importance of different degrees of regulations in the international labor markets for shaping the cross-country patterns in aggregate hours worked.[12]

2.3 International labor market institutions

This section focuses on LMIs that affect how firms adjust labor input along the two margins and thus can account for the patterns observed in the data. Abbritti and Weber (2010), Rumler and Scharler (2011), and Gnocchi et al. (2015) document that LMIs constraining job and worker flows (quantity adjustments) and institutions restraining the responsiveness of wages to shocks (price adjustments) are most important for shaping cyclical fluctuations in labor input. Since LMIs are deeply rooted in national preferences and therefore exhibit little variation over time and thus across countries (Campolmi and Faia, 2011; Bachmann and Felder, 2018), Table 2 reports the sample means of institutional indicators for the G7 countries.

LMIs that affect job and worker flows have attracted much attention in the literature.[13] Gnocchi et al. (2015) show that employment protection legislation is an important determinant of the incentives that drive job creation and job destruction and, as a result, of labor market adjustments. Particularly, strict employment protection legislation increases the costs associated with worker dismissals, and thus makes the use of the extensive margin to accommodate business cycle fluctuations very costly. This results in adjustments in hours worked along the intensive margin, since from the perspective of producing output the two margins are substitutes (Fang and Rogerson, 2009). Thus, reduced labor market fluidity lowers employment rates and the proportion of long-term unemployed increases. In contrast, the abolition of hiring costs is associated with an increased volatility of the extensive margin with respect to output (Blanchard and Wolfers, 2000; Hornstein et al., 2007; Davis and Haltiwanger, 2014).

[12] A growing literature examines various other factors that can explain differences in hours worked along the two margins, like tax and transfer programs (Prescott, 2004), demographic composition (Bick et al., 2019b), product market regulations (Fonseca, Lopez-Garcia, and Pissarides, 2001), or preferences (Blanchard, 2004).

[13] See, for example, Autor, Kerr, and Kugler (2007), Freeman (2008), Ohanian and Raffo (2012), Gnocchi et al. (2015), Llosa et al. (2015), Galí and van Rens (2017).

Table 2: **Labor market institutions**

	U.S.	Canada	U.K.	Japan	France	Germany	Italy	Avg. (G7)	Avg. (EA)
a. Job and worker flows									
Strictness of employment protection (OECD), 0 – 6 (strict)	0.26	0.92	1.17	1.62	2.39	2.65	2.76	1.68	2.60
Hiring and firing practices (GCI), 1 – 7 (extremely flexible)	5.14	4.59	4.35	3.06	2.64	2.82	2.58	3.60	2.68
Redundancy costs in weeks of salary (GCI)	0.00	20.08	16.63	5.04	23.90	50.08	6.46	17.56	26.81
b. Wage setting									
Flexibility of wage determination (GCI), 1 – 7 (individual company)	5.65	5.51	5.77	5.84	4.93	3.12	3.18	4.86	3.74
Coordination of wage-setting (ICTWSS), 1 – 5 (regularized pattern)	1.18	1.27	1.56	4.62	2.07	3.73	2.73	2.45	2.84
Government intervention in wage bargaining (ICTWSS), 1 – 5 (gov. authority)	1.36	1.27	1.90	1.00	3.13	2.24	2.80	1.96	2.73
c. Union power									
Union density rate, membership of wage and salary earners (ICTWSS)	24.90	32.69	38.29	25.72	12.60	28.84	39.96	29.00	27.13
Union coverage rate (CEP-OECD)	20.60	37.21	56.95	23.00	91.49	86.85	84.13	57.18	87.49
Centralization of wage bargaining (ICTWSS), 0 – 1 (high)	0.14	0.28	0.17	0.24	0.23	0.45	0.33	0.26	0.34
d. Efficiency and flexibility of the labor market									
Labor market efficiency (GCI), 1 – 7 (most flexible)	5.57	5.32	5.31	4.99	4.28	4.47	3.59	4.79	4.11

Notes: This table reports the sample means of labor market indicators. The averages for the euro area (EA) country grouping were computed using statistics for France, Germany, and Italy. The OECD index on the strictness of employment protection covers the time period 1985–2013. The GCI indicators published by the WEF cover the time period 2006–2016. The ICTWSS indicators (Visser, 2016) cover the time period 1970–2014. The union coverage rate from the CEP-OECD institutions dataset (Nickell, 2006) covers the time period 1970–2000. Further details are summarized in Table A.1. Labor market indicators for the remaining OECD countries are reported in Table B.4 in the Appendix.

The OECD index of the strictness of employment protection reported in Table 2 (panel a) indicates that the U.S., Canada, and the U.K. have a very loose employment protection legislation compared to France, Germany, and Italy. Japan has a score close to the average across the G7 countries. The indicator of hiring and firing practices displays a similar cross-country pattern. Thus, these practices are very flexible in the Anglo-Saxon countries, whereas hiring and firing is severely impeded by regulations in the European countries. Regarding the redundancy costs in weeks of salary, the two outliers are the U.S. with zero costs and Germany with 50 weeks of salary.[14] At the same time, the redundancy costs in the U.K., Canada, and France are relatively homogeneous and amount, on average, to 20 weeks of salary. Moderate costs are associated with firing a worker in Japan (5 weeks) and Italy (6 weeks).

To capture institutional characteristics targeting price adjustments in the labor market, Table 2 reports indicators that characterize the wage setting practices (panel b) and union power (panel c). Gnocchi et al. (2015) show that institutions promoting more flexible wage setting have positive effects on the volatility of unemployment and increase the correlation of

[14]Similarly, Veracierto (2008) documents that severance payments for blue-collar workers with 10 years of experience exceed 1 year of wages in several European countries, whereas they are nonexistent in the U.S.

real wages with labor productivity. Similarly, the theoretical model of Christoffel and Linzert (2006) predicts that wage bargaining rigidities are negatively associated with unemployment volatility. In addition, real wage adjustments may also be influenced by the bargaining power of workers that is given by the union authority. Christoffel and Linzert (2006) document that higher bargaining power of workers is associated with an upward pressure on wages, which lowers the expected profits of firms and causes the number of vacant jobs to fall.[15]

The indicators on the flexibility and coordination of wage setting (panel b) refer to the degree to which minor bargaining units take into account the coordinating activity by the major players. While in the Anglo-Saxon countries wages are mostly set by individual companies, the euro area countries adopt rather a regularized wage-setting pattern. Japan is an exception with, on the one hand, very flexible wage setting practices, which are, on the other hand, largely determined by confederations of large firms (Gnocchi et al., 2015). The latter is indicated by a high score for the degree of coordination of wage-setting. Furthermore, while the government intervention in wage bargaining in the Anglo-Saxon countries is rather moderate, governments in the euro area countries have a greater influence on the wage bargaining outcomes.

Panel (c) reports indicators measuring the union power. The union density rate measures the net union membership as a proportion of wage and salary earners in employment; the union coverage rate refers to the number of workers covered by collective agreements. The centralization of wage bargaining represents a summary measure that takes into account union authority over different levels. High union density rates are recorded for Italy, the U.K., and Canada, followed by Germany, Japan, and the U.K. The lowest union density rate is in France (12.60 percent). Despite the relatively low union density, the union coverage is very high in euro area countries with the highest rate in France (91.49 percent). In contrast, the lowest coverage rate is in the U.S. (20.60 percent). The contrasting pattern between the Anglo-Saxon and the euro area countries is also reflected in the indicator of the centralization of wage bargaining.

The efficiency and flexibility of the labor market (panel d), a summary indicator of institutions discussed above, indicates that labor markets in France, Germany, and Italy can be characterized as rigid relative to those in the U.S., the U.K., and Canada; the working practices in Japan are in the middle of the distribution of the considered indicators. Hence, the benchmark in the literature is to assume that the U.S. labor market has zero adjustment costs on employment and that the latter is the most efficient margin through which labor input can be adjusted (Llosa et al., 2015).

[15] An in depth discussion of international wage-setting institutions can be found in Freeman (2008). Furthermore, Nickell (1997) analyzes the link between union density and wage determination and finds that unions tend to raise pay and a greater union density generally raises unemployment. However, he points out that the negative effects can be offset if both the unions and employers can coordinate their wage bargaining activities.

3 Econometric framework

3.1 Identification of technology shocks

Since technology is not directly observable, existing identification schemes rely on theoretical considerations to derive technology shocks from observed data. The early literature obtained technology shocks as a residual from the growth accounting exercise based on a production function. However, the Solow (1957) residual failed to account for varying utilization of capital and labor. Therefore, Basu, Fernald, and Kimball (2006) and Fernald (2014) estimate modified sectoral production functions to obtain an index of aggregate utilization-adjusted technology change, that is the "purified" Solow residual.

Galí (1999) proposes using labor productivity a SVAR identified by long-run restrictions.[16] To improve the estimation precision over long-run identification in small samples, Uhlig (2004a) and Francis, Owyang, Roush, and DiCecio (2014) propose the medium-run identification scheme. Dedola and Neri (2007) and Peersman and Straub (2009) use sign restrictions obtained from model-based simulations to identify technology shocks in SVARs.

Following the vast majority of studies closely related to the current analysis (see Table B.1 in the Appendix), I implement the long-run identification scheme to estimate the dynamic responses of labor input to a technology shock. This approach relies on the assumption that only technology shocks may have a permanent effect on the level of productivity (Galí, 1999). Due to their methodologically appealing simplicity, long-run restrictions have been widely used to study the effects of technology shocks. Moreover, this approach gave rise to an active controversy and became an issue of extensive research (Faust and Leeper, 1997; Altig, Christiano, Eichenbaum, and Linde, 2002; Erceg, Guerrieri, and Gust, 2005; Chari, Kehoe, and McGrattan, 2008).

Following Erceg et al. (2005), Galí's long-run identification scheme represents a reliable structural approach to analyzing the effects of technology shocks in long samples.[17] Furthermore, Galí (2004) addresses potential shortcomings associated with weak identification and shows that shocks identified by long-run restrictions are indeed capturing exogenous variations in technology. In the same vein, Francis and Ramey (2005) examine the validity of the long-run identification assumption in a setting with several possible sources of permanent shocks and conclude that technology shocks appear to be uncorrelated with other key exogenous shocks.

3.2 The model

I consider the following bivariate SVAR model:

$$A(L)X_t = H\varepsilon_t, \quad \text{where} \quad \varepsilon_t \sim (0, \Sigma_\varepsilon), \tag{1}$$

[16] Other identification approaches use alternative observable measures of technology, like patents, spending on research and development (Shea, 1998) or books published in the field of technology (Alexopoulos, 2011) to obtain a series of technology shocks.

[17] Erceg et al. (2005) generate Monte Carlo simulations using an "empirically-reasonable" sample length of 180 quarters, which is also the case in this paper that uses data spanning from 1970:1 to 2016:4.

where the vector X_t is specified as $[\Delta z_t,\, \Delta l_t]'$.[18] Δz_t and Δl_t denote the log first differences of hourly labor productivity and total hours worked, respectively. The vector of structural shocks is $[\varepsilon_{1t},\, \varepsilon_{2t}]'$, where ε_{1t} is the technology shock and ε_{2t} is the non-technology shock. These shocks represent linear combinations of reduced-form error terms $\eta_t = H\varepsilon_t$ and are orthogonal to each other. $E\varepsilon_t\varepsilon_t^{'} = \Sigma_\varepsilon$ is the diagonal covariance matrix with $E\varepsilon_t\varepsilon_s^{'} = 0$ for t $\neq s$. The lag polynomial $A(L) = I - A_1 L - ... - A_p L^p$ stores the reduced-form coefficients on lagged variables, where p is the lag order.

The structural moving average SMA(∞) representation of X_t in terms of ε_t takes the form:

$$X_t = D(L)\varepsilon_t, \quad \text{where} \quad D(L) = A(L)^{-1}H. \tag{2}$$

The cumulative long-run effect of a structural shock in ε_t on future values of X_t is the sum of the structural MA coefficients $D(1) = A(1)^{-1}H$, where $A(1)$ is the sum of the reduced-form VAR coefficients. Thus, structural coefficients in $D(1)$ are identified if H and Σ_ε are identified. This can be achieved by imposing restrictions such that the matrix $D(1)$ is lower triangular.

To identify technology shocks ε_{1t}, I use the long-run identification scheme. This approach relies on the assumption that unit root in labor productivity originates exclusively in technology shocks. This implies that the cumulative long-run effect of a non-technology shock ε_{2t} on labor productivity is zero. Hence, the element $D_{12}(1)$ in the equation for labor productivity is zero. At the same time, both technology and non-technology shocks can have a permanent effect on labor input. Thus, the matrix $D(1)$ is lower triangular:

$$\begin{bmatrix} \Delta z_t \\ \Delta l_t \end{bmatrix} = \begin{bmatrix} D_{11}(1) & 0 \\ D_{21}(1) & D_{22}(1) \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}. \tag{3}$$

Let Ω be the long-run variance matrix of X_t, such that:

$$\Omega = A(1)^{-1}\Sigma_\eta A(1)^{-1'} = A(1)^{-1}H\Sigma_\varepsilon H^{'}A(1)^{-1'} = D(1)\Sigma_\varepsilon D(1)^{'}, \tag{4}$$

where Σ_η is the covariance matrix of the reduced-form error terms $\eta_t = H\varepsilon_t$. Using the unit standard deviation normalization that results in $\Sigma_\varepsilon = I$, expression (4) can be written as $\Omega = D(1)D(1)'$. Applying the lower triangular Cholesky factorization of Ω gives $Chol(\Omega) = D(1)$. Thus, the matrix H is identified by:

$$H = A(1)Chol[A(1)^{-1}\Sigma_\eta A(1)^{-1'}], \quad \text{since} \quad H = A(1)D(1). \tag{5}$$

Given that the structural shocks are not directly observable, their scale is arbitrary and has to be normalized (Stock and Watson, 2016). The unit effect normalization solves the scaling issue of the jth structural shock such that a unit increase in ε_{jt} induces a contemporaneous unit increase in the variable of interest X_{it} (Baumeister and Hamilton, 2015). This paper focuses on the effects of a technology shock ε_{1t} that induces a contemporaneous increase in the observed

[18] The constant term is omitted for exposition convenience.

variable X_{1t} (labor productivity Δl_t) by one percent. Written in terms of matrix H, the unit effect normalization implies dividing the first column by its first element:

$$H = \begin{bmatrix} 1 & h_{12} \\ h_{21}/h_{11} & h_{22} \end{bmatrix}. \tag{6}$$

To decompose technology-induced fluctuations in total hours worked into adjustments along the two margins, I follow the two-step approach proposed by Fève and Guay (2009, 2010). In the first step, I identify technology shocks using country-level SVARs as described above.[19] In the second step, I use recursive three-variable VARs with the corresponding technology shock series ordered first, followed by the two margins. I apply the Cholesky decomposition to obtain the impulse response functions (IRFs) of the two margins to these shocks.[20]

4 Results

4.1 Impulse response analysis

This section presents the baseline results for the G7 countries. All SVARs were estimated on a country-by-country basis with a constant and four lags.[21] The confidence intervals were computed using the wild bootstrap procedure (Davidson and Flachaire, 2008) with 500 replications. The focus of the analysis is on the short-run labor market effects of technology shocks, which is one of the central issues in the related literature.

4.1.1 Evidence for the U.S.

Since an overwhelming majority of studies focus on the U.S. (see Table B.1), I start with the discussion of the baseline results for the U.S. and examine their consistency with the previous literature. First, existing contributions use the official labor input series for the U.S. Therefore, I compare the baseline results obtained using the OR-dataset with the IRFs that I derive using the official series. Second, many studies rely on the direct, utilization-adjusted technology measure for the U.S. Thus, I also compute the IRFs of labor input measures from the OR-dataset to a technology shock estimated by Fernald (2014). Using disaggregate information at the industry-level, Fernald (2014) obtains a quarterly measure of purified total factor productivity (TFP) from a growth-accounting exercise that accounts for varying utilization of capital and labor. This measure is only available for the U.S.

[19] In the robustness section, I check the sensitivity of the baseline results with respect to an alternative medium-run identification scheme proposed by Uhlig (2004a) and to an alternative set of instruments in the VAR specification, which excludes total hours worked.

[20] In this setting, the ordering of the two margins does not affect the results. Moreover, the sum of the IRFs of the two margins to a technology shock corresponds to the IRF of total hours worked.

[21] Consistent with Francis and Ramey (2005), Francis (2009), I show in Figure B.4 in the Appendix that the baseline results remain unaffected by an alternative lag length in the VAR.

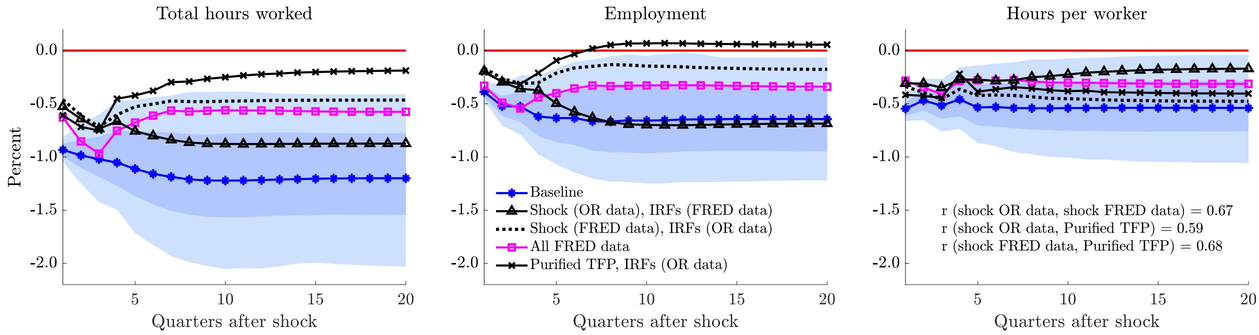

Figure 1: **U.S. labor input response to a technology shock**

Notes: Cumulative IRFs to a technology shock that is normalized to induce a contemporaneous 1% increase in labor productivity. IRFs are obtained from the estimation of 2- and 3-variable SVARs with four lags for the sample period 1970:1–2016:4. All variables are in log first differences. Shaded areas: 68% and 95% confidence intervals based on bootstrapping 500 draws. Data sources are Ohanian and Raffo (2012) and Fernald (2014). The official labor input series are from the Federal Reserve Economic Data (FRED).

Figure 1 shows the responses of labor input measures to a technology shock for the U.S. The main result from the baseline IRFs (blue lines with asterisk markers) is that a positive technology shock induces a sharp decline in total hours worked on impact. Furthermore, the adjustment of labor input to new technologies takes place along both the extensive and the intensive margin, which exhibit a roughly equal decline in the short run. The patterns of the labor input responses—aggregate and along the two margins—do not display much variation in the following periods and the effect of a technology shock remains persistently negative throughout the entire horizon.

Next I examine how the use of different data sources affects the results by regressing each labor input series on the technology shock as described in the previous section.[22] First, I compute the IRFs of the official labor input series to a technology shock obtained using the OR-dataset (black lines with triangle markers). Second, I analyze how labor input measures from the OR-dataset respond to a technology shock estimated using the official series (black dotted lines). Finally, I use only the official series to compute the IRFs (magenta lines with square markers). In sum, though quantitatively different, the IRFs of total hours worked and the two margins are broadly in line with the baseline results and lie within the 95% confidence intervals throughout the entire horizon, except for the impact responses. The latter display considerable differences in the magnitudes relative to the baseline results. However, when I use only the official series, the impact response of the extensive margin matches the baseline estimate. Furthermore, the patterns of the IRFs display similar shapes to the baseline IRFs only when I use the shock series obtained using the OR-dataset. Hence, while the time series from the two data sources are highly correlated (above 0.80), the two shock series have a lower correlation (0.67), which may explain the differences in the impact responses.

[22] Ohanian and Raffo (2012) use a different data construction methodology, which produces labor input measures for the U.S. that match the official series very well. The correlations between the constructed and the official growth rates of the population adjusted total hours worked, employment, and hours per worker are 0.89, 0.84, and 0.83, respectively. The correlation between the two measures of hourly labor productivity is 0.83.

As a final check, I compute the IRFs of labor input measures from the OR-dataset to a technology shock constructed by Fernald (2014).[23] While the results display qualitative similarities with the baseline outcomes for total hours worked and the intensive margin, the IRF point estimates for the former lie outside the 95% confidence intervals throughout the entire horizon. This is driven by response of the extensive margin, which displays a different pattern after roughly two years; the initial negative effect of a technology shock on the extensive margin is reversed over time, leading to a positive, though quantitatively small, long-term effect.

Overall, the IRFs of total hours worked and the extensive margin (regardless of the data source) to a technology shock obtained using the official series and to the purified TFP display patterns with a dip in the short-run followed by a slight reversal. In contrast, the respective IRFs to a technology shock obtained using the OR-dataset display a persistent decline. Elstner and Rujin (2019) use the official U.S. series and identify a technology shock using the long-run, medium-run, growth accounting, and Proxy-SVAR approaches. Though quantitatively different, the patterns of the IRFs of total hours worked display a similar shape across all models. This is consistent with the results in Galí (1999) and Basu et al. (2006).

Therefore, the differences in the IRFs described above are data-driven. They arise from the divergent responses of the extensive margin to technology shocks obtained using the official series and purified TFP, on the one hand, and those obtained using the OR-dataset, on the other hand. Thus, while the correlation between the former two shocks is 0.68 (Ramey (2016) reports the same correlation coefficient using a different sample period), the correlation between the technology shock obtained using the OR-dataset and purified TFP is smaller (0.59). The difference in these correlations may serve as a possible explanation of this finding.

4.1.2 International evidence

Figure 2 shows the results for the remaining G7 countries.[24] To ease comparison, international evidence is supplemented with the IRFs for the U.S. The first main result of this paper is that total hours worked show a persistently negative response to a technology shock across the G7 countries. Furthermore, while the initial decrease in total hours worked is significant across all countries, the long-run responses remain significantly below zero only in the U.S., the U.K., and France. For example, while the impact response of U.S. total hours worked is -0.93 percent, these responses in the remaining G7 countries range between -0.32 percent in Japan to -0.66 percent in Canada; and the average impact response across the six economies considered in Figure 2 is -0.50 percent. Finally, only in Japan, after a significantly negative impact response to a technology shock, total hours worked return to the pre-shock level.

The composition of labor adjustment along the two margins is shown in the last two columns of Figure 2. The results in the second column indicate substantial cross-country

[23] Studies that employ purified TFP to analyze the labor market effects of technology shocks are listed in Table B.1. Furthermore, Elstner and Rujin (2019) rely on purified TFP to study the international productivity spillover effect of U.S. technology shocks.

[24] Figure B.2 in the Appendix shows the results for Australia, Austria, Finland, Ireland, Korea, Norway, and Sweden.

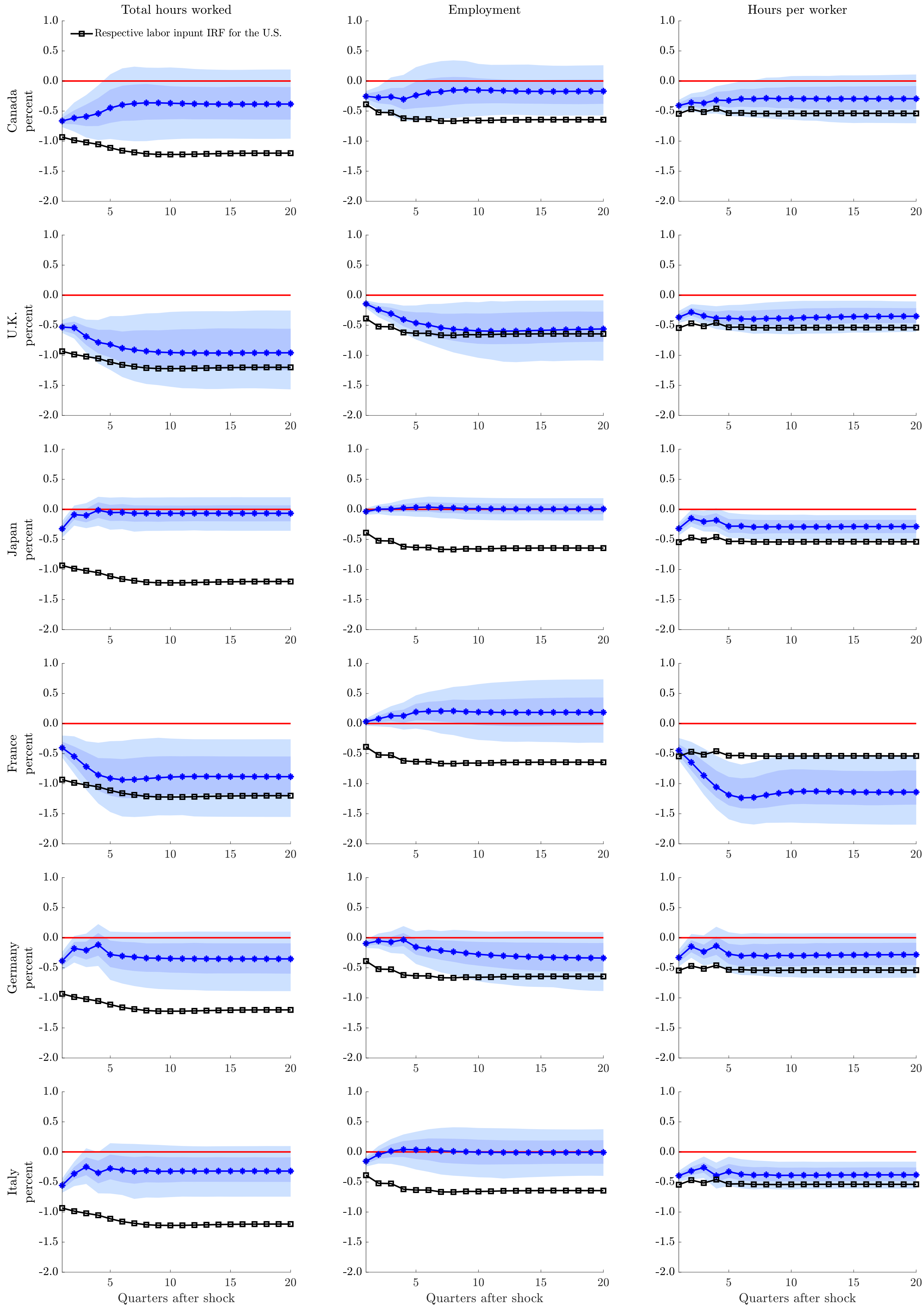

Figure 2: **Impulse responses to a technology shock**

Notes: Cumulative IRFs to a technology shock that is normalized to induce a contemporaneous 1% increase in labor productivity. IRFs are obtained from the estimation of 2- and 3-variable SVARs on a country-by-country basis for the period 1970:1–2016:4. All variables are in log first differences. Shaded areas: 68% and 95% confidence intervals based on bootstrapping 500 draws.

differences in the responses of the extensive margin to a technology shock. In particular, this shock generates an immediate and sharp fall in employment in the U.S. by 0.39 percent, which is the strongest effect observed across the G7 countries, followed by Canada with a fall in employment by -0.25 percent. Moreover, a technology shock has a permanent and significantly negative effect on the extensive margin only in the U.S. and in the U.K. Although the extensive margin in Italy and Germany drops significantly on impact—by 0.16 and 0.10 percent, respectively—the magnitude of these responses is considerably smaller than in the former countries. Furthermore, these effects are short-lived in Italy and employment returns to the pre-shock level after roughly two quarters. Finally, only in Japan, the response of the extensive margin remains muted throughout the entire horizon; and only in France, the adjustment along the extensive margin is positive, though quantitatively insignificant.

A different picture emerges for the adjustment along the intensive margin across countries, shown in the last column of Figure 2. First, the intensive margin displays a significantly negative impact response to a technology shock—which is considerably stronger than that of the extensive margin—across all countries. The magnitude of these effects ranges between 0.55 percent in the U.S. to 0.32 percent in Japan.

Second, technology shocks induce a permanent and significantly negative adjustment along both margins in the U.S. and in the U.K. Furthermore, in Japan, France, and Italy, where the IRFs of employment remained close to zero throughout the entire horizon, these shocks generate a permanent and significantly negative adjustment along the intensive margin. Thus, the latter is the main margin of labor adjustment to new technologies in these countries. In contrast, the intensive margin in Germany shows a significant drop only on impact and it declines significantly in Canada for up to six quarters following a technology shock.

Thus, the second key result of this paper is that the sources behind technology-induced fluctuations in total hours worked are heterogeneous across countries. For example, although the IRFs of total hours worked for the U.K. and France are quantitatively very similar, the composition of technology-induced fluctuations along the two margins is different: while the U.K. labor market uses both margins to accommodate technology shocks, the labor market in France relies mainly on the intensive margin. In addition, only in the U.S. and the U.K. the adjustment takes place to a greater extent along the extensive margin.

The results for the U.S. confirm the findings in previous studies (see Table B.1). Michelacci and Lopez-Salido (2007) and Canova et al. (2013) show that technology shocks substantially increase unemployment in the short run and affect the U.S. labor market primarily along the extensive margin. Hence, negative employment effects of technology shocks are associated with the time-consuming process of reallocation of workers across jobs.

Similarly, Warning and Weber (2018) find that technological innovations have considerable effects on both hires and the structure of labor demand in Germany. In particular, a shift towards higher qualification requirements in the newly filled vacancies affects the duration of the recruitment process. Following Jung and Kuhn (2014), the average search duration is higher in labor markets with a lower matching efficiency, that is the structure in matching unemployed workers to open positions. Their study shows that a lower matching efficiency in Germany can account for the differences in labor market outcomes compared to the U.S. Accordingly, Balleer (2012), Canova et al. (2013), Rahn and Weber (2019) show that the job finding rate (the rate at which unemployed workers find a job) responds negatively to a technology shock. Moreover, the compositional shift in labor demand is associated with a rise in the job separation rate (the rate at which employed workers lose their job), which can partly account for the technology-induced fall in hours worked (Balleer and van Rens, 2013). In sum, evidence provided in this paper is consistent with the Schumpeterian view that technological advances increase job destruction and job reallocation, and reduce aggregate employment.

Due to the limited availability of systematic measures of hours worked across countries, evidence on labor market effects of technology shocks in other advanced economies is scarce. One example is the study by Galí (2005) using annual data. The short-run responses of total hours worked to a technology shock in Figure 2 are in line with Galí (2005), except for Japan. Although Galí (1999) and Dupaigne and Fève (2009) provide international evidence on the employment effects of technology shocks, their results cannot be directly compared with the outcomes of my analysis. While the former studies identify technology shocks from SVARs with employment-based productivity and employment, I use hourly labor productivity and total hours worked to identify technology shocks for the G7 countries. Moreover, Galí (2005) argues against using an employment-based measure of labor productivity when estimating the effects of technology shocks identified by long-run restrictions.

4.2 The contribution of technology shocks

To assess the relevance of the findings discussed above, Table 3 reports the forecast error variance decomposition (FEVD) at different time horizons. Panel (a) indicates that the contribution of technology shocks to fluctuations in labor productivity is substantial and it increases over the considered horizon across all countries. However, some differences are apparent between the U.S. and the U.K. and the remaining G7 countries. While the contribution of technology shocks to the forecast error variance of labor productivity is roughly 70 percent in the U.S. and the U.K., it is above 90 percent in the remaining countries.

The results for labor input measures are reported in panels (b–d). With a contribution of roughly 60 percent in the first quarter after the shock, technology shocks are an important source of fluctuations in total hours worked in the U.S. and the U.K.; followed by Canada, where these shocks account for about 46 percent of the variance of total hours worked. Furthermore, technology shocks account for an important share in the variance of total hours worked in Italy of about 37 percent, and are—with roughly 20 percent—less important in Japan, France, and Germany.[25] However, over a five-year horizon, technology shocks decline in importance in the U.S. and the U.K. and reach roughly the same share in the variance of total hours worked as

[25] Rahn and Weber (2019) study unemployment dynamics in Germany conditional on a technology shock and also find that this shock does not seem to explain a large share of fluctuations in labor market variables.

Table 3: **Variance decomposition**

Horizon (quarters)	U.S.	Canada	U.K.	Japan	France	Germany	Italy	Avg. (G7)	Avg. (EA)
	a. Labor productivity								
1	65.16	92.84	70.72	99.13	99.02	92.70	99.81	88.48	97.18
4	75.05	95.37	69.79	99.12	99.81	94.63	95.85	89.95	96.76
8	86.22	97.64	80.07	99.57	99.93	97.48	97.53	94.06	98.31
20	94.31	99.06	91.71	99.83	99.98	99.22	99.10	97.60	99.43
	b. Total hours worked								
1	61.43	45.83	60.78	20.38	22.53	19.03	36.73	38.10	26.10
4	30.48	15.39	38.45	6.07	19.41	4.90	11.25	17.99	11.85
8	22.34	8.85	30.21	3.20	21.06	4.81	7.23	13.96	11.04
20	21.33	6.29	26.23	1.73	21.79	5.28	6.12	12.68	11.06
	c. Employment								
1	31.16	13.67	13.87	1.45	0.33	4.08	9.99	10.65	4.80
4	17.14	5.10	17.43	0.36	1.44	0.88	1.05	6.20	1.13
8	13.41	3.05	17.44	0.34	2.10	2.35	0.35	5.58	1.60
20	13.12	2.24	16.98	0.13	1.62	4.15	0.12	5.48	1.96
	d. Hours per worker								
1	41.47	35.80	44.27	24.93	29.43	17.22	33.79	32.41	26.81
4	25.41	22.28	37.82	13.02	37.27	6.07	24.55	23.77	22.63
8	18.99	12.66	32.48	16.30	47.54	6.85	24.93	22.82	26.44
20	14.95	7.42	29.01	19.13	50.21	7.17	28.07	22.28	28.48

Notes: This table reports the percentage contribution of a technology shock to the forecast error variance of labor productivity and labor input for the G7 countries. Averages for the euro area (EA) country grouping were computed using estimates for France, Germany, and Italy. The results for labor productivity and total hours worked are from 2–variable SVARs and the results for employment and hours per worker are from 3–variable SVARs. All models were estimated with four lags on a country-by-country basis. Sample period is 1970:1–2016:4 (U.K.: 1971:1–2016:4). The results for the remaining OECD countries are reported in Table B.5 in the Appendix.

in France. Moreover, the contribution of these shocks to the variance of total hours worked becomes negligible in the remaining countries. In sum, technology shocks are less important for fluctuations in total hours worked in the euro area countries compared to the average across the G7 countries at any horizon.

Panel (c) reports the results for the extensive margin. In the U.S., technology shocks explain around 31 percent of the variance of the extensive margin in the first period after the shock, which is the highest contribution observed across the G7 countries; followed by roughly 14 percent in the U.K. and Canada. In other countries, the contribution of technology shocks to fluctuations in the extensive margin is negligible throughout the entire horizon.

The opposite holds for the contribution of technology shocks to the forecast error variance of the intensive margin, reported in panel (d). Hence, technology shocks are an important source of fluctuations along the intensive margin in the euro area countries and in Japan. However, their share in the variance of the intensive margin is smaller than that reported for the Anglo-Saxon countries, which ranges in the first period after the shock between 36 percent in Canada to 44 percent in the U.K. Interestingly, France is the only country where the contribution of technology shocks to fluctuations in the intensive margin increases over the considered horizon and reaches 50 percent after five years, the highest share across advanced economies. Overall, the results for the two margins indicate that technology shocks explain a greater share of the variations in the intensive margin compared to the extensive margin across the G7 countries.

In sum, the results in Table 3 indicate an important role for technology shocks in explaining variations in total hours worked and the two margins in countries with flexible labor markets. In contrast, these shocks generate fluctuations in total hours worked primarily along the intensive margin in countries with stricter LMIs, whereas their role as a source of fluctuations in the extensive margin is negligible. Thus, higher labor market rigidity is associated with a lower volatility of employment and a higher volatility of hours per worker following a technology shock. This in turn results in a subdued responsiveness of total hours worked to this shocks. These results are in line with Llosa et al. (2015), who show that abstracting from the intensive margin necessarily eliminates a key feature of labor market adjustment to exogenous events.[26]

4.3 The role of institutions

This section examines whether the effects of technology shocks on international labor markets and their adjustment along the two margins can be related to differences in LMIs across countries. The literature shows that LMIs affect how economies respond to shocks.[27] Thus, labor market rigidity limits the responsiveness of labor input to any exogenous change (Solow, 1998) and because LMIs exhibit little variation over time and thus across countries, they affect these responses rather indirectly (Bachmann and Felder, 2018). Nevertheless, evidence on technology-policy interaction is scarce. For example, Hornstein et al. (2007) use a theoretical model to analyze the diverging labor market experiences in Europe and the U.S. induced by technology shocks. Hence, their results are specific to the modeling assumptions and to the nature of the shocks considered in the model (Gnocchi et al., 2015). Moreover, they focus on the aggregate data for 15 European countries.

Following Gnocchi et al. (2015), I examine the link between labor market outcomes of technology shocks and LMIs using Spearman rank correlation coefficients. To this end, I use the IRF and FEVD estimates for 14 advanced economies at a horizon of one and four quarters after the shock.[28] I compute Spearman rank correlations using the 14 IRF point estimates at each horizon at a time with each LMI. I perform the same exercise using the FEVD estimates. Spearman rank correlations are particularly useful in small samples, since the normality assumption does not hold. Furthermore, these correlations allow for non-linear relationships between variables and are robust to outliers (Gnocchi et al., 2015).

[26] Michelacci and Lopez-Salido (2007) also find that technology shocks account for a substantial share of the volatility of employment and aggregate hours worked in the U.S. Furthermore, Canova et al. (2013) show that in the U.S., technology shocks explain a substantial share of the volatility of unemployment and hours per worker and induce significant movements in labor market flows. Ramey (2004) notes that due to the wide variety of empirical results on the contribution of technology shocks to fluctuations in output and labor input, the quantitative importance of technology as a source of business cycles still remains a controversial issue.

[27] See, for example, Blanchard and Wolfers (2000), Veracierto (2008), Fang and Rogerson (2009), Thomas and Zanetti (2009), Blanchard and Galí (2010), Abbritti and Weber (2010).

[28] The countries considered in this analysis are determined by the data availability in the OR-dataset.

Table 4: **The link to LMIs**

	Horizon (quarters)	Total hours worked IRF	Total hours worked FEVD	Employment IRF	Employment FEVD	Hours per worker IRF	Hours per worker FEVD
a. Job and worker flows							
Strictness of employment protection (OECD), 0 – 6 (strict)	1	0.32	-0.41	0.51*	-0.52*	-0.07	-0.20
	4	0.44	-0.58**	0.61**	-0.65**	0.02	-0.03
Hiring and firing practices (GCI), 1 – 7 (extremely flexible)	1	-0.46*	0.42	-0.48*	0.51*	-0.10	0.33
	4	-0.40	0.48*	-0.62**	0.51*	-0.09	0.08
Redundancy costs in weeks of salary (GCI)	1	0.09	-0.17	0.25	-0.15	-0.19	-0.05
	4	0.02	-0.08	0.15	-0.14	-0.04	0.33
b. Wage setting							
Flexibility of wage determination (GCI), 1 – 7 (individual company)	1	-0.03	0.35	-0.22	0.29	-0.08	0.37
	4	-0.31	0.34	-0.51*	0.20	-0.24	0.27
Coordination of wage-setting (ICTWSS), 1 – 5 (regularized pattern)	1	0.39	-0.54**	0.50*	-0.58**	0.20	-0.49*
	4	0.73***	-0.50*	0.53*	-0.60**	0.44	-0.22
Government intervention in wage bargaining (ICTWSS), 1 – 5 (gov. authority)	1	-0.10	-0.07	0.29	-0.18	-0.29	0.00
	4	0.20	0.13	0.45	-0.09	0.14	0.39
c. Union power							
Union density rate, membership of wage and salary earners (ICTWSS)	1	-0.36	0.29	-0.16	0.09	0.01	0.08
	4	0.15	0.26	0.03	0.09	0.20	-0.01
Union coverage rate (CEP-OECD)	1	0.28	-0.50*	0.59**	-0.59**	0.11	-0.47
	4	0.18	-0.39	0.73***	-0.29	0.12	-0.07
Centralization of wage bargaining (ICTWSS), 0 – 1 (high)	1	0.17	-0.25	0.28	-0.35	0.23	-0.33
	4	0.45	-0.20	0.31	-0.45	0.41	-0.37
d. Efficiency and flexibility of the labor market							
Labor market efficiency (GCI), 1 – 7 (most flexible)	1	-0.38	0.45	-0.50*	0.45	-0.01	0.27
	4	-0.29	0.48*	-0.66**	0.45	0.02	-0.03

Notes: This table reports the Spearman rank correlation coefficients between the immediate and one year delayed cumulative IRFs of labor input to a technology shock (see Figure 1 and Figure B.2), respectively, and LMIs (see Table 2 and Table B.4). The same exercise is performed using the FEVD estimates for labor input (see Table 3 and Table B.5). The sample covers 14 countries that are available in the OR-dataset. Statistical significance at 10, 5, and 1 percent level is indicated by *, **, ***, respectively.

Table 4 reports the results.[29] Overall, LMIs influencing job and worker flows (panel a) are significantly related to both IRF and FEVD estimates, and the respective coefficients are higher at a one-year horizon. While the relationship between these LMIs and the extensive margin is statistically significant, the corresponding correlations for the intensive margin are quantitatively insignificant. That is, labor markets with more flexible employment protection legislation and hiring and firing practices are more likely to lay off workers following a technology shock. Furthermore, the flexibility of these institutions is positively associated with the importance of technology shocks as a source of fluctuations in the extensive margin. The latter has significant consequences for technology-induced fluctuations in total hours at a one-year

[29] Table 4 reports the results on individual LMIs without accounting for their interaction. Gnocchi et al. (2015) find that their results obtained for each LMI separately are in general similar to those based on interactions or combinations of LMIs. Similarly, Hornstein et al. (2007) examine the implications of both each individual LMI as well as allowing for interactions of different LMIs with technological change. They find that the policy bundle they consider has a qualitatively similar, though, a much stronger impact on the labor market outcomes of technology shocks than the sum of the impacts of each individual LMI.

horizon, evidenced by a significant correlation between LMIs influencing job and worker flows and FEVD estimates.

Similarly, LMIs that target wage setting practices and characterize union power (panels b and c) are significantly associated with technology-induced fluctuations along the extensive margin. In the first quarter after the shock, a regularized pattern in the coordination of wage-setting is negatively related to the contribution of a technology shock to fluctuations along both margins, which is also reflected in a significant correlation between the respective LMI and technology-induced fluctuations in total hours worked. The highest correlations are reported for the union coverage rate and the IRF point estimates for the extensive margin. Other LMIs in panels (b) and (c) are not significantly associated with the results from the SVAR analysis.

Finally, there is a strong negative correlation between the efficiency and flexibility of the labor market and the short-run response of the extensive margin to a technology shock and a significantly positive correlation (after one year) with the contribution of technology shocks to fluctuations along this margin. (panel d in Table 4). Thus, LMIs affect labor market outcomes of technology shock largely along the extensive margin. As a results, these LMIs are also significantly related to fluctuations in total hours worked following a technology shock. However, not all LMIs considered in this analysis seem to be significantly related with the results from the SVAR analysis.

In sum, cross-country heterogeneities in labor market effects of technology shocks along the extensive margin can be linked to differences in the strictness of international LMIs. In contrast, the correlations of the latter with the results for the intensive margin are overwhelmingly close to zero. Therefore, consistent with the conclusions in Llosa et al. (2015), my results suggest that LMIs only affect adjustment along the extensive margin. Furthermore, the importance of technology shocks as a source of fluctuations in labor input is greater in an environment with more flexible labor market regulations.

The results in Table 4 are consistent with previous studies. In particular, Bertola (1990) and Bentolila and Bertola (1990) document that the responsiveness of employment to shocks is inversely related to the strictness of the country's labor market regulations. For example, Bentolila and Bertola (1990) find that the magnitude of firing costs affects the firing policy of the firm much more than its hiring policy. They show that unexpected reductions of firing costs are associated with an insignificant increase in the firms's marginal propensity to hire, and strongly affect their willingness to fire. In the same vein, Llosa et al. (2015) find that higher dismissal costs lead to less adjustment along the employment margin and more adjustment along the intensive margin.[30]

Hornstein et al. (2007) develop a model with a strong technology-policy interaction in which technological change is implemented through creative destruction. Similarly to my results, they find that the key features of international LMIs can be related to differences in labor

[30] Llosa et al. (2015) show that an increase in the firing costs of only 10 percent of quarterly wages leads to a decline in the volatility of employment from 0.75 to 0.18 while the volatility of hours per worker doubles (from 0.26 to 0.52).

market outcomes across countries. Hence, while technological changes raise both equilibrium unemployment and its duration, more rigid institutions with generous benefits and higher firing costs exacerbate this long-run effect.[31]

To explain the finding that fluid labor markets adjust mainly along the extensive margin following a technology shock, Furlanetto, Sveen, and Weinke (2018) develop a New Keynesian model featuring capital accumulation, the two margins of labor adjustment, and labor market frictions in form of hiring costs. They find that the extent to which employment decreases in response to a technology shock depends on the degree of these frictions. Michelacci and Lopez-Salido (2007) consider a version of the Solow growth model with labor market frictions that induce sluggish job reallocation effects and reach similar conclusions. Hence, these findings can serve as a possible explanation of the considerable differences in the magnitude of technology-induced fluctuations along the extensive margin across countries with different employment protection laws.

5 Robustness checks

This section examines the robustness of the baseline results with respect to an alternative identification scheme of technology shocks, modifications in the empirical model, and the stochastic specification of labor input measures. For expositional clarity, I limit the illustration of the results to the U.S. and Canada, countries with flexible labor markets, and France and Germany, countries with rigid labor markets. Given the differences in the strictness of their LMIs, the four economies are of particular interest since among the G7 countries they also exhibit the largest differences in hours worked (see Figure B.1). The results for the remaining countries and the additional robustness checks are illustrated in, respectively, Figure B.3 and Figure B.4 in the Appendix.

First, to address the issues associated with the long-run identification discussed in Section 3, I employ the medium-run identification approach proposed by Uhlig (2004a,b), which maximizes the contribution of technology shocks to the forecast error variance of labor productivity at intermediate horizons.[32] Specifically, the medium-run identification addresses the potential difficulty of isolating technology shocks from other shocks that may affect labor productivity in the long run, such as tax rate shocks or changes in the social attitude to the workplace (Erceg et al., 2005). Figure 3 illustrates the results. Overall, the IRFs (magenta lines with square markers) are very close to the baseline results (blue lines with asterisk markers) and thus the qualitative conclusions remain unaffected by the medium-run identification scheme.

[31] Moreover, Felbermayr, Larch, and Lechthaler (2013, 2015) show that higher labor market frictions in one country can affect labor market outcomes in other countries through international trade. Thus, they find that the effect of foreign institutions on domestic unemployment ranges between 0.10 to 0.25 of the effect of domestic institutions and that the spillovers are greater when real wages are rigid.

[32] I use a horizon between three and ten years, as originally proposed by Uhlig (2004a). Elstner and Rujin (2019) show that the U.S. technology shocks obtained from the Uhlig model are highly correlated with the shocks obtained from the long-run identification approach as well as with the utilization-adjusted TFP.

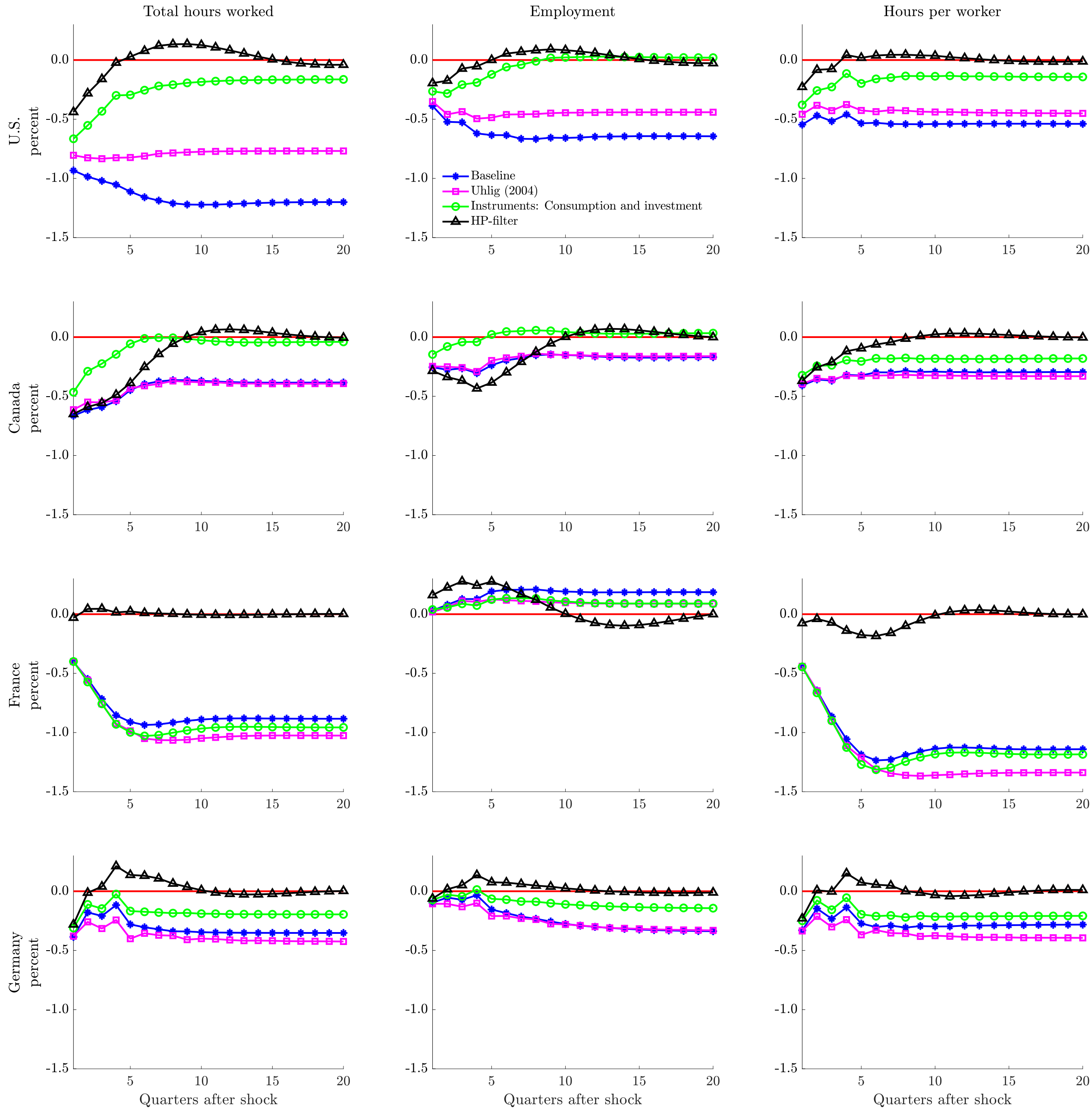

Figure 3: **Impulse responses to a technology shock from different specifications**

Notes: Cumulative IRFs to a technology shock that is normalized to induce a contemporaneous 1% increase in labor productivity. Impulse responses are obtained from the estimation of 2- and 3-variable SVARs with four lags on a country-by-country basis. The sample period is 1970:1–2016:4. All variables are in log first differences unless otherwise indicated. The Uhlig (2004a) model uses the medium-run identification scheme of technology shocks. The latter are identified as the innovations that maximize the FEV of labor productivity at a horizon between three and ten years. Next, I use real consumption-to-output and investment-to-output ratios as instruments instead of hours worked. The ratios are obtained by dividing consumption and investment, respectively, by real GDP. These data are from the OR-dataset. Finally, I estimate the SVARs using detrended labor input variables, which are obtained after applying the HP filter with smoothing parameter of 1600 to the logged series.

Second, to addresses the weak instrument problem emphasized by Christiano et al. (2003, 2004), I use the two-step approach proposed by Fève and Guay (2009, 2010). In the first step, I estimate country-level SVARs identified by long-run restrictions, which include the growth rates of hourly labor productivity, consumption-to-output ratio, and investment-to-output ratio. Following Fève and Guay (2009, 2010), the latter two variables seem to be promising instruments because these ratios may help to disentangle the permanent and transitory components of output. Moreover, in contrast to existing specifications, Fève and Guay (2009, 2010) suggest excluding hours worked from SVARs to improve the accuracy of the identified technology shocks. This consideration is based on the evidence provided in Fève and Guay (2007), who show that the uncertainty about the specification of hours in SVARs is more detrimental for the estimation of technology shocks and their impacts on hours than the information loss resulting from the omission of this variable. In addition, Sims (2011) shows that the inclusion of additional variables, like interest rate and inflation, is not necessary to identify a neutral technology shock, since the response of hours is the same with or without these variables. Given a consistent estimate of technology shocks in the first step, the IRFs of labor input measures to these shocks are estimated in a second step, as outlined in Section 3.

Estimating the system with consumption-to-output and investment-to-output ratios as instruments instead of total hours worked (IRFs depicted by green lines with circle markers) leaves the main conclusions regarding the short-run effects of technology shocks unaffected. Thus, while flexible labor markets—like in the U.S. and Canada—use both margins to adjust labor input to technology shocks, more rigid labor markets, like in France and Germany, rely heavily on the intensive margin in response to these shocks. Interestingly, while the results for the latter two countries are roughly the same as the baseline results, there is a considerable difference in the magnitude of the IRFs for the U.S. and Canada. However, the IRFs for the U.S. obtained from this specification display a similar magnitude and pattern as illustrated in Figure 1.

Numerous studies document that labor market effects of technology shocks that are identified by long-run restrictions are sensitive to the stochastic specification of labor input variables (Christiano et al., 2003, 2004; Francis and Ramey, 2005; Pesavento and Rossi, 2005). Therefore, I use an alternative transformation to obtain stationary labor input measures and detrend the series using the HodrickPrescott (HP) filter with a smoothing parameter of 1600.

The results from the two specifications of labor input variables share similar qualitative features. Thus, the short-run responses of total hours worked to a technology shock for the HP-filtered series (black lines with triangle markers) are in line with the baseline results. France is an exception, where the response of total hours worked remains muted throughout the entire horizon. For the two margins, the qualitative features of the short-run effects of technology shocks are unchanged. However, the magnitude of the effects in the U.S. is smaller compared to the baseline results and the response of the intensive margin in France is—in contrast to a sharp and permanent decline in the baseline IRF—only negligible.

Finally, I estimate the SVARs using sub-samples (see Figure B.4 in the Appendix). First, I follow Gambetti and Galí (2009) and Canova, Lopez-Salido, and Michelacci (2010) by relating the dynamics of the variables to the Great Moderation and use the sample starting in the mid-1980's. The results are in line with the baseline IRFs, though there are some considerable differences in the magnitude of the IRFs for the U.S. and France. In addition, I estimate the models using data for the sample period 1970:1–2006:4, which excludes the financial crisis of 2007–08 and the Great Recession and obtain similar results.

6 Conclusions

This paper makes the following contributions. First, it uses internationally harmonized, quarterly measures of total hours worked computed by Ohanian and Raffo (2012) to estimate the effects of neutral technology shocks on aggregate labor input for the G7 countries. Second, it decomposes technology-induced fluctuations in total hours worked into adjustments along the extensive and intensive margins. Finally, it links the cross-country heterogeneities in labor market effects of technology shocks to strictness of LMIs.

I identify country-specific technology shocks using long-run restrictions, as proposed by Galí (1999). Following Fève and Guay (2009, 2010), I estimate in the second step the effects of these shocks on labor input measures on a country-by-country basis. In a final step, I examine how cross-country heterogeneities in the responses along the two margins of labor input are related to various LMIs using the approach in Gnocchi et al. (2015).

The results support the view that technology shocks have contractionary effects on labor input in the short-run. Furthermore, the sources of fluctuations in total hours worked differ across countries. While technology shocks in countries with flexible labor markets lead to adjustment of labor input along both margins, more rigid labor markets respond largely along the intensive margin to these shocks. These findings are significantly associated with the differences in the strictness of international LMIs. In particular, differences in labor market responses to a technology shock along the extensive margin can be linked to institutional aspects that influence quantity and price adjustments. Furthermore, technology shocks have a greater role for labor input fluctuations in flexible labor markets.

Therefore, the results of this study contribute to the literature on the adjustment of labor input to exogenous shocks in the presence of labor market frictions and provide empirical support for the findings in the literature employing model-based simulations like Fang and Rogerson (2009), Hornstein et al. (2007), Furlanetto et al. (2018).

This conclusions have relevant implications. For example, Gnocchi et al. (2015) stress that, while labor market rigidities can in theory explain the nature of macroeconomic fluctuations, empirical evidence in this respect is still limited. Thus, the evidence in this paper provides insights into how the strictness of LMIs relates to labor market performance in a presence of a neutral technology shock. In line with the findings in Gnocchi et al. (2015), the results in this paper suggest that wage bargaining and employment protection institutions are important for shaping fluctuations in labor input in response to technological innovations.

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Appendix A Data

Table A.1: **Data sources and definitions**

Variable	Sample	Definitions and sources
Ohanian-Raffo dataset: Ohanian and Raffo (2012), http://andrearaffo.com/araffo/Research.html		
Total hours worked	1970:1–2016:4 1971:1–2016:4 (U.K.) 1974:1–2016:4 (SE)	Total hours worked series are obtained as the product of hours worked per worker and employment.
Employment	1970:1–2016:4	Time series are from national statistical offices and the OECD-Economic Outlook database.
Hours per worker	1970:1–2016:4 1971:1–2016:4 (U.K.) 1974:1–2016:4 (SE)	Computation of hours per worker series as well as country-specific data sources and details are summarized in Ohanian and Raffo (2012).
Population aged 15 to 64	1970:1–2016:4	Time series are from national statistical offices and the OECD-Economic Outlook database.
Real GDP	1970:1–2016:4	Time series are from the OECD-Economic Outlook database.
Real private consumption	1970:1–2016:4	Time series are from the OECD-Economic Outlook database.
Real gross fixed capital formation	1970:1–2016:4	Time series are from the OECD-Economic Outlook database.
The Global Competitiveness Index (GCI) Historical Dataset, World Economic Forum (WEF)		
Hiring and firing practices, 1 - 7 (extremely flexible)	2006–2016	In your country, how would you characterize the hiring and firing of workers? [1 = heavily impeded by regulations; 7 = extremely flexible].
Redundancy costs in weeks of salary	2006–2016	Redundancy cost measures the cost of advance notice requirements and severance payments due when terminating a redundant worker, expressed in weeks of salary. The average value of notice requirements and severance payments applicable to a worker with 1 year of tenure, a worker with 5 years and a worker with 10 years is considered. One month is recorded as 4 and 1/3 weeks. Further details are provided by The World Bank http://www.doingbusiness.org/en/methodology/labor-market-regulation.

Table A.1: ***(Continued)***

Variable	**Sample**	**Definitions and sources**
Flexibility of wage determination, 1 - 7 (individual company)	2006–2016	In your country, how are wages generally set? [1 = by a centralized bargaining process; 7 = by each individual company].
Labor market efficiency, 1 - 7 (most flexible)	2006–2016	This indicator measures the flexibility of a labor market to shift workers from one economic activity to another rapidly and at low cost, and to allow for wage fluctuation without much social disruption.
Data Base on Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts (ICTWSS) Visser (2016), `http://uva-aias.net/en/ictwss`		
Coordination of wage-setting, 1 - 5 (regularized pattern)	1970–2014 1998–2014 (KR)	5 = maximum or minimum wage rates/increases based on centralized bargaining by peak association(s), by a powerful and monopolistic union confederation, and/or by influential large firms. 4 = wage norms or guidelines (recommendations) based on centralized bargaining by peak association(s), by a powerful and monopolistic union confederation, and/or regularized pattern setting coupled with high degree of union concentration. 3 = negotiation guidelines based on centralized bargaining by peak associations with or without government involvement, informal centralization of industry-level bargaining, government arbitration or intervention. 2 = mixed industry and firm-level bargaining, with no or little pattern bargaining and relatively weak elements of government coordination through the setting of minimum wage or wage indexation. 1 = fragmented wage bargaining, confined largely to individual firms or plants.
Government intervention in wage bargaining, 1 - 5 (gov. authority)	1970–2014	5 = the government imposes private sector wage settlements, places a ceiling on bargaining outcomes or suspends bargaining; 4 = the government participates directly in wage bargaining (tripartite bargaining, as in social pacts); 3 = the government influences wage bargaining outcomes indirectly through price-ceilings, indexation, tax measures, minimum wages, and/or pattern setting through public sector wages; 2 = the government influences wage bargaining by providing an institutional framework of consultation and information exchange, by conditional agreement to extend private sector agreements, and/or by providing a conflict resolution mechanism which links the settlement of disputes across the economy and/or allows the intervention of state arbitrators or Parliament; 1 = none of the above.

Table A.1: ***(Continued)***

Variable	**Sample**	**Definitions and sources**
Union density rate, membership of wage and salary earners	1970–2013 1970–1996 (AU) 1970–2012 (KR, SE) 1970–1980 (U.S.)	Net union membership as a proportion of wage and salary earners in employment: (0 - 100) = (Net Union Membership) * 100 / (Wage and Salary Earners in Employment)
Centralization of wage bargaining, 0 - 1 (high)	1970–2013 1970–2012 (CA, FR, JP, SE) 1970–2012 (KR, SE) 1970–2011 (DE) 1971–2013 (AU) 1970–2009 (U.S.) n/a (KR)	Summary measure of centralization of wage bargaining, taking into account both union authority and union concentration at multiple levels; weighting the degree of authority or vertical coordination in the union movement with the degree of external and internal unity, and union concentration or horizontal coordination, taking account of multiple levels at which bargaining can take place and assuming a non-zero division of union authority over different levels.
The OECD Indicators		
Strictness of employment protection, 0 - 6 (strict)	1985–2013	The OECD indicator of employment protection is a synthetic indicator of the strictness of regulation on dismissals. It measures the strictness of employment protection against individual dismissal (regular contracts) and is expressed on a scale 0 - 6 (most strict).
Union coverage rate	1970–2000 1980–2000 (AT, FR, JP, SE) n/a (IE, KR)	The CEP-OECD Union Coverage refers to the number of workers covered by collective agreements normalized on employment. In this case the data were collected by Wolfgang Ochel. Further details may be found in Nickell (2006).
Federal Reserve Economic Data (FRED), Federal Reserve Bank of St. Louis		
Nonfarm Business Sector: Real Output Per Hour of All Persons, Index 2009=100, Quarterly, Seasonally Adjusted	1970:1–2016:4	U.S. Bureau of Labor Statistics, Nonfarm Business Sector: Real Output Per Hour of All Persons [OPHNFB], retrieved from FRED, Federal Reserve Bank of St. Louis; `https://fred.stlouisfed.org/series/OPHNFB`
Nonfarm Business Sector: Hours of All Persons, Index 2009=100, Quarterly, Seasonally Adjusted	1970:1–2016:4	U.S. Bureau of Labor Statistics, Nonfarm Business Sector: Hours of All Persons [HOANBS], retrieved from FRED, Federal Reserve Bank of St. Louis; `https://fred.stlouisfed.org/series/HOANBS`

Table A.1: ***(Continued)***

Variable	**Sample**	**Definitions and sources**
Nonfarm Business Sector: Employment, Million jobs, Quarterly, Seasonally Adjusted	1970:1–2016:4	U.S. Bureau of Labor Statistics, Nonfarm Business Sector: Employment [PRS85006013], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/PRS85006013
Civilian Noninstitutional Population, Thousands of Persons, Quarterly, Not Seasonally Adjusted	1970:1–2016:4	U.S. Bureau of Labor Statistics, Civilian Noninstitutional Population [CNP16OV], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CNP16OV
Fernald (2014), http://www.johnfernald.net/TFP		
Utilization-adjusted quarterly-TFP series for the U.S. Business Sector	1970:1–2016:4	The data on inputs, including capital, are used to produce a quarterly series on total factor productivity. In addition, the dataset implements an adjustment for variations in factor utilization–labor effort and the work week of capital. The utilization adjustment follows Basu et al. (2006).

Notes: All definitions are from the original sources. The data set covers 14 countries: Australia (AU), Austria (AT), Canada (CA), Finland (FI), France (FR), Germany (DE), Ireland (IE), Italy (IT), Japan (JP), Norway (NO), Korea (KR), Sweden (SE), U.K., and the U.S.

Appendix B Additional tables and figures

Table B.1: **Summary of empirical studies on technology shocks**

Study	Country	Sample	Labor input measure	Other variables in the model	Labor response on impact
a. Identification by *long-run restrictions*					
Galí (1999)	U.S. Canada U.K. Germany France Italy Japan	1948:1–1994:4 1962:1–1994:4 1962:1–1994:3 1970:1–1994:4 1970:1–1994:4 1970:1–1994:3 1962:1–1994:4	Δ Hours worked Δ Employment Δ Employment Δ Employment (HP) Employment Δ Employment Δ Employment	Δ Labor prod. per hour Δ Labor prod. per employee Δ Labor prod. per employee Δ Labor prod. per employee Δ Labor prod. per employee Δ Labor prod. per employee Δ Labor prod. per employee	– – – – – – 0
Galí (2004)	Euro Area	1970:1–2002:4	Δ Employment	Δ Labor prod. per employee	–
Galí (2005)	G7 countries	1970–2002	Δ Hours worked	Δ Labor prod. per hour	– (+ in JP)
Galí and Rabanal (2005)	U.S.	1948:1–2002:4	Δ Hours worked	Δ Labor prod. per hour	–
Christiano et al. (2003)	U.S.	1948:1–2001:4	(Log) Hours worked Δ Hours worked	Δ Labor prod. per hour	+ –
Christiano et al. (2004)	U.S.	1950–1989	(Log) Hours worked	Δ TFP	+
Pesavento and Rossi (2005)	U.S.	1948:1–2001:4	(Log) Hours worked Δ Hours worked Quasi–Δ hours worked	Δ Labor prod. per hour	+ – –
Francis, Owyang, and Theodorou (2003)	U.S.	1948:1–2000:4	Δ Hours worked	Δ Labor prod. per hour	–
Francis, Ramey, Uhlig, and Basu (2004)	U.S.	1892–2002 1892–1940 1949–2002	(Log, quadratic trend, Δ) Hours worked	Δ Labor prod. per hour	–, –, + (respectively) –, –, + (respectively) –, –, – (respectively)
Francis and Ramey (2005)	U.S.	1947:1–2003:1	Δ Hours worked	Δ Labor prod. per hour	–
Francis (2009)	U.K.	1855–2002	(HP) Employment	Δ Labor prod. per employee	–
Francis and Ramey (2009)	U.S.	1948:1–2007:4	(Log) Hours worked Δ Hours worked	Δ Labor prod. per hour	+ –
Vigfusson (2004)	U.S.	1972:1–2001:4	(Log) Hours worked Δ Hours worked Δ Hours worked	Δ "Purified" TFP Δ "Purified" TFP Δ Labor prod. per hour	near-zero
Fisher (2006)	U.S.	1955:1–1979:2 1982:3–2000:4	(Log) Hours worked	Δ Investment price Δ Labor prod. per hour Δ Output	– **0**
Chang and Hong (2006)	U.S.	1958–1996	Δ Hours worked	Δ TFP	+ / –
Collard and Dellas (2007)	U.S.	1970:1–2001:4	(linearly detrended) Hours worked Δ Hours worked	Δ Labor prod. per hour (Log) Real exchange rate (Log) Trade balance	– –
Fernald (2007)	U.S.	1951:2–2004:2	(Log) Hours worked	Δ Labor prod. per hour	–
Michelacci and Lopez-Salido (2007)	U.S.	1972:1–1993:4	Job creation rate Job destruction rate Job reallocation rate (Log) Employment (Log) Hours per employee	Δ Labor prod. per employee (Log) Investment (Log) Consumption Δ Relative investment price	– + + – +

Table B.1: ***(Continued)***

Study	Country	Sample	Labor input measure	Other variables in the model	Labor response on impact
Liu and Phaneuf (2007)	U.S.	1949:2–2003:4	(Log) Hours worked Δ Hours worked	Δ Labor prod. per hour Δ Nominal wages Δ Nominal prices	near-zero –
Lindé (2009)	U.S.	1959:1–2001:4	(Log) Hours worked Δ Hours worked	Δ Labor prod. per hour	+ –
Fève and Guay (2009)	U.S.	1948:1–2003:4	(Log) Hours worked Δ Hours worked	Δ Labor prod. per hour (Log) Consumption-to-output ratio	– –
Fève and Guay (2010)	U.S.	1948:1–2003:4	(Log) Hours worked Δ Hours worked	Δ Labor prod. per hour (Log) Consumption-to-output ratio	– –
Dupaigne and Fève (2009)	U.S. Canada Japan U.K. Germany France Italy	1978:1–2003:4	Δ Employment	Δ Labor prod. per employee	near-zero – – – – – –
Canova et al. (2010)	U.S.	1955:1–2000:4	(Log) Hours worked Δ Hours worked	Δ Labor prod. per hour Δ Investment price	+ –
Canova et al. (2013)	U.S.	1967:2–2010:1	(Log) Hours worked (Log) Unemployment (Log) Job separation rate (Log) Job finding rate	Δ Investment price Δ Labor prod. per hour	– + + –
Balleer (2012)	U.S.	1955:1–2004:4	Job finding rate Job separation rate	Δ Labor prod. per hour Δ Relative investment price	– +
Chaudourne, Fève, and Guay (2014)	U.S.	1949–1996	(Log) Hours worked Δ Hours worked	Δ Labor prod. per hour Δ Solow residual Δ "Purified" TFP	– – –
Cantore, Ferroni, and León-Ledesma (2017)	U.S.	1948:1–2009:1	(Log) Hours worked Δ Hours worked	Δ Labor prod. per hour Δ "Purified" TFP	– –
b. Identification by *medium-run restrictions*					
Uhlig (2004a)	U.S.	1889–2002	(Log) Hours worked	(Log) Labor prod. per hour	near-zero
Francis et al. (2014)	U.S.	1948:2–2009:4	(Log) Hours worked	(Log) Labor prod. per hour (Log) Consumption (Log) Investment	–
c. Identification by *sign restrictions*					
Dedola and Neri (2007)	U.S.	1953:1–2003:4	(Log) Hours worked	(Log) Labor prod. per hour (Log) Real wages (Log) Real consumption (Log) Real investment (Log) Inflation (Log) Short-term interest rate	+
Peersman and Straub (2009)	Euro Area	1982:1–2002:4	(Log) Hours worked (Log) Employment	(Log) Output (Log) Prices Short-term interest rate (Log) Real wages	+ +

Table B.1: ***(Continued)***

Study	Country	Sample	Labor input measure	Other variables in the model	Labor response on impact
d. *Growth accounting* framework					
Basu et al. (2006)	U.S.	1949–1996	Δ Hours worked Δ Employment	Δ "Purified" TFP	– –
Carlsson (2003)	Sweden	1967–1993	Δ Hours worked	Δ Utilization-corrected TFP Δ Output	–
e. *Other approaches*					
Shea (1998)	U.S.	1959–1991	(Log) Hours worked	(Log) TFP (Log)R&D spending or (Log) Patents (Log) Capital (Log) Materials	+
Alexopoulos (2011)	U.S.	1955–1995	(Log) Hours worked	Books published in the field of technology	+

Notes: This table summarizes influential studies on the labor input effects of technology shocks. The details on the selected characteristics relate to the baseline model specification and the corresponding baseline outcomes in the respective empirical analyses. The reader is referred to the original studies for definitions and detailed explanations of the reported variables.

Table B.2: **Unit root tests**

	Labor productivity		Total hours worked		Employment		Hours per worker	
	level	Δ	level	Δ	level	Δ	level	Δ
	Baseline: G7 countries							
U.S.	-2.08	-3.75**	-1.58	-4.80***	-1.11	-4.45***	-3.32*	-3.68**
Canada	-1.59	-4.52***	-3.44**	-4.55***	-2.68	-4.11***	-3.33*	-2.97
U.K.	1.25	-4.46***	-2.15	-4.00**	-2.03	-4.00**	-2.18	-3.47**
Japan	-3.15	-4.22***	-1.36	-4.03**	-1.55	-2.90	0.52	-4.22***
France	-2.23	-4.14***	-1.57	-3.15*	-1.82	-3.11	-1.46	-3.50**
Germany	-1.51	-3.89**	-0.72	-4.02***	-1.38	-4.22***	-0.26	-3.96**
Italy	-2.78	-3.23*	-2.59	-3.13	-2.94	-2.98	-2.74	-3.47**
	OECD countries							
Australia	-1.95	-3.46**	-1.92	-4.48***	-2.21	-4.09***	-1.16	-4.65***
Austria	-2.92	-4.36***	-2.39	-4.53***	0.26	-4.12***	-3.55**	-3.36*
Finland	-0.95	-4.20***	-2.30	-3.98**	-2.12	-3.65**	-1.51	-4.19***
Ireland	-1.88	-3.85**	-2.30	-3.21*	-2.23	-2.86	-1.95	-2.78
Korea	-1.96	-3.34*	-2.71	-4.24***	-2.42	-4.62***	-2.18	-4.34***
Norway	-0.30	-4.04***	-3.08	-4.40***	-2.13	-4.15***	-2.16	-4.11***
Sweden	-1.55	-3.50**	-2.81	-3.80**	-2.19	-3.13	-2.48	-2.82

Notes: ADF t-statistics for the null hypothesis of a unit root and KPSS LM-statistics for the null hypothesis that the data are stationary. Time series are specified in log-levels and log first differences. Test equations include an intercept and a time trend. Lags for the ADF test equations were chosen optimally based on SIC up to max=12 and the maximum lag order for KPSS tests was chosen from an automatic bandwidth selection routine. *(**) indicate rejection at 5(1) percent level. Sample period: 1970:1-2016:4 (U.K. 1971:1-2016:4 and Sweden 1974:1-2016:4). Data source: Ohanian and Raffo (2012).

Table B.3: **Business cycle statistics**

		Australia	Austria	Finland	Ireland	Korea	Norway	Sweden	Avg.	Avg. (G7)
		a. Correlations of labor productivity with output								
Labor productivity	Δy	0.76**	0.41**	0.40**	0.52**	0.54**	0.37**	0.58**	0.51	0.71
		b. Correlations of labor input variables with output and productivity, respectively								
Total hours worked	Δy	0.18*	0.60**	0.23**	0.43**	0.21**	0.15*	0.40**	0.31	0.48
	Δz	-0.49**	-0.35**	-0.80**	-0.53**	-0.71**	-0.86**	-0.51**	-0.61	-0.33
Employment	Δy	0.16*	0.34**	0.30**	0.37**	0.35**	0.16*	0.38**	0.29	0.49
	Δz	-0.34**	-0.01	-0.21**	-0.47**	-0.19**	-0.28**	-0.12	-0.23	-0.07
Hours per worker	Δy	0.09	0.36**	0.12	0.11	0.05	0.11	0.14	0.14	0.31
	Δz	-0.32**	-0.28**	-0.79**	-0.25**	-0.76**	-0.84**	-0.48**	-0.53**	-0.40
		c. Volatility of labor input variables relative to output and productivity, respectively								
Total hours worked	Δy	0.77	0.94	1.51	0.97	1.13	1.86	0.95	1.16	0.80
	Δz	0.68	1.16	0.94	0.95	0.86	0.94	0.89	0.92	0.86
Employment	Δy	0.57	0.42	0.57	0.83	0.39	0.55	0.69	0.57	0.48
	Δz	0.50	0.52	0.36	0.81	0.29	0.28	0.65	0.49	0.51
Hours per worker	Δy	0.56	0.91	1.37	0.55	0.98	1.73	0.85	0.99	0.66
	Δz	0.49	1.12	0.85	0.53	0.74	0.88	0.79	0.77	0.71
		d. Relative volatility of the extensive to the intensive margin								
Ratio		1.02	0.47	0.42	1.51	0.40	0.32	0.82	0.58	0.72

Notes: This table reports correlations of labor productivity (Δz) with output (Δy) in panel (a); and labor input measures with output and labor productivity, respectively, in panel (b). The asterisks * (**) indicate statistical significance at 5 (1) percent level. Panel (c) reports the ratios of standard deviations of labor input measures to the standard deviation of output and labor productivity, respectively. Panel (d) reports the ratios of the standard deviation of the extensive margin (employment) to the standard deviation of the intensive margin (hours per worker), based on statistics from (c). For comparison, I also report the average statistics for the G7 countries from Table 1. Sample period is 1970:1–2016:4 (Sweden 1974:1-2016:4). Data source: Ohanian and Raffo (2012).

Table B.4: **Labor market institutions**

	Australia	Austria	Finland	Ireland	Korea	Norway	Sweden	Avg.	Avg. (G7)
a. Job and worker flows									
Strictness of employment protection (OECD), 0 – 6 (strict)	1.32	2.61	2.39	1.40	2.59	2.33	2.70	2.19	1.68
Hiring and firing practices (GCI), 1 – 7 (extremely flexible)	3.46	3.49	3.65	3.83	3.59	2.84	2.99	3.41	3.60
Redundancy costs in weeks of salary (GCI)	7.03	12.86	19.64	22.21	65.56	11.27	21.38	22.85	17.56
b. Wage setting									
Flexibility of wage determination (GCI), 1 – 7 (individual company)	4.35	2.51	2.97	3.99	5.35	3.73	3.28	3.74	4.86
Coordination of wage-setting (ICTWSS), 1 – 5 (regularized pattern)	2.64	4.29	4.42	3.42	3.12	4.24	4.11	3.75	2.45
Government intervention in wage bargaining (ICTWSS), 1 – 5 (gov. authority)	2.93	2.09	3.82	3.22	4.24	3.58	2.42	3.19	1.96
c. Union power									
Union density rate, membership of wage and salary earners (ICTWSS)	46.32	44.88	70.51	46.20	13.10	55.49	77.73	50.60	29.00
Union coverage rate (CEP-OECD)	83.30	98.42	94.47	n/a	n/a	69.51	86.61	86.46	57.18
Centralization of wage bargaining (ICTWSS), 0 – 1 (high)	0.53	0.91	0.43	0.44	n/a	0.55	0.53	0.57	0.26
d. Efficiency and flexibility of the labor market									
Labor market efficiency (GCI), 1 – 7 (most flexible)	4.82	4.61	4.81	4.91	4.33	4.98	4.77	4.75	4.79

Notes: This table reports the sample means of labor market indicators. For comparison, I also report the average statistics for the G7 countries from Table 2. The OECD index on the strictness of employment protection covers the time period 1985–2013. The GCI indicators published by the WEF cover the time period 2006–2016. The ICTWSS indicators (Visser, 2016) cover the time period 1970–2014. No data on the centralization of wage bargaining are available for Korea. The union coverage rate from the CEP-OECD institutions dataset (Nickell, 2006) covers the time period 1970–2000. No data are available for Ireland and Korea. Further details are summarized in Table A.1.

Table B.5: **Variance decomposition**

Horizon (quarters)	Australia	Austria	Finland	Ireland	Korea	Norway	Sweden	Avg.	Avg. (G7)
	a. Labor productivity								
1	89.78	99.41	90.35	92.68	97.73	94.43	92.33	93.81	88.48
4	92.87	99.83	94.21	82.44	98.69	96.12	87.02	93.03	89.95
8	95.39	99.71	96.68	88.33	99.11	97.42	92.30	95.57	94.06
20	97.93	99.81	98.77	95.73	99.60	98.91	96.82	98.22	97.60
	b. Total hours worked								
1	55.73	12.84	33.55	59.48	35.21	36.07	62.41	42.18	38.10
4	26.57	6.86	15.29	55.89	14.34	24.83	25.28	24.15	17.99
8	16.24	4.63	7.85	47.51	8.82	17.56	13.57	16.60	13.96
20	11.85	3.85	3.20	39.79	5.31	10.72	9.78	12.07	12.68
	c. Employment								
1	28.21	0.04	1.82	33.94	1.75	1.14	3.07	9.99	10.65
4	14.74	0.47	2.01	30.29	0.34	0.77	0.42	7.01	6.20
8	7.47	0.33	9.33	24.33	0.34	3.26	0.12	6.45	5.58
20	4.26	0.19	16.04	22.88	0.92	6.26	0.19	7.25	5.48
	d. Hours per worker								
1	29.44	6.89	30.52	27.69	41.13	31.30	49.47	30.92	32.41
4	12.78	2.84	28.48	27.00	31.94	27.32	36.70	23.86	23.77
8	7.70	2.03	27.44	24.00	28.62	25.05	30.48	20.76	22.82
20	6.45	1.15	30.98	20.24	27.91	24.69	28.16	19.94	22.28

Notes: This table reports percentage contribution of a technology shock to the forecast error variance of productivity and labor input for the OECD countries. For comparison, I also report the average statistics for the G7 countries from Table 3. The results for labor productivity and total hours worked are from 2–variable SVARs and the results for employment and hours per worker are from 3–variable SVARs. All models were estimated with four lags on a country-by-country basis. Sample period is 1970:1–2016:4 (Sweden: 1974:1–2016:4).

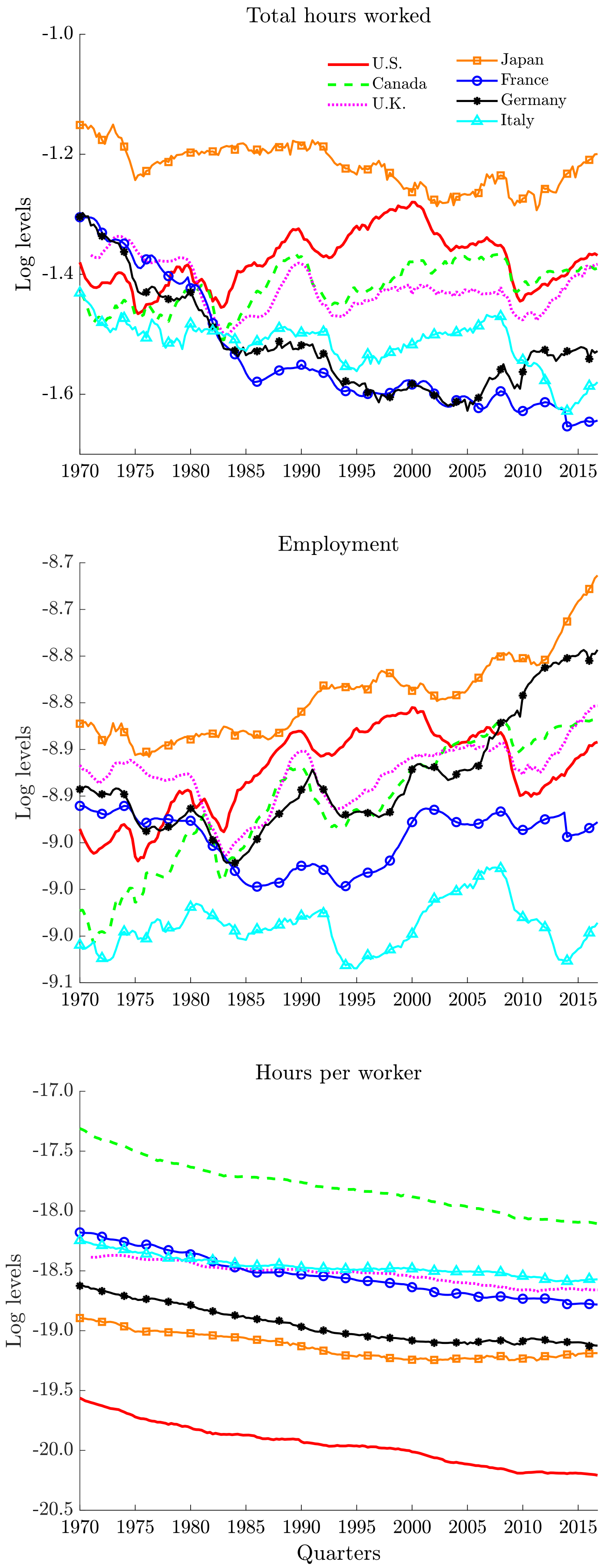

Figure B.1: **Labor input measures for the G7 countries**

Notes: All measures are normalized by the working-age population and expressed in log levels. Data are from the OR-dataset for the sample period 1970:1–2016:4.

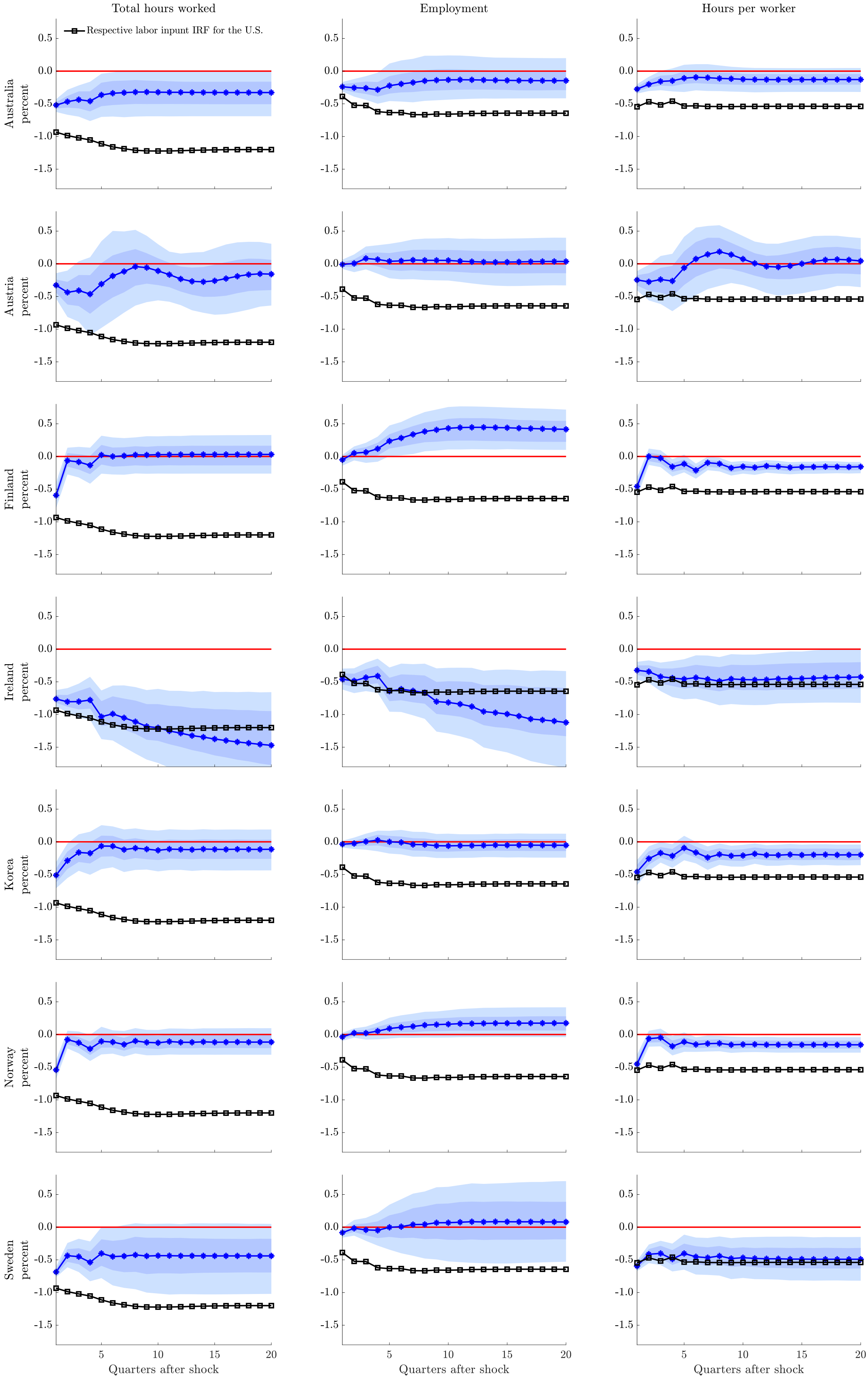

Figure B.2: **Impulse responses to a technology shock**

Notes: Cumulative IRFs to a technology shock that is normalized to induce a contemporaneous 1% increase in labor productivity. IRFs are obtained from the estimation of 2- and 3-variable SVARs on a country-by-country basis for the period 1970:1–2016:4. All variables are in log first differences. Shaded areas: 68% and 95% confidence intervals based on bootstrapping 500 draws.

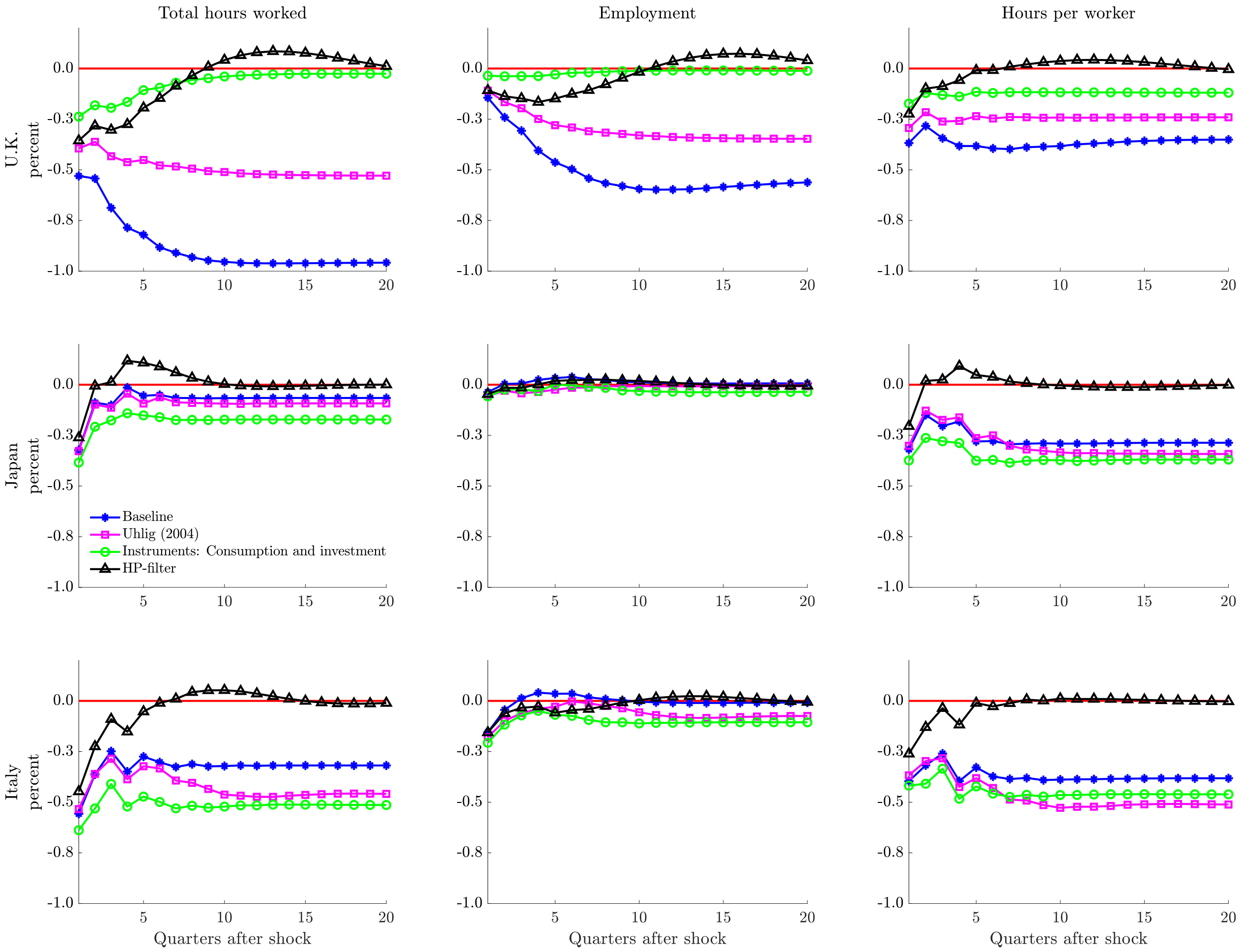

Figure B.3: **Impulse responses to a technology shock from different specifications**

Notes: Cumulative IRFs to a technology shock that is normalized to induce a contemporaneous 1% increase in labor productivity. Impulse responses are obtained from the estimation of 2- and 3-variable SVARs with four lags on a country-by-country basis. The sample period is 1970:1–2016:4 (U.K. 1971:1–2016:4). All variables are in log first differences unless otherwise indicated. The Uhlig (2004a) model uses the medium-run identification scheme of technology shocks. The latter are identified as the innovations that maximize the FEV of labor productivity at a horizon between three and ten years. Next, I use real consumption-to-output and investment-to-output ratios as instruments instead of hours worked. The ratios are obtained by dividing consumption and investment, respectively, by real GDP. These data are from the OR-dataset. Finally, I estimate the SVARs using detrended labor input variables, which are obtained after applying the HP filter with smoothing parameter of 1600 to the logged series.

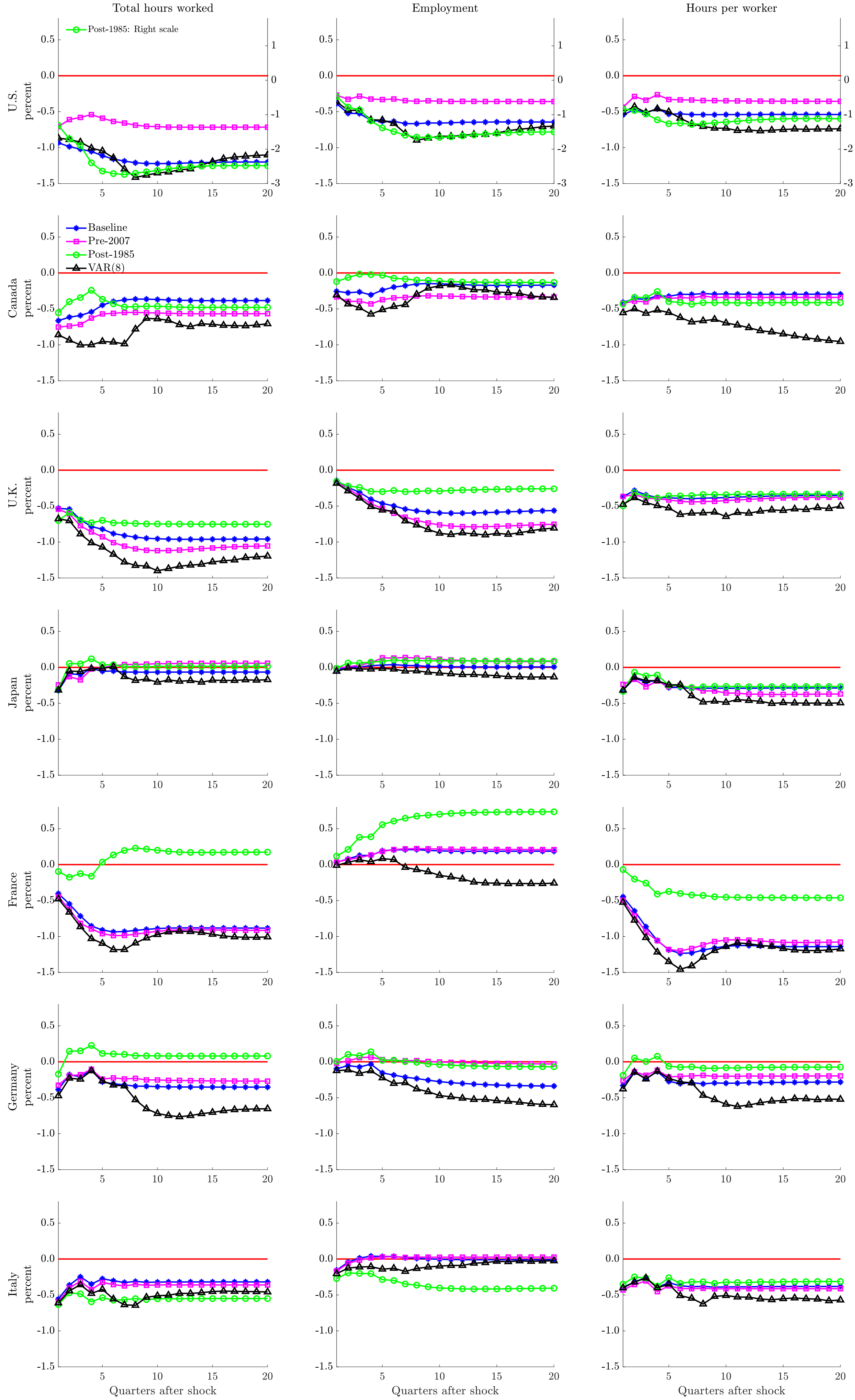

Figure B.4: **Additional robustness checks**

Notes: Cumulative IRFs to a technology shock that is normalized to induce a contemporaneous 1% increase in labor productivity. IRFs are obtained from 2- and 3-variable SVARs on a country-by-country basis. All variables are in log first differences and all models are estimated with four lags unless otherwise indicated. The pre-2007 and post-1985 specifications use the sample periods 1970:1–2006:4 and 1985:1–2016:4, respectively. The VAR(8) is estimated for the sample period 1970:1–2016:4 with eight lags.