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Abstract

Technological change has been biased towards replacing routine labor over the past four decades. We study the implications of those shifts in the task composition of labor demand over the business cycle. We build quarterly time series on hours worked and task premiums from the CPS and assess the effects of routine-biased technological change by estimating a VAR model with long-run exclusion and sign restrictions. The decline in total hours worked is driven by routine-biased technology shocks through a decline in routine hours. These shocks appear quantitatively relevant and generate recognizable aggregate fluctuations pointing out their relevance to business cycles.

Keywords: routine-biased technological change, job polarization, VAR, long-run restrictions, hours worked, business cycle.

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1 Introduction

A core purpose of macroeconomics is to grasp an understanding of the business cycle. In that respect, modern macroeconomics provides two dominant theories of the business cycle: the Real Business Cycle (RBC) and the New-Keynesian (NK) theories. To discriminate between the two theories, a long-standing but widely open literature uses VAR techniques to measure the effects of technology shocks on labor input. Gali (1999) provided what is considered to be compelling evidence that technology shocks have recessionary effects on hours worked endorsing the NK over the RBC framework. In this paper, we revisit the technology-hours debate by reassessing the provided evidence in light of Routine-Biased Technological Change (RBTC), i.e. a specific type of technological development.

Technological change has dramatically shaped the labor market of developed economies in the last four decades. Strong evidence notably recollected by Autor and Dorn (2013) and Goos, Manning, and Salomons (2014) depicts a polarization of the labor market in most advanced economies. Middle-paid jobs are robustly disappearing while high-paid and low-paid jobs are expanding generating a surge in wage inequalities especially in the U.S. The main hypothesis offered to explain job polarization is the routine-biased technological change hypothesis. It conveys the idea that technological change, manifested through the diffusion of new information, communication and robotic technologies, is biased towards *replacing* labor in routine tasks. In this context, technological change significantly shifts the composition of labor demand away from middle-paid jobs because they mainly require routine tasks that are easily automated by new technologies. On the contrary, high-paid jobs involve cognitive abilities and low-paid jobs require manual dexterity and face-to-face interactions that are less inclined to automation. While RBTC has been extensively thought as a long-run gradual process, recent research argues that those shifts in the composition of labor demand occur mainly during economic downturns (Jaimovich and Siu, 2018). In that respect, RBTC and thus the heterogeneity of labor input might be key to untangle the debated effect of technology shocks on hours worked over the business cycle.

In contrast, benchmark RBC and NK theories treat labor as an homogeneous factor. In that case, RBC model predicts that a positive technology shock induces an expansionary effect on hours worked.[1] The labor market is pivotal. Technology shocks shift labor demand which increases the wage, and produce a substitution effect that incites households to increase hours worked. On the contrary, the NK theory predicts that a positive technology shock has a recessionary effect on hours worked.[2] Nominal rigidities are crucial since they constrain

[1] Among others, examples include Kydland and Prescott (1982), King, Plosser, and Rebelo (1988), Plosser (1989) and King and Rebelo (1999).

[2] Examples include Smets and Wouters (2007), Gali (2008), Walsh (2005), Trigari (2009) and Galí (2010).

firms to the demand. Therefore, a positive technology shock increases the performance of inputs. However, firms adjust hours worked downward because of the sluggish demand. Less inputs are required to reach the same amount of output.

The evidence provided in Gali (1999) in favor of the NK theory relies on a Structural Vector Autoregressive model (SVAR). This approach allows him to interpret the observed negative correlation between hours worked and labor productivity. He breaks down structural shocks into technological and non-technological components. The identification of the technology shock hinges on long-run exclusion restrictions as pioneered by Blanchard and Quah (1989). The author argues that the aggregate technology shock is the only disturbance that has a permanent effect on labor productivity. He finds that the response of hours worked conditional on a technology shock is negative and that technological shocks are not able to generate recognizable business cycles. At first sight, these results seem difficult to reconcile with the RBC theory and are interpreted as evidence in favor of the NK theory.

In this paper, we reassess Gali (1999)'s findings by investigating whether shifts in the composition of labor demand induced by RBTC can account for the recessionary effect of technology shocks. In light of this process, we then reevaluate the importance of technological shocks in driving aggregate fluctuations. Considering RBTC and thus labor as an heterogeneous factor might weaken Gali (1999)'s conclusion by casting doubts on his identification strategy. The acknowledgment of RBTC implies that the technology shock he identified entangles distinct disturbances that impact labor productivity permanently. These disturbances have presumably very different implications for our understanding of the effect of technology shocks on hours worked over the business cycle. For instance, RBTC might generate a sharp reallocation process stemming from significant shifts in the task composition of labor demand. This phenomenon could induce a decline in hours worked. This fall would not only be due to nominal rigidities - as supported by the NK theory - but also to the real effect of a vigorous reallocation process induced by technological change.

We basically deal with this identification issue by decomposing Gali's technology shock into two main components. The first component affects labor demand uniformly in the long run regardless of the task performed. We define it as a neutral technology shock. The second component affects the task content of hours worked in the long run. It includes two elements that shift the task composition of labor demand and supply. We defined them correspondingly as RBTC and a task-supply shock. We proceed first of all by building quarterly time series of hours worked and task premiums by using the Outgoing Rotation Groups from the Current Population Survey between 1989 and 2017. We define abstract, routine and manual occupational groups as in Cortes, Jaimovich, Nekarda, and Siu (2014). Task premiums are controlled for composition bias, and relative hours worked are computed in efficiency units to account for demographic and skill heterogeneity as suggested by Autor, Katz, and Kearney (2008). Then, we estimate a SVAR model to disentangle the effects of neutral technology shocks from those of task-related shocks. We identify those disturbances by deriving long-run exclusion and sign restrictions from a general equilibrium model built upon a wide strand of literature on skill- and task-biased technological change. Estimating a SVAR subject to combined long-run exclusion and sign restrictions is a challenging assignment that we undertake by using an approach recently developed by Arias, Ramirez, and Waggoner (2014).

Our main results suggest that the aggregate technology shock identified as in Gali (1999) captures strong shifts in the task composition of labor demand as well as a decrease in hours worked. This observation validates our insight that RBTC matters and justifies our decomposition of technology shocks into neutral and task-related components. In doing so, we find that hours worked and especially routine hours drop after RBTC. Neutral and task-supply shocks have no conclusive effects or at least of smaller magnitude on hours worked. Thus, we argue that most of the fall in hours worked is due to a shift in the task composition of labor demand due to RBTC. Furthermore, disentangling technological shocks is key when assessing the drivers of aggregate fluctuations. Technological shocks are not able to generate recognizable business cycles when we rely on Gali (1999)'s identification restrictions while they generate the bulk of aggregate fluctuations through RBTC when we disentangle them.

A meaningful implication of our results is that task heterogeneity matters for the study of business cycles. In that sense, our main contribution is to the business cycle literature. By investigating the effect of RBTC on hours worked, we reassess Gali (1999)'s evidence on the effect of technology shocks on hours worked in the light of the heterogeneity of labor. In that way, we closely relate to Balleer and van Rens (2013). The authors analyze the effects of skill-biased and investment-biased technological change on hours worked over the business cycle. We distinguish ourselves from them in at least two ways. First, we study task-biased rather than skill-biased technological change. We argue that abstract, routine and manual occupational groups react differently to technological change both in the long run and over the business cycle. Thus, it is worth investigating labor heterogeneity from a task perspective. Second, we differentiate ourselves with respect to our identification scheme. Using the empirical strategy of Arias, Ramirez, and Waggoner (2014), we are able to disentangle neutral from task-biased structural technology shocks. In their complete specification with long-run sign restrictions, Balleer and van Rens (2013) do not identify jointly skill-biased and neutral technology shocks. As a result, our empirical strategy allows us to break down technology shocks into shocks affecting labor uniformly and differently across tasks.

We also contribute to the polarization literature in at least two ways. Firstly, seminal papers such as Autor, Levy, and Murnane (2003), Autor and Dorn (2013) and Goos, Manning, and Salomons (2014) claim that job polarization is primarily generated by routine-biased technological change in the long run. Barany and Siegel (2018) further study the drivers of employment reallocation across sectors and occupations within a general equilibrium model. They find that the occupational bias of technology is by far the most important driver of productivity and employment reallocation trends. However, nothing guarantees that such shocks drive business cycle fluctuations in occupational hours worked. By decomposing productivity disturbances into a neutral and a task-biased component, we are able to tell whether technological change affects labor uniformly or differently across task groups over the business cycle. One limitation of our approach is that we do not provide a more exhaustive decomposition of disturbances. This issue lies outside the range of our paper.

Secondly, we believe to be the first attempting to identify RBTC over the business cycle within a SVAR framework. Some studies focus mainly on recessionary events rather than on the overall economic cycle. For example, Cortes, Jaimovich, Nekarda, and Siu (2014) claim that displacement of routine workers mostly occur during recessionary events. The collapse of routine per capita employment is accounted mainly by inflows and outflows between routine employment and non-employment that have little to do with demographic trends. Jaimovich and Siu (2018) further relate recent jobless recoveries to job polarization. Other studies look at the business cycles properties of occupational employment but do not explicitly look at RBTC. For instance, Foote and Ryan (2015) claim that middle-skill occupations are more cyclical than other occupations partly because they are found in more volatile industries. They also claim that middle-skill job matches are the most quickly dissolved when a recession occurs because of weak long-run prospects. Charlot, Fontaine, and Sopraseuth (2019) argue that half of unemployment variations comes from the ins and outs of routine employment. Such patterns suggest that the disappearance of routine jobs has a non-negligible influence in shaping unemployment fluctuations. To our knowledge, Shim and Yang (2016) is the only paper to study occupational employment fluctuations by using a SVAR.[3] The authors attempt to study the effect of an aggregate technology shock on hours worked identified as in Gali (1999). The core of our paper argues that this identification strategy entangles shocks that have different implications on hours worked over the business cycle.

The paper is organized as followed. In section 2, we develop a general equilibrium model with RBTC. We derive theoretical long-run restrictions in order to identify the corresponding shocks. In section 3, we describe the data, and display some stylized facts. In section 4, we present the VAR model and the identification strategy. In section 5, we present the outcomes of the VAR analysis. Section 6 concludes.

[3]Strickly speaking, Breidemeier, Juessen, and Winkler (Forthcoming) also study the dynamics of occupational employment but in the context of fiscal policy shocks.

2 A general equilibrium model

In this section, we develop a general equilibrium model to study the effects of technology shocks over the business cycle.[4] This approach has two purposes: deriving long-run restrictions to identify structural shocks in the data and showing that routine automation generates a persistent decline in hours worked even in the absence of nominal rigidities. We display the model and present the main implications of the results.

2.1 The model

2.1.1 Firms

Consider an economy in which firms produce output Y_t by combining different tasks in the form of abstract $H_{a,t}$, routine $H_{r,t}$, manual $H_{m,t}$ labors, and automation capital K_t. They maximize their profits:

$$\Pi_t \;\; = \;\; Y_t - W_{a,t}H_{a,t} - W_{r,t}H_{r,t} - W_{m,t}H_{m,t} - R_tK_t.$$

where $W_{i,t}$ and R_t refer to the wage of workers performing task i for $i \in [a, r, m]$ and the rental rate of capital, respectively. The production function is increasing and concave in all its arguments, and exhibits constant return to scale. A Constant Elasticity of Substitution production function satisfies those properties. The production technology is described by the following function

$$Y_t \;\; = \;\; \left[\alpha_a H_{a,t}^{\frac{\varepsilon-1}{\varepsilon}} + \alpha_r \left[\eta H_{r,t}^{\frac{\mu-1}{\mu}} + (1-\eta)\, K_t^{\frac{\mu-1}{\mu}}\right]^{\frac{\mu}{\mu-1}\frac{\varepsilon-1}{\varepsilon}} + \alpha_m H_{m,t}^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}} \tag{1}$$

where $\eta \in [0, 1]$ and α_j are distribution parameters with $\alpha_a + \alpha_r + \alpha_m = 1$. The elasticity of substitution between tasks is $\varepsilon > 0$ while the elasticity of substitution between capital and routine labor is $\mu > 0$. In line with Autor and Dorn (2013), we assume that automation technologies and routine labor are substitutes $\mu > 1$. We also assume that automation devices are more substitutable with routine labor than with other tasks and that tasks are complements $\varepsilon < 1$. First-order conditions associated to abstract, manual, routine labors and automation capital are respectively

$$W_{a,t} \;\; = \;\; X_{1,t}^{\frac{1}{\varepsilon-1}} \alpha_a H_{a,t}^{\frac{-1}{\varepsilon}} \tag{2}$$

[4] The model is built upon a wide strand of literature on skill- and task-biased technological change. We rely notably on Krusell, Ohanian, RÌos-Rull, and Violante (2000), Lindquist (2004), Cantore, Ferroni, and León-Ledesma (2017), Greenwood, Hercowitz, and Krusell (1997) and Barany and Siegel (2018).

$$
\begin{aligned}
W_{m,t} &= X_{1,t}^{\frac{1}{\varepsilon-1}} \alpha_m H_{m,t}^{\frac{-1}{\varepsilon}} && (3)\\
W_{r,t} &= X_{1,t}^{\frac{1}{\varepsilon-1}} \alpha_r X_{2,t}^{\frac{\varepsilon-\mu}{\varepsilon(\mu-1)}} \eta H_{r,t}^{\frac{-1}{\mu}} && (4)\\
R_t &= X_{1,t}^{\frac{1}{\varepsilon-1}} \alpha_r X_{2,t}^{\frac{\varepsilon-\mu}{\varepsilon(\mu-1)}} (1-\eta) K_t^{\frac{-1}{\mu}} && (5)
\end{aligned}
$$

where $X_{1,t} = \alpha_a H_{a,t}^{\frac{\varepsilon-1}{\varepsilon}} + \alpha_r X_{2,t}^{\frac{\mu}{\mu-1}\frac{\varepsilon-1}{\varepsilon}} + \alpha_m H_{m,t}^{\frac{\varepsilon-1}{\varepsilon}}$ and $X_{2,t} = \eta H_{r,t}^{\frac{\mu-1}{\mu}} + (1-\eta) K_t^{\frac{\mu-1}{\mu}}$.

Under the assumption of perfect competition, we obtain the following task premiums by combining equations (2) to (4)

$$
\begin{aligned}
\log\left(\frac{W_{a,t}}{W_{r,t}}\right) &= \log\left(\frac{\alpha_a}{\alpha_r \eta}\right) - \frac{1}{\varepsilon}\log\left(\frac{H_{a,t}}{H_{r,t}}\right) \\
&\quad + \frac{\mu-\varepsilon}{\varepsilon(\mu-1)} \log\left(\eta + (1-\eta)\left(\frac{K_t}{H_{r,t}}\right)^{\frac{\mu-1}{\mu}}\right) \\
\log\left(\frac{W_{r,t}}{W_{m,t}}\right) &= \log\left(\frac{\alpha_r \eta}{\alpha_m}\right) - \frac{1}{\varepsilon}\log\left(\frac{H_{r,t}}{H_{m,t}}\right) \\
&\quad + \frac{\varepsilon-\mu}{\varepsilon(\mu-1)} \log\left(\eta + (1-\eta)\left(\frac{K_t}{H_{r,t}}\right)^{\frac{\mu-1}{\mu}}\right).
\end{aligned}
$$

By analogy to Krusell, Ohanian, RÌos-Rull, and Violante (2000), we have capital-routine task substitutability if abstract and manual labors are less substitutable by automation capital than routine labor ($\mu > \varepsilon$). In that case, a rise in the automation capital stock will *ceteris paribus* increase (resp. decrease) the abstract (resp. routine) premium. This is the *capital-routine substitutability effect*. Furthermore, a rise in relative abstract to routine hours and routine to manual hours will ceteris paribus decrease respectively the abstract and routine premiums for any values of ε and μ. Those capture *relative supply effects*.

2.1.2 Households

The economy is inhabited by three types of infinitely lived agents grouped into abstract, routine and manual households. There is a measure θ_j of each type of agent $j = a, r, m$. The population is normalized to one such that $\theta_a + \theta_r + \theta_m = 1$. Agents are born at time zero. They are assigned to a particular task at birth and are endowed with a unit of time. Individuals supply their unit of time if employed and none if unemployed. In a given household, individuals are perfectly insured against unemployment such that they consume the same amount of goods $c_{j,t}$ whether they are employed or not. Representative household preferences of each type are captured by utility functions of the form

$$u_{j,t}\left(c_{j,t},n_{j,t}\right) \;=\; \frac{c_{j,t}^{1-\sigma}}{1-\sigma}-\zeta_{j,t}\frac{n_{j,t}^{1+\psi}}{1+\psi} \tag{6}$$

where $n_{j,t}$ is the fraction of household j members employed. By doing so, we assume that fluctuations in labor inputs are arising from the extensive rather than the intensive margin. Parameters $\sigma > 0$ and $\psi > 0$ are respectively the coefficient of relative risk aversion and the inverse Frisch elasticity of labor supply. We introduce intratemporal preference shocks $\zeta_{j,t}$ in order to capture potential shifts in task supplies.

The law of motion of automation capital is

$$K_{t+1} \;=\; (1-\delta)K_t + Z_t I_t. \tag{7}$$

where δ is the depreciation rate of automation capital, I_t captures investment and Z_t embodies RBTC. The real price of investment goods is $1/Z_t$ since it captures the number of consumption units that must be exchanged to acquire an efficiency unit of the investment good. Hence, a positive shock in Z_t reduces the cost of investing in automation devices thus accelerating their diffusion across the economy.

A benevolent social planner governs the economy and maximizes the following welfare function by choosing sequences of individual consumption $c_{j,t}$, fraction of individuals employed within a household $n_{j,t}$ and automation capital K_{t+1}

$$\mathbb{W}_t \;=\; \mathbb{E}_0\sum_{t=0}^{\infty}\beta^t\left[\Omega_a\theta_a U_{a,t}\left(c_{a,t},n_{a,t}\right)+\Omega_r\theta_r U_{r,t}\left(c_{r,t},n_{r,t}\right)+\Omega_m\theta_m U_{m,t}\left(c_{m,t},n_{m,t}\right)\right] \tag{8}$$

subject to the aggregate resource constraint

$$Y_t \;=\; C_{a,t}+C_{r,t}+C_{m,t}+I_t \tag{9}$$

and equations (1), (6) and (7). Ω_j are the social planner's preference weights such that $\Omega_a+\Omega_r+\Omega_m = 1$. Aggregate consumption and hours worked are linked to their individual counterparts as $C_{j,t} = \theta_j c_{j,t}$ and $H_{j,t} = \theta_j n_{j,t}$. First-order conditions arising from the benevolent social planner's program are

$$\frac{\Lambda_t}{Z_t} \;=\; \beta\mathbb{E}_t\left[\Lambda_{t+1}\left(R_{t+1}+\frac{(1-\delta)}{Z_{t+1}}\right)\right] \tag{10}$$

$$\Lambda_t \;=\; C_{a,t}^{-\sigma}\theta_a^{\sigma}\Omega_a \tag{11}$$

$$\Lambda_t \;=\; C_{r,t}^{-\sigma}\theta_r^{\sigma}\Omega_r \tag{12}$$

$$\Lambda_t = C_{m,t}^{-\sigma}\theta_m^{\sigma}\Omega_m \tag{13}$$

$$W_{a,t} = \zeta_{a,t}H_{a,t}^{\psi}C_{a,t}^{\sigma}\theta_a^{-\psi-\sigma}\Omega_a \tag{14}$$

$$W_{r,t} = \zeta_{r,t}H_{r,t}^{\psi}C_{r,t}^{\sigma}\theta_r^{-\psi-\sigma}\Omega_r \tag{15}$$

$$W_{m,t} = \zeta_{m,t}H_{m,t}^{\psi}C_{m,t}^{\sigma}\theta_m^{-\psi-\sigma}\Omega_m \tag{16}$$

where Λ_t is the Lagrangian multiplier associated to the resource constraint. They display respectively the Euler equation, marginal utilities of consumption and labor supply conditions for each type of agent.

Finally, we close the model by assuming that shocks follow random walk processes

$$\log(Z_t) = \log(Z_{t-1}) + \nu_{z,t} \tag{17}$$

$$\log(\zeta_{a,t}) = \log(\zeta_{a,t-1}) + \nu_{a,t} \tag{18}$$

$$\log(\zeta_{r,t}) = \log(\zeta_{r,t-1}) + \nu_{r,t} \tag{19}$$

$$\log(\zeta_{m,t}) = \log(\zeta_{m,t-1}) + \nu_{m,t} \tag{20}$$

where $\nu_{j,t}$ are white noises for $j = z, a, r, m$.

2.1.3 Equilibrium

An equilibrium consists of a set of decision rules $H_j(S)$ and $C_j(S)$ for $j = a, r, m$ depending on the state variables $S = [K, Z, \zeta_a, \zeta_r, \zeta_m]$ that solve (i) the social planner's welfare maximization problem and (ii) the firms' first-order conditions. We have a system of eighteen equations (1) to (5), (7) and (9) to (20) describing the equilibrium processes of eighteen variables $(Y, I, C_a, C_r, C_m, \Lambda_t, K, R, H_a, H_r, H_m, W_a, W_r, W_m, Z, \zeta_a, \zeta_r, \zeta_m)_t$.

From there, our aim is twofold. First, we derive long-run restrictions that will be subsequently used to identify structural shocks in the data. Second, we show that RBTC can generate a fall in hours worked through routine labor when we have capital-routine substitutability even in the absence of nominal rigidities. We proceed by providing a comparative statics analysis displayed in Appendix A. We solve the initial steady state in which we normalize structural shocks to one. We conduct a comparative statics analysis by looking at the change of steady state after a permanent change in each shock (Table A.1). This gives us the long-run effect of permanent shocks.

2.2 Calibration

We now parametrize the model. We set the discount factor β to .99 and the depreciation rate δ to .025. We proxy the proportion of each type of agent θ_j by the average share of hours worked in each type of task corrected for composition biases over the 1989Q1 to 2016Q4 period which gives us $\theta_a = 43.98\%$, $\theta_r = 47.94\%$ and $\theta_m = 8.08\%$. The inverse Frisch elasticity of labor supply ψ is equal to 2. We assume log utility in consumption by setting the coefficient of relative risk aversion σ to 1. According to our assumptions and in line with the polarization literature, we assume that automation capital and routine labor are substitutes while tasks are complements by setting ε and μ equal to .5 and 1.5, respectively. The CES distribution parameter α_a is arbitrarily set to 1/3 while $\alpha_r = 0.6619$, $\eta = 0.7726$, and the social planner's preference weights $\Omega_a = 0.4633$ and $\Omega_r = 0.3114$ are calibrated simultaneously. They are calibrated such that the initial steady state wage premiums ($W_a/W_r = 1.5413$, $W_r/W_m = 1.4364$) and relative hours ($H_a/H_r = 0.9338$, $H_r/H_m = 6.0471$) are equal to their respective sample average.

2.3 Comparative statics

We now present the main results from the comparative statics analysis from which we derive identifying restrictions on the long-run effect of structural shocks. We also show that total hours worked decline through routine labor after RBTC when we have capital-routine substitutability and task complementarity. We summarize the theoretically-grounded restrictions in Table 1 and display the entire comparative statics analysis in Table A.1.

Shocks/Variables		$\frac{Y}{H}$	$\frac{W_a}{W_r}$	$\frac{H_a}{H_r}$
RBTC	(Z_t)	>0	>0	>0
Task supply	$(\zeta_{a,t},\zeta_{r,t})$	$*$	<0	>0

Table 1: Comparative statics

Notes: We display signs of long-run responses to a positive one percent permanent change in corresponding shocks. We denote by * the ambiguous variation in the variable of interest.

We are able to disentangle task-supply shocks from RBTC in the data with sign restrictions on labor productivity, abstract premium and relative abstract to routine hours. RBTC is captured by a positive shock on Z_t. This shock increases labor productivity by reducing the cost of investing in automation capital accelerating its diffusion across the economy. Since automation capital and routine labor are substitutes, RBTC generates a compositional shift in labor demand away from routine labor. Thus, the abstract premium increases as well as abstract to routine hours. On the contrary, the routine premium decreases as well as routine to manual hours. Therefore, premiums and corresponding relative hours worked evolve in the same direction.

RBTC is not the only shock affecting the composition of labor in the long run. Task-supply shocks also affect premiums and relative hours in the long run. A positive abstract to routine relative supply shock occurs either through a decline in $\zeta_{a,t}$ or an increase in $\zeta_{r,t}$. A negative shock in $\zeta_{a,t}$ reduces the dis-utility of working of abstract workers. The abstract premium decreases while abstract to routine hours increase reflecting the rise in the supply of abstract labor. Labor productivity falls due to decreasing returns in abstract labor. The responses of the routine premium and routine to manual hours are close to zero. A positive shock in $\zeta_{r,t}$ shifts preferences of routine workers towards leisure. The abstract premium decreases while abstract to routine hours increase. The routine premium increases while routine to manual hours decrease. Routine labor supply decreases. Since routine labor becomes more costly, firms substitute capital for routine labor. In that case, labor productivity increases reflecting the higher productivity of abstract and manual workers. Hence, task premiums and corresponding relative hours evolve in opposite directions whether task-supply shocks arise from $\zeta_{a,t}$ or $\zeta_{r,t}$. However, the change in labor productivity is ambiguous.

It is also noteworthy that technological shocks are able to generate a persistent fall in total hours worked even in the absence of nominal rigidities. RBTC decreases total hours worked in the long run through a strong fall in routine labor. The intuition is as follows. RBTC stimulates the diffusion of automation capital by increasing the efficiency at which investment is transformed into automation devices. Firms substitute automation capital for routine labor as it becomes available leading to a persistent decline in routine hours. RBTC also reallocates labor towards abstract and manual jobs because of their complementarity with capital. However, the slight rise in abstract and manual hours does not counterbalance the decline in routine hours leading to a permanent fall in total hours. Thus, a RBC model is able to generate a persistent fall in total hours worked after a technological shock even without nominal rigidities. In this case, capital-routine substitutability is key.

3 Data

In this section, we first describe the data used to estimate the effects of technology shocks. Second, we display descriptive statistics to discuss salient facts about technological change and the polarization of the U.S. labor market both over the long run and the business cycle.

3.1 Data construction

We start by presenting the data and construction of time series used both in the descriptive and the VAR analysis. We seasonally adjust the resulting time series using the X-13 algorithm developed by the US Census Bureau.

Sample. We build quarterly series of task premiums, relative employment, relative supply, hours, real wages and population from the IPUMS CPS micro data from 1989Q1 to 2018Q1.[5] We cannot use IPUMS CPS before 1989Q1 because they do not provide information on wages. The Census Bureau reports that the CPS includes errors for these series prior to 1989. We use the Outgoing Rotation Group which provides information on wage and salary for individuals interviewed in their 4th and 8th waves. We restrict our attention to civilian non-military 16-64 year-old individuals with 0 to 39 years of potential experience.[6] We study wages and hours worked restricting further our sample by including only those employed in non-farm occupations with positive real hourly wages. We focus on private non-farm employment to stay as close as possible to Balleer and van Rens (2013).

Weekly hours worked. Our main measure of hours of work is the usual weekly hours worked at the main job. When this information is not reported we replace it by a second measure of hours worked existing in the CPS, namely actual hours. However, the latter is available only since 1994. Observations with no values for both actual and usual hours are considered as missing. Zero hour observations are also considered as missing. Finally, we trim observations on hours that lie within the 0.5 and the 99.5 percentiles of observations.

Real hourly wage. The hourly wage is computed as the ratio of usual weekly earnings over usual weekly hours worked at the main job. Usual weekly earnings include overtime, tips and commission. For hourly workers, usual weekly earnings are the maximum between the reported usual weekly earnings and the imputed weekly earning (reported hourly wage times usual weekly hours worked at the main job). We correct top-coded wage observations with a fixed factor method as Acemoglu and Autor (2011). Top-coded weekly earnings are multiplied by 1.5 in order to get an approximate of the mean above threshold (top-coded value). Other imputation methods are available but they all aim at correcting top-coded observations by some factor. Weekly earnings observations with zero earnings are treated as missing. We clean computed hourly wages by trimming observations less than 0.3 and above 99.7 percentiles of observations. All variables are obtained by weighting observations with the earning study weights. Hourly wage is also weighted by usual weekly hours worked at the main job. We use the non-seasonally adjusted monthly consumer price Index research series using current methods (CPI-U-RS) on all items in order to deflate hourly wages.[7] For quarters where the CPI-U-RS is not available, we use the non-seasonally CPI-U which is

[5] Flood, King, Rodgers, Ruggles, and Warren (2018): `https://cps.ipums.org/cps/`.

[6] Restrictions on years of potential experience are typical in the literature studying inequality such as in Autor and Dorn (2013), Acemoglu and Autor (2011) and Balleer and van Rens (2013). Those restrictions are probably justified economically because of plausible selection bias.

[7] `https://www.bls.gov/cpi/research-series/home.htm`.

close to the CPI-U-RS after 2001 according to the BLS.[8] We compute the quarterly average CPI. Quarterly real wages are expressed in 2015Q1 dollars.

Task premiums. We compute task premiums by calculating composition-adjusted log wage ratio of abstract to routine workers ($W_{a,t}/W_{r,t}$) as well as routine to manual workers ($W_{r,t}/W_{m,t}$). Following Cortes, Jaimovich, Nekarda, and Siu (2014)'s task classification, we map individual wage data in three occupational groups namely abstract, routine and manual, and control for change in gender, ethnicity, marital status, education and potential experience.[9] Due to the extent of heterogeneity and the size of the sample available, we use two gender (men and women), four potential experience (0-9, 10-19, 20-29 and 30-39 years) and four educational (less than high school, high-school degree, some college, college degree and more) categories. Following Autor, Katz, and Kearney (2008), Acemoglu and Autor (2011) and Balleer and van Rens (2013), we estimate standard Mincerian earnings functions where log wages are explained by a constant, the ethnicity, the marital status and a quartic function of years of potential experience for each task-gender-education-experience group. This specification allows potential experience, ethnicity and marital status to have different effects on log wages of each group. The composition-adjusted average log wage for each of the 96 task-gender-education-experience groups for a given quarter is the predicted log wage from those regressions for each respective group keeping constant other control variables. Average log wages by task in each quarter are obtained by a weighted average of relevant task-gender-education-experience composition-adjusted average log wages using fixed weights equal to the mean share of total hours worked by each group over 1989Q1 to 2018Q1. We then compute task premiums by taking the corresponding log wage differentials.

Relative hours worked. Relative hours worked are defined as the log ratio of abstract to routine and routine to manual total hours worked in efficiency units. We first compute total hours worked (by all employed workers in the restricted sample) for each of the 96 task-gender-education-experience groups. We then account for the heterogeneity of workers by expressing total hours worked in efficiency units. We normalize each task-gender-education-experience composition-adjusted wage by the composition-adjusted wage of high-school graduate routine male workers with 15 years of potential experience in the contemporaneous quarter. We then compute an efficiency unit measure for each cell as the arithmetic mean of the latter corresponding relative wage measure over 1989Q1 to 2018Q1. Finally, we aggregate hours

[8] `https://www.bls.gov/cpi/data.htm`.

[9] Cortes, Jaimovich, Nekarda, and Siu (2014) base their study on four task groups. In our case, we aggregate their classification to three task groups. Abstract workers include non-routine cognitive workers. Routine workers encompass routine cognitive and routine manual workers while manual workers only include non-routine manual workers.

worked to three task groups by averaging relevant hours worked using efficiency unit measures as weights. We obtain our relative hours worked variables by taking the log ratio of abstract to routine and of routine to manual total hours worked in efficiency units.

Total hours worked. Total hours worked in task i and in aggregate at a quarterly rate are computed as

$$TotalHours_{i,t} = \frac{52}{4} AvgHours_{i,t} e_{i,t} \tag{21}$$

where $AvgHours_{i,t}$ is the average weekly usual hours worked and $e_{i,t}$ is the fraction of employed workers in the working age population for the corresponding task or in aggregate.

Labor productivity. Labor productivity is taken from Ohanian and Raffo (2012). It is defined as the ratio between real output and total hours worked. The availability of this variable restricts our analysis to the 1989Q1-2016Q4 period.

3.2 Stylized facts

We now document several stylized facts. Time series are consistent with shifts in the composition of labor demand away from routine towards abstract and manual labor both over the long run and the business cycle. Those shifts appear tightly linked with the negative unconditional correlation between productivity and hours worked described by Gali (1999).

Figure 1 plots the abstract and routine wage premiums corrected for composition bias (W_a/W_r, W_r/W_m) as well as logs of relative hours worked in efficiency units (H_a/H_r, H_r/H_m). The abstract premium increases significantly contrarily to the routine premium which decreases between 1989Q1 and 2016Q4. Indeed, the abstract premium is approximately equal to 0.47 log points at the end of the sample period. This implies that the wage of the average abstract worker is 60% higher than the wage of the average routine worker. The wage differential between these two occupational groups is of 0.37 log points ($\approx$ 45%) at the beginning of our sample period. We observe the opposite qualitative pattern for the routine premium. In 1989Q1, the average routine worker earns a wage 49% higher than the average manual worker. In 2017Q4, the wage differential between routine and manual workers amounts to only 39%. Concomitantly, the amount of hours spent in abstract occupations relative to routine occupations increases sharply. The quantity of hours spent in routine occupations relatively to manual ones decreases significantly. Despite clear trends, these two measures of relative hours are not immune from cyclical fluctuations. During the Great Recession of 2008, abstract to routine hours substantially increase whereas routine to manual hours decrease.

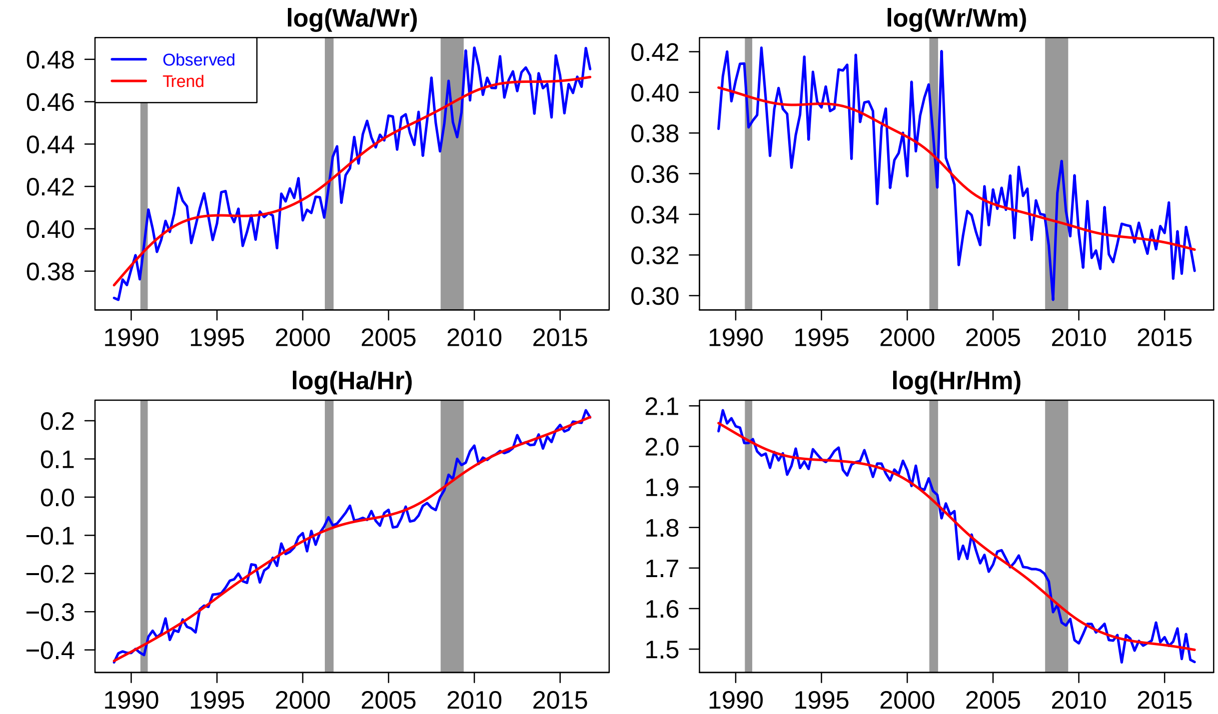

Figure 1: Task premiums and relative hours over the 1989-2017 period
Notes: Data are constructed as described in subsection 3.1. All time series are seasonally adjusted using x13. Measures of task premiums are controlled for changes in experience, gender and educational attainment while relative hours are expressed in efficiency units. We capture trends by using the HP-filter ($\lambda = 1600$).

The mirroring dynamics of task premiums and relative hours worked reveals the long-run shifts in labor demand that lead to job polarization.

Figure 2 displays the evolution of total hours per capita at the aggregate level and by task. Job polarization manifests through a downward trend in the level of routine hours and upward trend in the levels of abstract and manual hours. In line with Jaimovich and Siu (2018), hours of work spent in routine jobs fall dramatically during busts. Such a finding suggests that job polarization accelerates during recessions. However, a less documented finding is that the fall in hours worked also extends to abstract occupations. This is especially true for the last two recessions of our sample period. Furthermore, recovery is not perceptible for routine workers. This confirms that jobless recoveries are essentially accounted by the disappearance of routine jobs.

Table 2 reports business cycle moments for task premiums, relative hours as well as for labor productivity and total hours worked. Cyclical components are obtained with the HP-filter with a smoothing parameter λ of 1600. It appears that the long-run shifts in the composition of labor demand exhibited by time series seem to occur also over the business cycle. Indeed, the abstract and routine premiums are mildly negatively correlated: when the

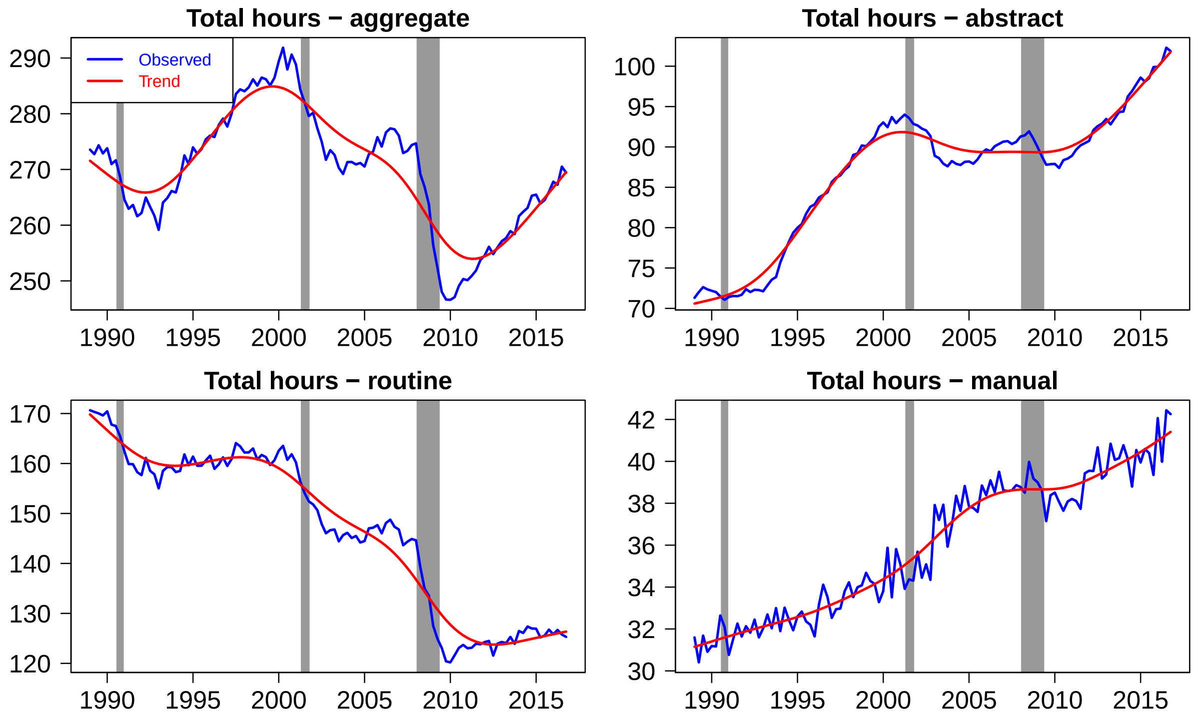

Figure 2: Total usual hours per capita by task over the 1989-2017 period
Notes: Data are constructed as described in subsection 3.1. All time series are seasonally adjusted using x13. We capture trends by using the HP-filter ($\lambda = 1600$).

first one increases the second one tends to fall. Furthermore, the abstract premium (resp. routine) is negatively (resp. positively) correlated with routine to manual hours. However, we do not observe any significant correlation between the abstract premium and abstract to routine relative hours.

These compositional shifts in labor demand away from routine labor seem tightly linked to the negative correlation between productivity and hours worked documented by Gali (1999). The abstract premium is positively correlated with labor productivity but negatively correlated with total hours worked. The first correlation suggests a pro-cyclical pattern of the abstract premium. The second one could be seen as a first indication that positive changes in the abstract premium are associated with a fall in total hours. We find the opposite for the routine premium. Furthermore, abstract to routine hours are negatively correlated with total hours while routine to manual hours are positively correlated with them. Abstract to routine hours display no significant correlation with labor productivity whereas routine to manual hours are negatively correlated with the latter.

Those comments rely only on unconditional moments. In the following sections, we use a SVAR model to properly identify technology shocks and assess whether they account for a fall in hours worked through changes in the composition of labor demand.

		Correlation				
	SD	W_r/W_m	H_a/H_r	H_r/H_m	Y/H	H
W_a/W_r	0.0090	-0.2126*	0.1767	-0.3005*	0.3942*	-0.3492*
W_r/W_m	0.0162	-	0.0648	0.2003*	-0.1010	0.1485
H_a/H_r	0.0204	-	-	-0.2934*	-0.0216	-0.4760*
H_r/H_m	0.0275	-	-	-	-0.3219*	0.5509*
Y/H	0.0075	-	-	-	-	-0.5250*
H	0.0147	-	-	-	-	-

Table 2: Business cycle moments

Notes: SD stands for standard deviation. Data are constructed as described in subsection 3.1. Variables are in logs and HP-filtered with $\lambda = 1600$. Significance of at least five percent ($*$). Table B.2 displays the same business cycle moments for variables in first difference of their logarithm.

4 A VAR model

In this section, we describe the VAR model, the estimation procedure and restrictions used to identify structural shocks discussed in this paper.

4.1 Bayesian estimation

The effects of structural shocks are estimated by modelling selected U.S. macroeconomic time series within a VAR framework. Our reduced-form VAR model can be written as follows:

$$Y_t = B_c + \sum_{k=1}^{p} B_k Y_{t-k} + \nu_t \tag{22}$$

with $B = [B_c, B_1, ..., B_k]$ the matrix of coefficients and ν_t the matrix of reduced-form residuals with covariance matrix $E(\nu_t \nu_t') = \Omega$. Our baseline set of endogenous variables Y_t includes growth rates of labor productivity, abstract premium, total hours worked, abstract to routine and routine to manual relative hours worked in the U.S. economy.[10] The ordering of variables into the vector Y_t is varying depending on the identified shocks. The sample spans the 1989Q1-2016Q4 period. This time length restriction follows the availability of the labor productivity variable.

Our reduced-form VAR is estimated within a Bayesian framework. We follow Balleer and van Rens (2013), Canova, Lopez-Salido, and Michelacci (2013) and Balleer (2012) by employing the Minnesota prior. Such a prior reflects the idea that the data generating process of the variables in level included in Y_t is a univariate unit root so that in first differences each of them is stationary. The prior incorporates a fixed residual variance determining the

[10]After testing for the presence of unit roots for each variable in level, all variables enter the VAR in first differences of their logarithm. Appendix B provides the results of ADF and KPSS tests.

tightness on own lags, other lags as well as the decay of the lags. This reflects the belief that lower-order lag coefficients are more likely to matter. The Minnesota prior is flexible enough to allow the inclusion of a generous number of eight lags. It allows us to get rid of the inability of long restrictions to generate permanent effects of technology shocks.[11] Two additional points should be made about the use of the Minnesota prior in our context. First, it provides stable results in the presence of some "noisy" variations of the abstract premium due to some measurement errors. Second, it does not affect long-run restrictions. We check the robustness of our main results by considering alternative priors and specifications, and find that our key results do not depend on our initial choice.

4.2 Identification

After the estimation of the reduced-form VAR model, the next step consists in identifying meaningful economic shocks. Concretely, we map reduced-form residuals ν_t to structural shocks ω_t which are serially and contemporaneously uncorrelated by imposing meaningful economic restrictions. The structural VAR model can be written as follows:

$$Y_t \quad = \quad A_0^{-1} A_c + \sum_{k=1}^{p} A_0^{-1} A_k Y_{t-k} + A_0^{-1} Q \omega_t \tag{23}$$

where ω_t is the matrix of structural shocks with covariance matrix $E\left(\omega_t \omega_t'\right) = I_N$ and $A_k = A_0 B_k$ the matrices of structural parameters with A_0^{-1} the structural impact matrix. The matrix Q is a rotation matrix that allows for sign restrictions with $QQ' = I_N$. We can link the covariance matrix of reduced-form residuals to some function of structural parameters by imposing restrictions since $E\left(\nu_t \nu_t'\right) = A_0^{-1} A_0^{-1\prime} = \Omega$. Specifically, we impose meaningful economic restrictions on the long-run structural impulse responses, which measures the long-run effects of structural shocks on variables:

$$LR \quad = \quad \left(I_N - \sum_{k=1}^{p} A_0^{-1} A_k \right)^{-1} A_0^{-1} Q. \tag{24}$$

This matrix can be directly mapped to reduced-form parameters with a sufficient number of restrictions since it is related to the long-run forecast error variance

$$LR' LR \quad = \quad \tilde{C} \Omega \tilde{C}' \tag{25}$$

[11]Indeed, when Faust and Leeper (1997) show that long-run effects could not be precisely estimated in finite samples. Chari, Kehoe, and McGrattan (2008) demonstrate that researchers need extremely long time series to infer reliable long-run effects of technology shocks.

with $\tilde{C} = (I_N - \sum_{k=1}^{p} B_k)^{-1}$ since $B_k = A_0^{-1} A_k$.

Specification I					
Order/Shock	Shock 1	Shock 2	Shock 3	Shock 4	Shock 5
	Technology	Other non-technology			
$\log(Y/H)$	$*$	0	0	0	0
$\log(H)$	$*$	$*$	0	0	0
$\log(W_{a,t}/W_{r,t})$	$*$	$*$	$*$	0	0
$\log(H_{a,t}/H_{r,t})$	$*$	$*$	$*$	$*$	0
$\log(H_{r,t}/H_{m,t})$	$*$	$*$	$*$	$*$	$*$
Specification II					
Order/Shock	Shock 1	Shock 2	Shock 3	Shock 4	Shock 5
	Supply	RBTC	Neutral	Other non-tech	
$\log(H_{a,t}/H_{r,t})$	> 0	> 0	0	0	0
$\log(W_{a,t}/W_{r,t})$	< 0	> 0	0	0	0
$\log(Y/H)$	$*$	> 0	> 0	0	0
$\log(H)$	$*$	$*$	$*$	$*$	$*$
$\log(H_{r,t}/H_{m,t})$	$*$	$*$	$*$	$*$	$*$

Table 3: Specifications - Long-run exclusion and sign restrictions

Notes: The first column displays the variables used in the VAR as well as their ordering in ascending order. All variables are entered in first difference of their logarithm. > 0 indicates a positive long-run response of the variable to the shock identified in column, < 0 indicates a negative long-run response, 0 indicates a non-permanent response and $*$ indicates an unrestricted long-run response.

In this paper, we employ two specifications summarized in Table 3. Specification I relies on a longstanding literature -initiated by Blanchard and Quah (1989) and Gali (1999)- employing long-run exclusion restrictions to identify technology shocks. In this case, the technology shock is the only shock that affects productivity permanently. We convert draws from the posterior distribution of reduced-form parameters to draws from the posterior distribution of structural parameters. Hence, we map reduced-form residuals to structural shocks uniquely for each Bayesian draw. This is done by ordering productivity first in the VAR and using a Cholesky decomposition of the long-run forecast error variance: $chol(LR'LR)$.[12]

The second specification combines long-run sign and exclusion restrictions. The challenge is to convert draws from the posterior distribution of the reduced-form parameters with draws from the space of orthogonal matrices conditional on exclusion restrictions for Q to draws from the posterior distribution of candidate structural parameters. We retain from those candidate structural models only those for which the long-run impulse responses LR satisfy sign restrictions. We tackle this issue by using the algorithm developed by Arias, Ramirez, and Waggoner (2014). We provide details on the algorithm in Appendix C.

[12] The rotation matrix is implicitly equal to the identity matrix since we do not impose any sign restrictions.

The algorithm employed in specification II has important economic implications. From our point of view, following this strategy is necessary for at least two reasons. First, using only zero long-run restrictions in a framework where the abstract premium is ordered first and labor productivity second is unsatisfactory. In that context, any positive long-run changes in the abstract premium could originate from an increase in W_a coupled with a rise in labor productivity (technological progress) or a fall in W_r coupled with a decline in labor productivity (technological regress). Second, the strategy proposed by Balleer and van Rens (2013) has its own drawbacks. They also combine zero and sign restrictions. In their context, the skill-biased technology shock implies variations in the same direction of the premium and labor productivity. Their skill-biased technology shock is identified, but the second shock is a mixture of neutral and unskilled-biased technology shocks. In Balleer and van Rens (2013)'s specification, the matrix of long-run effects is block recursive and the second shock is restricted to induce variations in the opposite direction than the one assumed for the skill-biased technology shock. The methodology developed by Arias, Ramirez, and Waggoner (2014) allows us to deal with the non block recursivity of our specifications. As a result, it enables us to disentangle task-biased from neutral technology shocks.

In specification II, we identify a neutral technology shock, a routine-biased technology shock and task-supply shocks. Routine-biased technology and task-supply shocks capture shifts in the task composition of labor demand. So we propose a new ordering of variables: the growth rates of first abstract to routine hours worked followed by the abstract premium, labor productivity and other variables. Both neutral technology and RBTC shocks affect labor productivity positively in the long run. We do not restrict the long-run response of labor productivity after a task-supply shock. Indeed, a positive abstract supply shock could decrease labor productivity because of diminishing returns in each input. In contrast, a negative routine supply shock could increase it due to the higher efficiency of abstract workers. RBTC affects relative hours and the task premium in the same direction while task-supply shocks affect those variables in opposite directions in the long run. Neutral shocks have no permanent effect on them. By definition, the relative amount of hours worked should not change because the demand for each type of task alters in the same direction and in equal proportion.

5 Results

In this section, we present results obtained from the structural VAR analysis. We display results from the two specifications in order to grasp the implication of each identification restriction. Thus, we first investigate the effect of technology shocks traditionally identified as in Gali (1999). Second, we disentangle the effects of RBTC, neutral and task-supply shocks as identified in specification II. Finally, we assess the importance of technological shocks for aggregate fluctuations under both specifications.

5.1 Specification I - Is Gali's technological shock neutral?

We present impulse response functions from a VAR with technology shocks identified as in Gali (1999). In that respect, there is a unique technology shock affecting labor productivity permanently. This identification strategy is consistent with a wide range of theoretical models such as standard RBC or demand-driven NK models. We proceed by ordering in the VAR growth rates of labor productivity followed by abstract premium, total hours worked and relative hours. In all Figures depicting impulse responses, we report the median and the Bayesian confidence interval of structural impulse responses. As diagnostic device, we also plot median target responses as defined by Fry and Pagan (2011).[13]

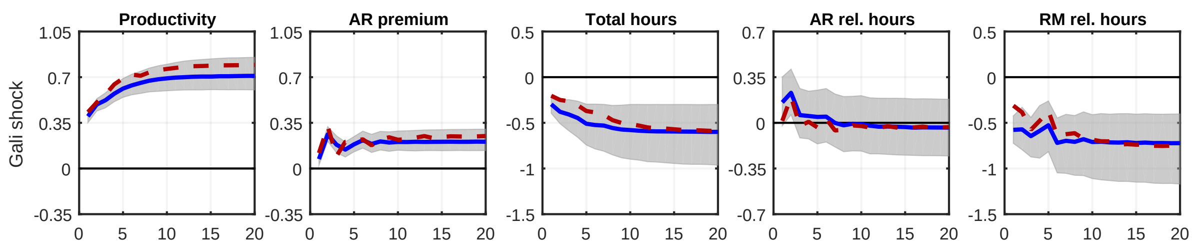

Figure 3: Impulse response functions to Gali's technology shocks
Notes: Impulse responses to a one-standard deviation shock are reported. Solid lines represent the median of impulse responses. Grey areas correspond to the 68% of the posterior distribution. Dashed lines capture the median-target responses as defined by Fry and Pagan (2011).

Figure 3 plots the impulse responses of variables of interest to technology shocks. Positive technology shocks lead to an increase in labor productivity along with a fall in total hours worked. Both effects seem to be fully realized within 4-5 quarters. Our finding is clearly in line with Gali (1999). The drop in total hours is usually interpreted as evidence in favor of demand-driven NK models featuring price rigidities. The novelty of our approach relies on the inclusion in the structural VAR of variables capturing the shifts in task labor demand that led to job polarization, especially the abstract premium. Its response is significantly positive. Furthermore, routine to manual relative hours strongly decrease. Curiously, the response of abstract to routine hours is not significant probably reflecting the influence of other shocks

[13] According to Fry and Pagan (2011), median responses capture model uncertainty rather than sample uncertainty. They are not necessarily coming from the same structural model. The authors solve this issue by selecting the model for which impulse responses are the closest to pointwise posterior medians. Those selected impulse response functions are known as median targets. Nevertheless, this method does not necessarily provide a measure of the central tendency of structural models.

as shown subsequently. Those patterns suggest that technology shocks are biased towards replacing routine labor. They capture shifts in the task composition of labor demand away from routine workers.

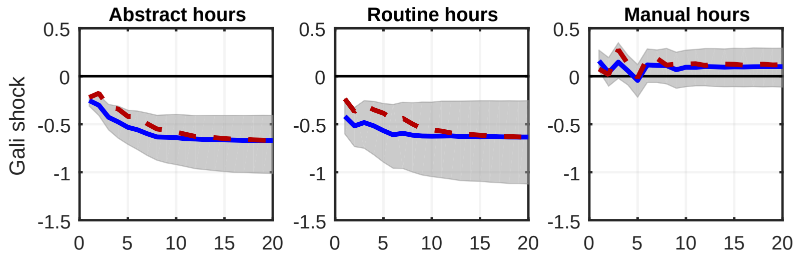

Figure 4: Impulse response functions to Gali's technology shocks - Hours by task
Notes: Impulse responses to a one-standard deviation shock are reported. Solid lines represent the median of impulse responses. Grey areas correspond to the 68% of the posterior distribution. Dashed lines capture the median-target responses as defined by Fry and Pagan (2011).

Hence, we ask how those shifts in the task composition of labor demand manifest through changes in hours by task. To answer that question, we impute impulse responses of hours worked by task from relative hours and total hours measures included in the structural VAR. Figure 4 plots the corresponding impulse responses. Routine hours fall significantly after a technology shock while the response of manual hours remains insignificant throughout the adjustment path. This explains the negative response of routine to manual hours. Like routine hours, hours spent in abstract tasks decrease significantly explaining the non-significant response of abstract to routine hours. We show subsequently that this is partly due to the effects of shocks that are not yet identified but entangled with the currently identified shock. In a nutshell, the evidence indicates that Gali's technological shock appears biased towards replacing routine labor. This comforts the intuition that this shock actually entangles distinct structural disturbances that impact labor productivity permanently.

5.2 Specification II - RBTC, neutral and task-supply shocks

We now present results derived from the second specification for which the overall Gali's technological shock is disaggregated into neutral technology, RBTC and task-supply shocks. In doing so, we reorder endogenous variables of the VAR so that growth rates of abstract to routine hours, abstract premium and productivity enter first followed by our two measures of relative hours. Productivity is impacted positively by both neutral shocks and RBTC in the long run while we do not put any restriction for abstract supply shocks. Furthermore, RBTC affects the abstract premium and abstract to routine hours in the same direction while task-supply shocks affect those variables in opposite directions in the long run.

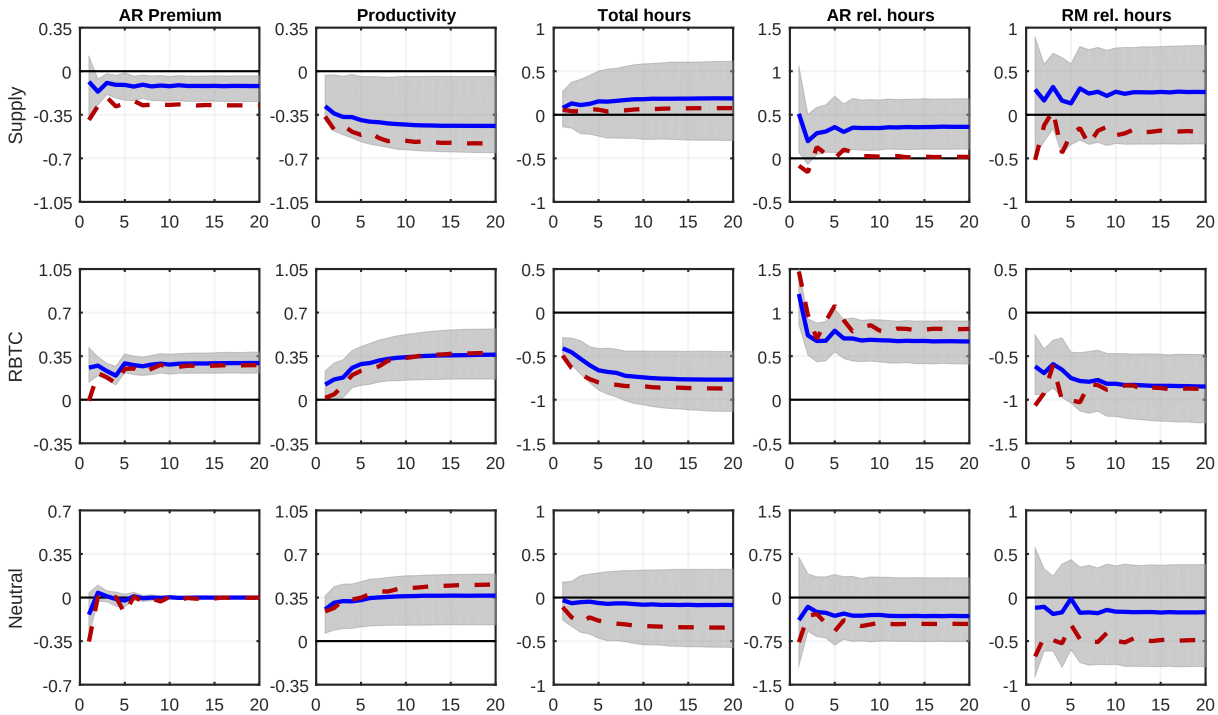

Figure 5: Impulse response functions to task-supply, RBTC, and neutral technology shocks
Notes: Impulse responses to a one-standard deviation shock are reported. Solid lines represent the median of impulse responses. Grey areas correspond to the 68% of the posterior distribution. Dashed lines capture the median-target responses as defined by Fry and Pagan (2011).

Figure 5 displays the impulse responses of variables entered in the VAR. As expected, RBTC raises the abstract premium and abstract to routine hours significantly while it decreases routine to manual hours. This technology shock clearly captures shifts in the task composition of labor demand away from routine labor. Furthermore, it increases productivity and strongly decreases total hours worked. On the contrary, neutral shocks have a near zero effect on task-related variables reflecting the neutral aspect of those shocks. They only have a significant positive impact on productivity. Surprisingly, the median response of total hours worked is close to zero and responses are inconclusive about the sign. Abstract supply shocks slightly decrease the abstract premium and increase abstract to routine hours while decreasing productivity reflecting decreasing returns in abstract labor. Total hours' response is also close to zero and inconclusive about the sign. This indicates that the fall in hours worked is mostly due to shocks that are biased towards replacing routine labor. Those results nuance the NK argument that price rigidities explain the drop in hours worked after a positive technology shock. Our findings favor the idea that compositional shifts of labor demand away from routine labor are responsible for such a drop in hours worked.

We now scrutinize the dynamics of total hours by task displayed in Figure 6. Except for an increase in abstract hours after task-supply shocks, impulse responses of hours worked by

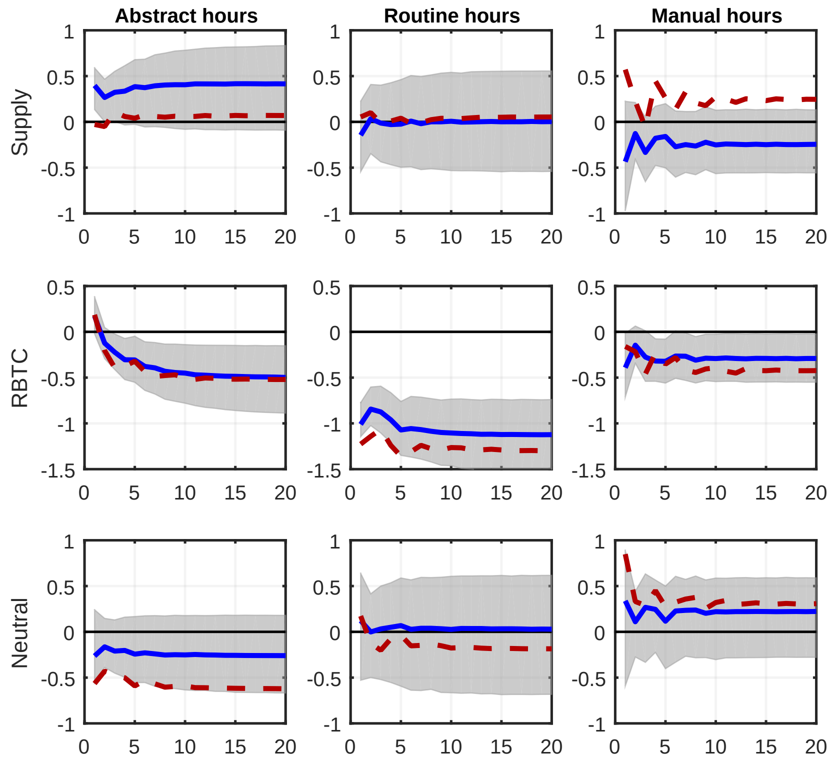

Figure 6: Impulse response functions to RBTC shocks - Hours by task
Notes: Impulse responses to a one-standard deviation shock are reported. Solid lines represent the median of impulse responses. Grey areas correspond to the 68% of the posterior distribution. Dashed lines capture the median-target responses as defined by Fry and Pagan (2011).

task are insignificant and inconclusive after neutral and task-supply shocks. Such responses are consistent with the dynamics of abstract to routine hours and routine to manual hours observed previously. After RBTC, routine hours worked decrease sharply while the falls in abstract and manual hours are weaker but significant. Responses of hours worked reveal an important aspect of labor reallocation arising from RBTC. RBTC associates rising labor productivity and thus technological advancement with lower labor input. In addition, RBTC does not account for the observed upward trends in abstract and manual hours worked which are consequently the result of other economic forces.

As depicted in Figure 7, the task composition of hours worked shifts away from routine towards abstract and manual hours even though they all decline in level after RBTC. Therefore, RBTC generates job polarization over the business cycle along with a decline in hours worked. Moreover, the fall in hours worked arises mainly through routine hours due to the biased nature of RBTC.

Our explanation of the fall in hours worked after RBTC relies on the idea that technological shocks induce severe shifts in the composition of labor demand away from routine

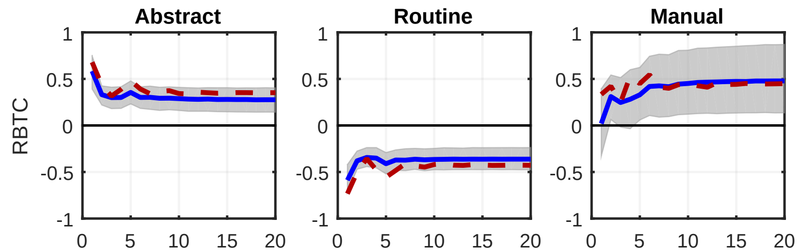

Figure 7: Impulse response functions to RBTC shocks - Share of hours worked by task
Notes: Impulse responses to a one-standard deviation shock are reported. Solid lines represent the median of impulse responses. Grey areas correspond to the 68% of the posterior distribution. Dashed lines capture the median-target responses as defined by Fry and Pagan (2011).

labor. Those significant shifts in labor demand reflect the substitution of capital for routine labor in order to perform routine tasks. In that respect, the process of labor reallocation induced by RBTC should occur primarily through the extensive margin namely employment per capita. By adding hours per worker by task in the VAR, we are able to decompose total hours worked impulse responses into intensive and extensive margin components. Figure D.1 displays the impulse responses for each of those components after a RBTC shock. It is clear that the response of hours worked to RBTC is mainly driven by the extensive margin namely employment especially for routine employment. Those findings corroborate the idea that the process of labor reallocation induced by RBTC is occurring especially through a drastic decline in routine employment per capita. In appendix E, we present a set of robustness checks that confirm those findings. Hence, most of the drop in hours worked arising from disturbances affecting labor productivity permanently stems from a shift in the task composition of labor demand due to RBTC.

5.3 Technological shocks and aggregate fluctuations

We now reassess the importance of technological shocks in explaining aggregate fluctuations in light of task-biased technological change. We show that disentangling technological shocks is crucial to determine the drivers of economic fluctuations. We proceed in two steps. First, we get a first insight into the relevance of technological shocks for aggregate fluctuations by looking at the Forecast Error Variance Decomposition (FEVD) under both specifications. Second, we look at historical decompositions of output and total hours worked to assess whether technological shocks generate recognizable business cycles.

5.3.1 How important are technology shocks for aggregate fluctuations?

Table D.1 displays a FEVD of the VAR based on the first specification at business cycle frequencies after one to 32 quarters. In that case, we only identify technological shocks defined as in Gali (1999). These shocks account for a significant share of the business cycle variance of labor productivity from 95% to 99% after respectively eight and 32 quarters. On the contrary, they explain a low share of the abstract premium volatility at first, that progressively increases with time from 20% to 26% after eight and 32 quarters. Furthermore, they explain almost none of the abstract to routine hours worked volatility with a share of around two percent at any horizon. They explain a larger share of fluctuations in routine to manual hours from 19% to 21% after eight and 32 quarters. Concerning total hours worked, they account for 23% of their volatility over all horizons. In Table D.2, we provide the FEVD for hours worked by task. We find that technology shocks explain from 29% to 32% of abstract hours fluctuations and approximately 16% for routine hours after eight and 32 quarters. On the contrary, manual hours fluctuations explained by technology shocks reach at most two percent after 32 quarters. It appears that fluctuations in aggregate labor productivity are well explained by technology shocks identified as in Gali (1999) contrarily to total hours and task-related variables. This is partly because the technology shock entangles a variety of neutral and task-biased disturbances that have different effects on those variables. This hides the contribution of each type of disturbances to the volatility of those variables.

Table D.3 displays a decomposition of the forecast error variance of the VAR based on specification II. Disentangling RBTC, neutral and task-supply shocks leads to a sizable increase in the share of the business cycle volatility explained by structural shocks of most variables compared to the first specification. For instance, structural shocks now explain 50% to 60% of the abstract premium volatility against 20% to 26% in specification I. This is also the case for total hours worked with a share of about 50% to 60% against approximately 24%. However, the contribution of each structural shock varies substantially across variables. RBTC accounts for 19% of the volatility of productivity after eight quarters against 29% for neutral shocks and 41% for task-supply shocks. Furthermore, RBTC captures most of the volatility of task-related variables. For example, it explains 37% of the volatility of the abstract premium against three percent for neutral shocks and ten percent for task-supply shocks. For total hours worked, RBTC captures around 40% of its volatility against six percent for neutral shocks and seven percent for task-supply shocks after eight quarters. As shown in Table D.4, this is primarily stemming from routine hours since RBTC accounts for 56% of their volatility after eight quarters while only for 12% and eight percent of the volatility of respectively abstract and manual hours. Those figures reflect the importance of RBTC in shaping total hours worked especially through routine hours over the business cycle these past four decades.

5.3.2 Do technological shocks generate recognizable business cycles?

We have shown that RBTC accounts for most of the fall in total hours impulse responses and that those shocks contribute substantially to total hours worked fluctuations. However, those results only describe the average movements in the data. We now follow Gali (1999) by asking whether those shocks generate recognizable business cycles. Thus, we decompose output, and total hours worked historical time series into technology and non-technology components and measure to which extent they account for observed fluctuations. Our focus is set on the median target model defined by Fry and Pagan (2011).

	Observed	Specification I		Specification II			
		Tech	Non-Tech	Supply	RBTC	Neutral	Other NT
corr(Y,H)	0.78*	-0.71*	0.99*	-0.75*	0.95*	-0.42*	0.98*
corr(H,Y/H)	-0.53*	-0.92*	0.29	-0.81*	-0.67*	-0.94*	0.73*
corr(Y,Y/H)	-0.01	0.93*	0.45*	1.00*	-0.41*	0.70*	0.85*

Table 4: Unconditional and conditional correlations estimates
Notes: H, Y and Y/H refer to hours worked, output and labor productivity, respectively. We retrieve the cumulative contribution of each shock to (log) output, (log) hours worked and (log) productivity time series from estimated structural VAR models. We use the HP-filter ($\lambda = 1600$) on resulting time series to isolate business cycle fluctuations. Then, we compute correlations between H, Y and Y/H conditional on each structural shock. The corresponding components time series are depicted in Figures D.2 and D.3.

Table 4 displays unconditional and conditional correlation estimates between total hours worked, output and labor productivity from both specifications. We obtain results in line with Gali (1999) when we rely on his identification restrictions. Those results are interpreted as a failure of RBC theory to capture the essence of business cycle fluctuations for two reasons. First, technological shocks are not able to replicate the observed procyclicality of labor inputs (0.78). They generate negative comovements of hours worked and output (-0.71) while non-technological shocks generate positive comovements of those variables (0.99). This implies that the bulk of fluctuations are mainly driven by non-technological shocks while standard RBC theory claims that business cycles are driven by technological shocks. A look at the entire historical decomposition of output and hours worked (Figure D.4) confirms that non-technological shocks account for most of those variables' fluctuations under the first specification as observed by Gali (1999). Second, technology shocks should generate positive comovements of productivity and hours worked according to standard RBC theory which is not the case empirically (-0.92). It is usually interpreted as evidence supporting the new-Keynesian view of sticky prices.

In contrast, we obtain a different picture when we disentangle technological shocks by relying on the second specification. RBTC generates positive comovements of output and hours

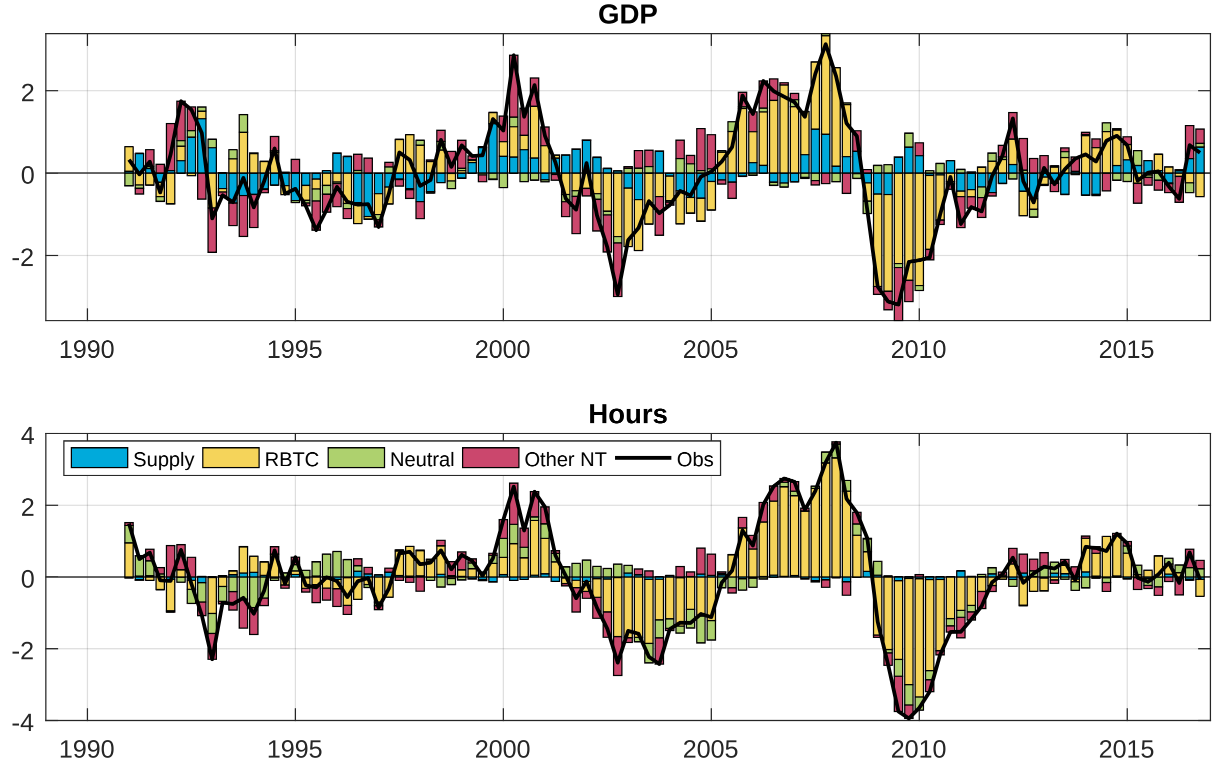

Figure 8: Specification II - Historical decomposition of GDP and total hours
Notes: We retrieve the cumulative contribution of each shock to (log) output and (log) hours worked time series from the estimated structural VAR identified using specification II restrictions. We use the HP-filter ($\lambda = 1600$) on the resulting time series to isolate business cycle fluctuations.

worked (0.95) which is a central characteristic of business cycles while neutral technological (-0.42) and task-supply (-0.75) shocks capture negative comovements of those variables. Other non-technological shocks also generate positive comovements of output and hours worked (0.98). This suggests that both RBTC and other non-technological shocks are candidate drivers of aggregate fluctuations. In order to discriminate between the two types of shocks, we depict the entire historical decomposition of output and hours worked in Figure 8 to provide a wider picture of aggregate fluctuations. It is clear that RBTC is an important driver of business cycle fluctuations in hours worked and output under the second specification. Those shocks seem to drive the bulk of aggregate fluctuations especially since the early 2000s. Furthermore, RBTC generates negative comovements of hours worked and productivity (-0.67). While this seems to be at odds with standard RBC theory, this is coherent with the idea that technological change induces a decline in hours worked through capital labor substitutability. It is also noteworthy that neither technological nor non-technological shocks are able to capture the slight countercyclical productivity movements (-0.01) under the first specification. On the contrary, RBTC is the only type of disturbance that generates countercyclical productivity movements (-0.41) under our second specification. This finding is in line with Jaimovich and Siu (2012) who claim that the reallocation of labor away from routine jobs induced by technological change occurs especially during recessions. While a standard RBC model is not able to generate countercyclical productivity movements, a model of creative destruction can capture this feature. Outdated routine jobs, being easily substitutable by new technologies, are getting scrapped during recession because they become unprofitable leading to a rise in productivity.[14]

In a nutshell, those results suggest that business cycles seem driven by non-technology shocks when technological shocks are aggregated as in Gali (1999) while they are driven by task-biased technological shocks when relying on our second specification. Even though this analysis does not provide a thorough examination of the determinants of aggregate fluctuations, it stresses the importance of considering the nature of technological change.

6 Conclusion

During the last four decades, the U.S. has experienced job polarization because technological change has been biased towards replacing routine labor. In light of such development, we reassess the evidence provided in Gali (1999) by asking if the observed shifts in the task composition of labor demand away from routine labor are accountable for the recessionary effect of technology shocks on hours worked. We then assess whether technological shocks are able to generate recognizable business cycles.

We build quarterly time series on hours worked, task premiums and relative hours from the IPUMS Current Population Survey to estimate the effect of structural shocks on the data. A preliminary look of the facts suggests that the composition of labor demand is shifting away from routine labor both over the long run and the business cycle. Furthermore, it appears that such phenomenon is tightly linked to the observed negative relationship between labor productivity and total hours worked first documented by Gali (1999).

We then estimate the effect of technological shocks by relying on a VAR model. We identify structural shocks by combining theoretically grounded long-run exclusion and sign restrictions. Those restrictions are derived from a Real Business Cycle model with capital-routine substitutability. This allows us to disentangle structural shocks from one another.

[14]The reversal in the cyclicality of labor productivity is a recent feature that occurred in the mid 1980s. Caballero and Hammour (1994) claim that old firms, having an obsolete technology, can more easily become unprofitable and be scrapped in a recession than recent ones while Berger (2012) suggests that firms lay off unproductive workers during recessions. Both explanations imply countercyclical productivity movements. Among others, Barnichon (2010), Galí and van Rens (2014) and Garin, Pries, and Sims (2018) also document and propose alternative interpretations of the reversal in output and productivity comovements.

Our results show that technology shocks identified as in Gali (1999) are biased towards replacing routine labor. Then, we disentangle neutral shocks from routine-biased technological and task-supply shocks. We find that most of the decline in total hours worked is driven by routine-biased technology shocks through a strong fall in routine hours worked. We then provide a wider picture of business cycle fluctuations. We argue that business cycles seem driven by non-technology shocks when technological shocks are aggregated as in Gali (1999) while they are driven by task-biased technological shocks when they are disentangled.

Even though we do not provide a thorough exploration of aggregate fluctuations' determinants, this paper stresses the importance of considering the nature of technological change. We do not however look at the asymmetries generated by technological change. This is particularly relevant since drops in routine employment appear episodic. Recessions might purge the economy from least profitable firms which probably rely intensively on routine labor. The asymmetric nature of business cycles is key to understand whether recessions generate waves of creative destruction. This issue is left for future research.

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Appendices

A Comparative statics analysis

		Percent deviation from SS0		
Relative variables	SS0	Z_t	$\zeta_{a,t}$	$\zeta_{r,t}$
Y/H	0.6185	0.2611	-0.0652	0.0594
H_a/H_r	0.9338	0.1771	-0.2893	0.2934
H_r/H_m	6.0471	-0.1768	0.0410	-0.2926
W_a/W_r	1.5413	0.3544	0.4165	-0.4082
W_r/W_m	1.4364	-0.3532	0.0819	0.4099
Aggregate variables				
Output	0.6046	0.2426	-0.2152	-0.0990
Consumption	0.5282	0.2219	-0.1938	-0.1222
Investment	0.0764	0.3860	-0.3635	0.0614
Capital	3.0565	1.3899	-0.3635	0.0614
Rental rate	0.0351	-0.9901	-0.0000	-0.0000
Total hours	0.9775	-0.0185	-0.1502	-0.1583
Abstract hours	0.4349	0.0658	-0.3075	-0.0190
Routine hours	0.4657	-0.1111	-0.0183	-0.3115
Manual hours	0.0770	0.0658	-0.0592	-0.0190
Abstract wage	0.6444	0.3537	0.1852	-0.1601
Routine wage	0.4181	-0.0007	-0.2303	0.2492
Manual wage	0.2911	0.3537	-0.3120	-0.1601

Table A.1: Comparative statics analysis

Notes: SS0 provides the initial steady state values for which all shocks are normalized to one. The other columns display percentage deviations of the new steady state values from the initial values following a positive one percent permanent change in corresponding shocks.

B Univariate time series analysis

B.1 Unit root tests

Variable	ADF test H_0 : unit root	KPSS test H_0 : stationarity
Levels		
AR premium	Not rejected	Rejected
Labor productivity	Not rejected	Rejected
Total hours	Not rejected	Rejected
AR relative hours	Not rejected	Rejected
RM relative hours	Not rejected	Rejected
First differences		
AR premium	Rejected	Not rejected
Labor productivity	Rejected	Not rejected
Total hours	Rejected	Not rejected
AR relative hours	Rejected	Not rejected
RM relative hours	Rejected	Not rejected

Table B.1: Unit root tests
Notes: Results of unit root tests are based on a degree of significance of five percent. Unit root tests for variables in level are done with and without trend. Unit root tests for first differences are done with and without constant. Results of unit root tests are insensitive to other alternatives.

B.2 Robustness of business cycle moments

		Correlation				
	SD	W_r/W_m	H_a/H_r	H_r/H_m	Y/H	H
W_a/W_r	1.2395	-0.1340	0.1513	-0.1934*	0.2110*	-0.1303
W_r/W_m	2.2739	-	0.0344	0.0844	0.0983	0.0299
H_a/H_r	2.3862	-	-	-0.1392	-0.0027	-0.4098*
H_r/H_m	3.2604	-	-	-	-0.1128	0.0187
Y/H	0.6160	-	-	-	-	-0.2576*
H	0.7961	-	-	-	-	-

Table B.2: Business cycle moments
Notes: SD stands for standard deviation. Data are constructed as described in subsection 3.1. Variables are in first difference of their logarithm. Significance of at least five percent ($*$).

C VAR algorithm

We combine long-run exclusion and sign restrictions in order to identify structural shocks. In our case, this approach is challenging because the structural model is not block-recursive.

When combining both types of restrictions, sign restrictions need to be applied on candidate long-run impulse responses that satisfy long-run exclusion restrictions. In other words, we need to draw a rotation matrix Q conditional on zero restrictions. Otherwise, the probability of drawing a rotation matrix for which candidate long-run impulse responses satisfy the exclusion restrictions is near zero. This would invalidate the impulse responses as well as decompositions of forecast error variance. When the model has a block-recursive form, we can use sub-rotation matrices as in Balleer and van Rens (2013). In our case, the structural model is not block-recursive. We tackle this issue by relying on a solution proposed by Arias, Ramirez, and Waggoner (2014). We summarize the algorithm as followed.

Step 1 We draw N sets (B,Ω) from the posterior distribution of reduced-form parameters.[C.1]

Step 2 For each of the N draws, we compute $\Xi = \left(I_N - \sum_{k=1}^{p} B_k\right)^{-1} L_0$ where $L_0 = chol(\Omega)$. This allows us to obtain long-run impulse responses of orthogonalized shocks which are not yet structural shocks as they might not fulfill the identifying restrictions.

Step 3 For each of the N draws, we draw one orthogonal matrix Q such that the candidate long-run impulse response $\widetilde{LR} = \Xi Q$ satisfies the long-run zero restrictions. We obtain a candidate structural model. In order to do so, we draw Q conditional on exclusion restrictions by using a Gram-Schmidt orthogonalization process. This allows us to build a matrix Q iteratively that is orthogonal and that fulfills the exclusion restrictions.

Step 4 We retain from those N candidate structural models only those for which long-run impulse responses $\widetilde{LR}$ satisfy long-run sign restrictions. Therefore, we obtain the posterior distribution of structural models that satisfy both kinds of long-run restrictions.

[C.1] We set $N = 1000$ in specification I and $N = 50000$ in specification II and III.

D Additional results

D.1 Impulse responses

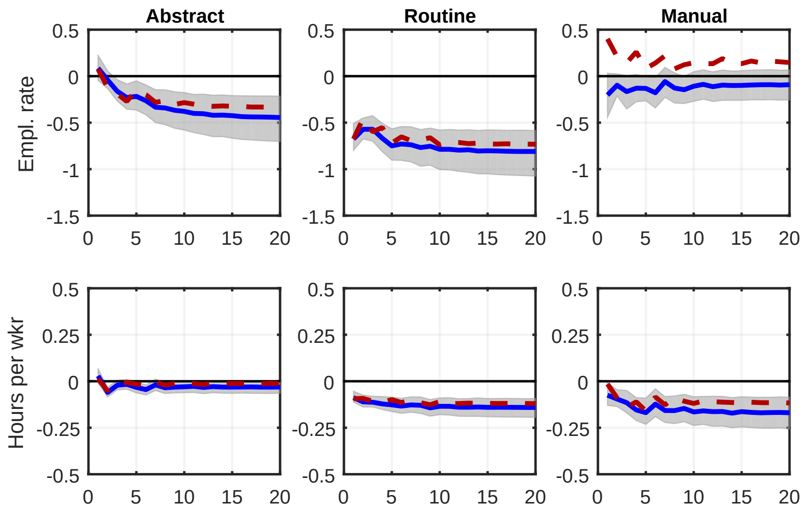

Figure D.1: Impulse response functions to RBTC shocks - Extensive vs intensive margins
Notes: Impulse responses to a one-standard deviation shock are reported. Solid lines represent the median of impulse responses. Grey areas correspond to the 68% of the posterior distribution. Dashed lines capture the median-target responses as defined by Fry and Pagan (2011).

D.2 Forecast error variance decompositions

Horizon	1	4	8	16	32
AR Premium	1.08	15.46	19.69	23.15	25.56
	[0.17,2.70]	[10.17,21.40]	[12.51,28.68]	[13.55,35.85]	[13.88,40.14]
Productivity	79.35	89.37	95.16	97.90	99.04
	[61.21,91.33]	[78.56,95.84]	[89.76,98.08]	[95.63,99.17]	[98.09,99.61]
Total hours	24.29	22.87	23.73	24.13	24.01
	[10.98,42.91]	[9.76,42.11]	[8.74,42.49]	[7.76,43.70]	[6.97,44.00]
AR rel. hours	1.04	2.35	2.44	2.48	2.45
	[0.09,4.11]	[0.84,6.89]	[0.90,6.75]	[0.83,6.98]	[0.64,7.66]
RM rel. hours	8.81	16.07	18.92	20.75	21.45
	[4.72,13.88]	[7.96,27.02]	[8.28,33.09]	[8.23,37.32]	[7.97,39.97]

Table D.1: Forecast error variance decomposition with Gali's shock
Notes: We report the median and in brackets 68% Bayesian confidence bands from the posterior distribution.

Horizon	1	4	8	16	32
Abstract hours	10.20	23.44	28.86	30.72	31.53
	[6.25,15.41]	[12.51,36.14]	[13.95,44.81]	[14.32,48.83]	[13.90,50.86]
Routine hours	11.22	15.41	15.99	16.61	17.08
	[3.48,23.26]	[5.62,31.45]	[4.66,33.16]	[3.88,35.35]	[3.52,36.22]
Manual hours	0.79	1.77	2.01	2.10	2.19
	[0.11,2.23]	[0.69,4.10]	[0.93,5.04]	[0.81,6.55]	[0.60,8.15]

Table D.2: Forecast error variance decomposition with Gali's shock - Hours by task
Notes: We report the median and in brackets 68% Bayesian confidence bands from the posterior distribution.

Horizon	1	4	8	16	32
AR Premium					
Supply	4.61	9.97	9.78	9.55	8.92
	[0.39,27.72]	[3.90,28.52]	[3.27,28.85]	[2.61,31.09]	[1.96,32.04]
RBTC	13.77	27.40	37.14	45.55	49.91
	[4.28,36.16]	[15.89,47.22]	[23.16,57.22]	[28.10,65.20]	[31.04,70.56]
Neutral	5.73	4.48	2.88	1.58	0.81
	[0.63,20.69]	[1.40,12.41]	[1.00,7.66]	[0.55,4.12]	[0.29,2.15]
Productivity					
Supply	41.18	43.24	41.39	40.00	39.23
	[5.86,78.40]	[6.03,79.27]	[6.29,78.29]	[6.16,76.98]	[5.81,76.48]
RBTC	7.66	12.54	19.16	22.77	24.68
	[0.69,26.46]	[1.67,33.37]	[3.19,41.25]	[4.41,47.53]	[5.23,50.40]
Neutral	32.31	32.07	29.09	27.61	26.73
	[3.84,65.15]	[4.09,64.49]	[3.87,60.55]	[3.70,57.58]	[3.49,56.39]
Total hours					
Supply	6.63	7.43	7.36	7.33	7.26
	[0.57,25.79]	[0.83,27.21]	[0.79,27.45]	[0.86,27.97]	[0.84,27.75]
RBTC	46.40	39.05	39.76	39.87	39.71
	[22.39,69.10]	[17.34,62.95]	[17.05,63.02]	[16.83,62.83]	[16.59,63.01]
Neutral	6.15	6.07	6.03	6.02	5.99
	[0.50,25.15]	[0.71,26.29]	[0.63,27.10]	[0.60,26.92]	[0.52,26.79]
AR rel. hours					
Supply	8.95	8.64	9.55	10.31	11.48
	[0.79,37.18]	[1.43,34.79]	[1.46,37.32]	[1.45,40.56]	[1.34,42.30]
RBTC	48.95	50.90	50.14	47.86	46.41
	[24.73,77.38]	[25.15,76.72]	[23.94,76.11]	[22.14,75.31]	[20.52,74.76]
Neutral	18.66	18.71	19.92	20.75	21.55
	[1.57,54.49]	[2.73,52.32]	[2.67,54.06]	[2.67,56.29]	[2.56,58.16]
RM rel. hours					
Supply	6.42	8.46	8.50	8.04	8.03
	[0.64,27.43]	[2.04,27.16]	[1.78,27.83]	[1.32,28.30]	[1.09,28.47]
RBTC	10.15	18.87	23.82	26.84	28.30
	[2.06,23.36]	[6.97,36.29]	[9.04,43.78]	[10.27,49.00]	[10.85,51.99]
Neutral	5.57	7.17	6.81	6.49	6.27
	[0.37,30.58]	[1.72,30.75]	[1.58,30.02]	[1.20,29.65]	[0.92,29.78]

Table D.3: Forecast error variance decomposition with abstract supply, RBTC and neutral technology shocks

Notes: We report the median and in brackets 68% Bayesian confidence bands from the posterior distribution.

Horizon	1	4	8	16	32
Abstract hours					
Supply	25.27	20.85	17.75	16.46	16.06
	[4.59,55.49]	[4.54,48.34]	[3.37,45.79]	[2.54,45.31]	[2.09,45.00]
RBTC	5.50	10.19	12.31	14.63	16.08
	[0.55,23.26]	[5.29,21.30]	[4.02,30.75]	[3.09,37.32]	[2.74,39.63]
Neutral	21.31	14.57	11.63	9.30	8.63
	[2.32,53.55]	[4.16,35.25]	[3.13,33.35]	[2.01,32.34]	[1.45,31.75]
Routine hours					
Supply	4.61	5.66	5.26	5.55	5.58
	[0.45,21.02]	[1.33,21.09]	[1.04,21.08]	[0.92,21.04]	[0.74,20.94]
RBTC	65.71	57.39	55.64	54.35	53.59
	[37.93,84.34]	[31.61,75.19]	[29.20,74.06]	[27.50,73.42]	[26.42,73.14]
Neutral	11.60	9.55	8.77	8.59	8.08
	[1.18,39.54]	[1.87,30.98]	[1.38,30.31]	[1.09,29.90]	[0.92,29.79]
Manual hours					
Supply	9.08	10.32	10.08	10.02	9.96
	[1.13,31.04]	[2.64,29.83]	[2.57,30.07]	[2.28,30.05]	[1.78,30.90]
RBTC	5.23	7.22	8.13	8.70	8.95
	[0.58,15.55]	[1.86,18.62]	[1.96,21.61]	[1.79,24.48]	[1.49,25.72]
Neutral	11.06	12.66	12.99	13.03	13.06
	[0.91,37.82]	[2.93,36.45]	[2.81,37.12]	[2.31,39.12]	[1.87,39.85]

Table D.4: Forecast error variance decomposition with abstract supply, RBTC and neutral technology shocks - Hours by task

Notes: We report the median and in brackets 68% Bayesian confidence bands from the posterior distribution.

D.3 Historical decompositions

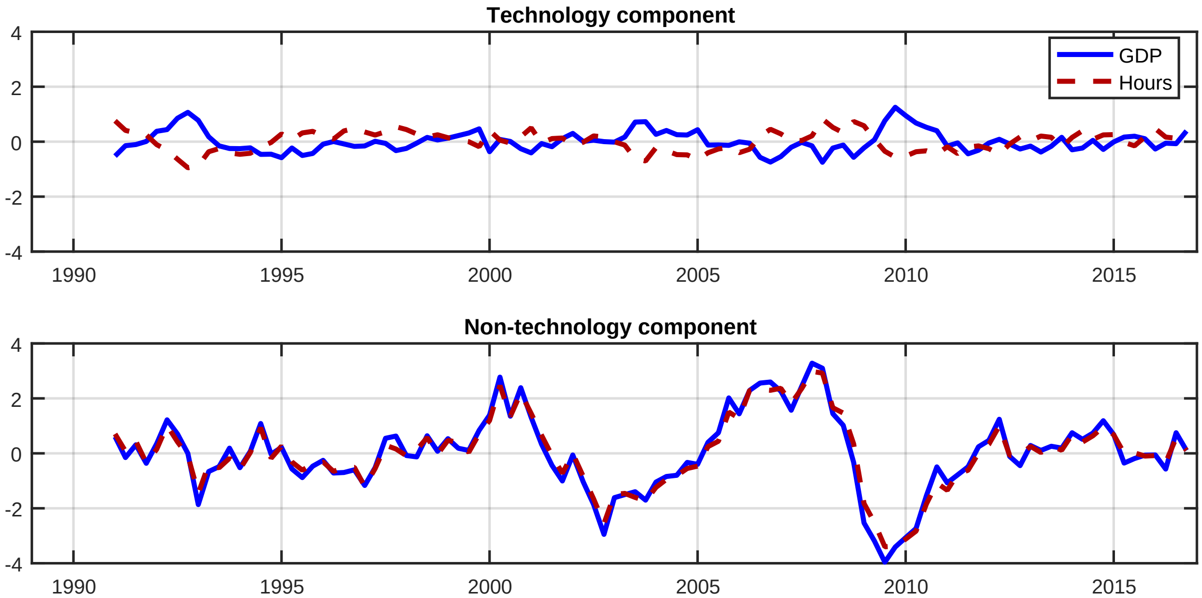

Figure D.2: Specification I - Historical decomposition of GDP and total hours
Notes: We retrieve the cumulative contribution of each shock to (log) output and (log) hours worked time series from the estimated structural VAR identified using specification I restrictions. We use the HP-filter ($\lambda = 1600$) on the resulting time series to isolate business cycle fluctuations.

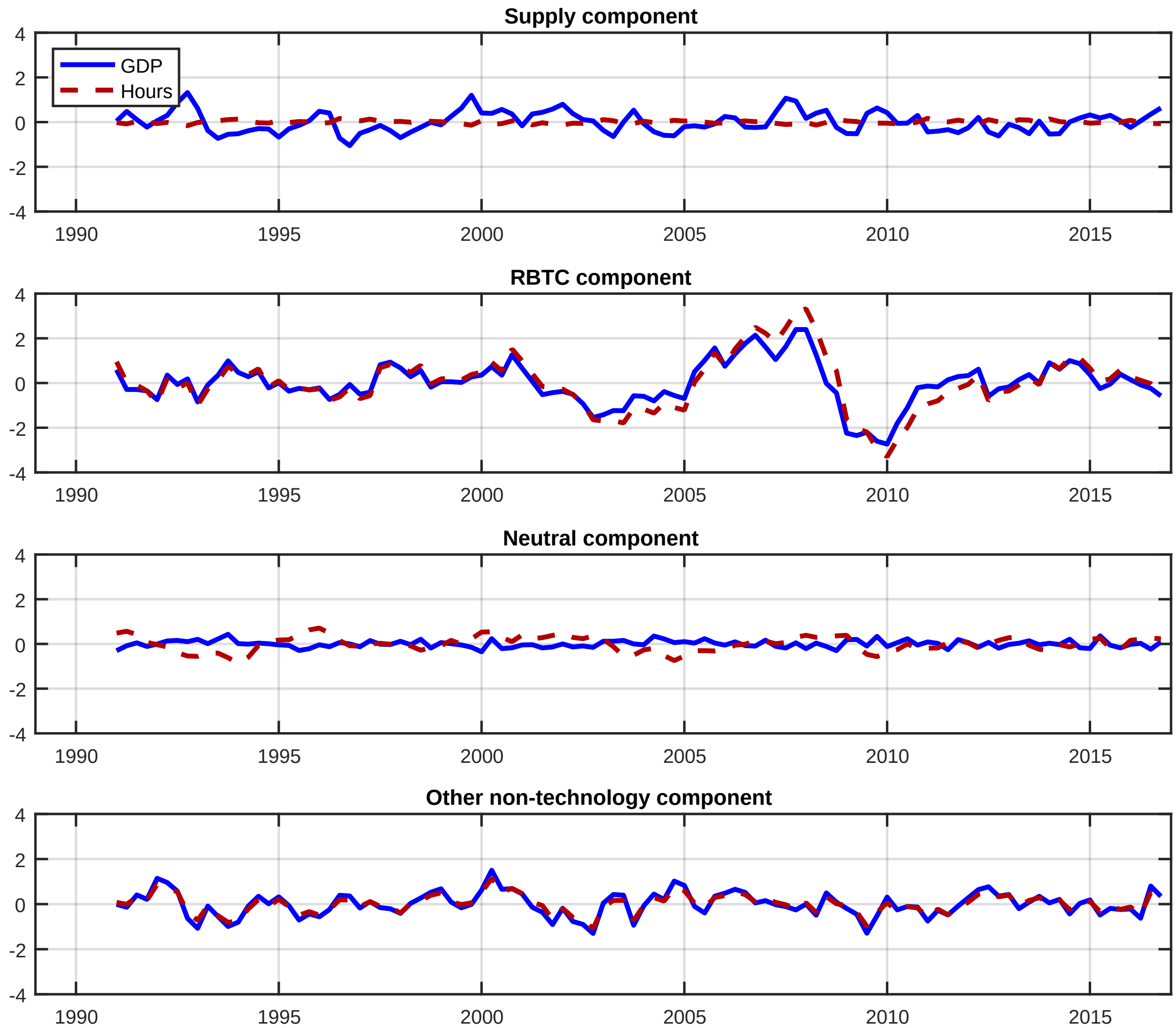

Figure D.3: Specification I - Historical decomposition of GDP and total hours
Notes: We retrieve the cumulative contribution of each shock to (log) output and (log) hours worked time series from the estimated structural VAR identified using specification II restrictions. We use the HP-filter ($\lambda = 1600$) on the resulting time series to isolate business cycle fluctuations.

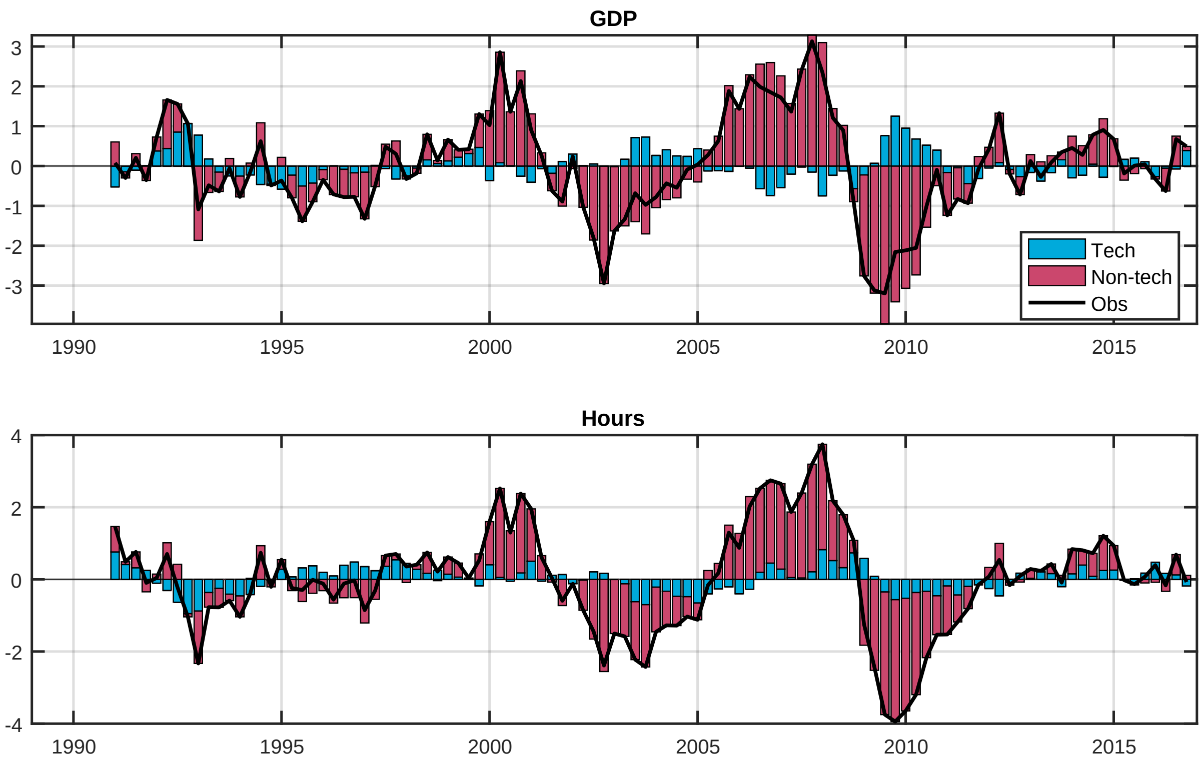

Figure D.4: Specification I - Historical decomposition of GDP and total hours
Notes: We retrieve the cumulative contribution of each shock to (log) output and (log) hours worked time series from the estimated structural VAR identified using specification I restrictions. We use the HP-filter ($\lambda = 1600$) on the resulting time series to isolate business cycle fluctuations.

E Empirical robustness

In order to establish whether our results are robust, we run an array on robustness check. All alternative specifications are based on specification II, namely the one that separately identifies RBTC from task-supply shocks and neutral technology shocks. Figures E.1 and E.2 report results obtained from our alternative specifications. For the sake of clarity, we report only median impulse responses. Complete results, with all confidence intervals, remain available upon request.

Alternative measures of labor productivity. In our baseline specification, we use the labor productivity measure from Ohanian and Raffo (2012). To test the sensitivity of our results to this initial choice, we run two alternative models. In the first one, the labor productivity variable is replaced by the utilization-adjusted Total Factor Productivity (TFP) computed by Fernald (2012). In the spirit, the computation is close to the one conducted by Basu, Fernald, and Kimball (2006) but the resulting time series are derived on a quarterly rather than an annual basis. In the second one, we use a labor productivity variable based on our measure of total hours derived from the CPS. Corresponding median impulse responses are displayed in blue squares in the first case and in sky-blue crosses in the second case.

Alternative Bayesian specifications. Another important robustness check is to establish if results are affected when we change modeling choices related to the Bayesian environment of the VAR model. In our baseline specification, we rely on a Minnesota prior incorporating a fixed residual variance and a lag decay, so that eight lags could be included in the model. Our baseline model is different from specifications using a flat prior (OLS equivalent) or a Normal Inverted-Wishart prior as developed by Kadiyala and Karlsson (1997). Consequently, we consider four robustness checks. First, we keep the baseline structure but the VAR lag length is reduced to two. Second, we conserve the Minnesota prior and the generous lag length of the baseline specification but we use a linear decay rather than a harmonic one. Third, we use an OLS equivalent flat prior with only two lags. Fourth, we relax the fixed residual variance assumption by using the prior developed by Kadiyala and Karlsson (1997). As in our baseline model, this prior uses the same average values for the VAR coefficients but it generalizes the Minnesota prior by providing an estimation of the residual variance. Results obtained with those alternative specifications are respectively depicted in Figures E.1 and E.2 using orange triangles, green circles, pink diamonds and red inverted triangles.

Shorter sample period. It remains possible that our results are an artefact due to our sample period and the inclusion of the post Great Recession period. To deal with this issue, we estimate the same VAR as in the baseline but with a shorter sample ending in 2006Q4. IRFs obtained from such a model are displayed in brown crosses.

Comments. As shown in Figures E.1 and E.2, results are quite insensitive to our set of robustness checks both from a qualitative and a quantitative point of view. Each time, estimated IRFs closely follow those obtained in the baseline specification (depicted in black). We observe the same weak responses of relative hours and hours by task after task-supply and neutral technology shocks. By contrast, RBTC unambiguously declines total hours. It also increases abstract to routine hours while it decreases routine to manual hours. Those patterns are then translated into a fall in hours by task. As found in our baseline specification, the fall of routine hours is by far the largest after RBTC.

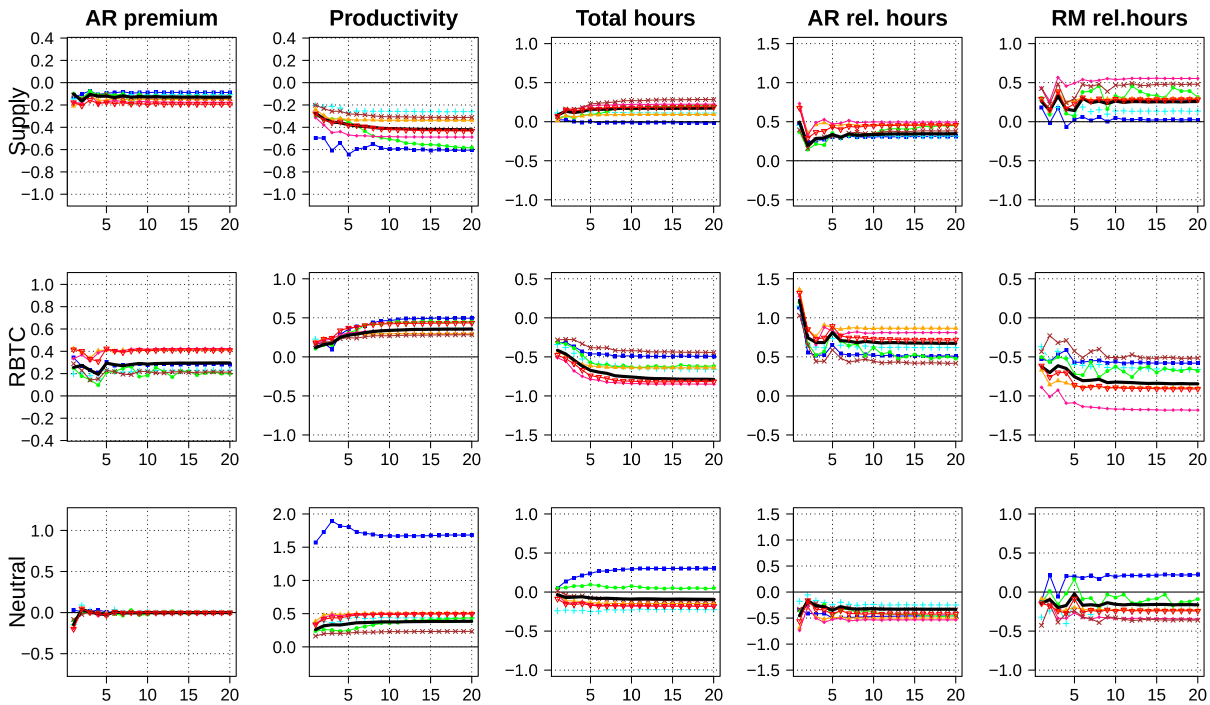

Figure E.1: Impulse response functions to task-supply, RBTC, and neutral technology shocks - Robustness

Notes: Impulse responses to a one-standard deviation shock are reported. Blue square lines correspond to the model estimated with the TFP variable of Fernald (2012) rather than with labor productivity. Sky-blue cross lines correspond to the model estimated with our measure of labor productivity based on CPS data. Green circle lines correspond to the model estimated with eight lags and a linear decay. Pink diamond lines correspond to the model estimated with two lags and a flat prior. Red inverted triangles lines correspond to the model estimated with the prior of Kadiyala and Karlsson (1997). Orange triangle lines correspond to the model estimated with two lags. Brown cross lines correspond to the model estimated for the sample 1989Q1-2006Q4 and black solid lines correspond to the baseline specification of subsection 5.2.

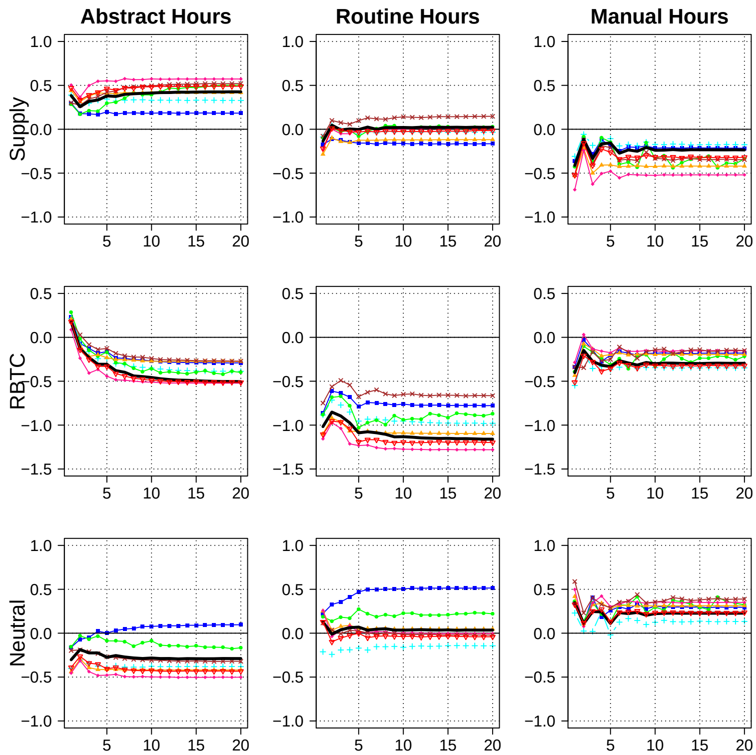

Figure E.2: Median impulse response functions of hours by task to task-supply, RBTC, and neutral technology shocks - Robustness

Notes: Impulse responses to a one-standard deviation shock are reported. Blue square lines correspond to the model estimated with the TFP variable of Fernald (2012) rather than with labor productivity. Sky-blue cross lines correspond to the model estimated with our measure of labor productivity based on CPS data. Green circle lines correspond to the model estimated with eight lags and a linear decay. Pink diamond lines correspond to the model estimated with two lags and a flat prior. Red inverted triangles lines correspond to the model estimated with the prior of Kadiyala and Karlsson (1997). Orange triangle lines correspond to the model estimated with two lags. Brown cross lines correspond to the model estimated for the sample 1989Q1-2006Q4 and black solid lines correspond to the baseline specification of subsection 5.2.