Routine-Biased Technological Change and Hours Worked over the Business Cycle

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Abstract

Technological change has deeply shaped the U.S. labor market over the past four decades. It has been biased towards replacing routine labor through automation. We document business cycle features exhibited by routine-biased technological change. We ask if shifts in the task composition of labor demand away from routine labor account for the recessionary effect of technology shocks on hours worked initially documented by Gali (1999). We show that such shifts in labor demand are able to generate a fall in hours worked within a Real Business Cycle model with capital-routine substitutability. We then bridge the gap between theory and data by building quarterly time series on hours worked and task premiums from the Current Population Survey. We assess the effects of routine-biased technological change in the data by estimating a VAR model. Structural shocks are then identified by combining long-run exclusion and sign restrictions grounded in economic theory. Our results highlight that most of the decline in total hours worked is driven by routine-biased technology shocks through a decline in routine hours. This shock accounts for a significant amount of hours worked fluctuations pointing out its relevance over the business cycle.

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

JEL classifications: E24, E32, J23, J24, J31.

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1 Introduction

A core purpose of macroeconomics is to grasp an understanding of the economic 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 imput. 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. At first sight, this result seems difficult to reconcile with RBC theory and is interpreted as evidence in favor of NK theory.

In this paper, we reassess Gali (1999)'s finding by investigating whether shifts in the composition of labor demand induced by RBTC can account for the recessionary effect of technology shocks. 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. Those shocks 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, Rubio-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 conclude that most of the fall in hours worked is due to a shift in the task composition of labor demand due to RBTC. Nevertheless, we find that Gali (1999)'s conclusion is robust to the extent that abstract and manual hours worked slightly decline after RBTC. This implies that the effect of RBTC on hours worked reflects a mixture of compositional shifts in labor demand and nominal rigidities. However, the compositional shift in labor demand appears predominant since hours worked do not decline strongly after a neutral technology shock.

A meaningful implication of our results is that task heterogeneity of labor 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). In their paper, 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 also worth investigating labor heterogeneity from a task perspective. Second, we differentiate ourselves with respect to our identification scheme. Using the empirical strategy of Arias, Rubio-Ramirez, and Waggoner (2014), we are able to disentangle, in the same model, neutral from task-biased structural technology shocks. In their complete specification with long-run sign restrictions, Balleer and van Rens (2013) are unable to 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 our 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 the overall economic cycle. For example, Cortes, Jaimovich, Nekarda, and Siu (2014) claim that displacement of routine workers mostly occurs 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

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

of the VAR analysis. Section 6 concludes.

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 the recessionary effects of technology shocks on hours worked can be driven by routine automation 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:

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

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

[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).

and automation capital are respectively

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

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: abstract, routine and manual workers. 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 and are assigned to a particular task at birth. Their preferences are captured by a utility function of the form

$$U_{j,t}\left(\tilde{c}_{j,t}, \tilde{h}_{j,t}\right) = \left(\frac{\tilde{c}_{j,t}^{1-\sigma}}{1-\sigma} - B_{j,t}\frac{\tilde{h}_{j,t}^{1+\psi}}{1+\psi}\right) \tag{6}$$

where $\tilde{c}_{j,t}$ and $\tilde{h}_{j,t}$ denote respectively consumption and hours worked for an individual agent of type j. 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 $B_{j,t}$ 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 $\tilde{c}_{j,t}$, hours worked $\tilde{h}_{j,t}$ and automation capital K_{t+1}

$$\mathbb{W}_t = \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\theta_a U_{a,t}\left(\tilde{c}_{a,t}, \tilde{h}_{a,t}\right) + \theta_r U_{r,t}\left(\tilde{c}_{r,t}, \tilde{h}_{r,t}\right) + \theta_m U_{m,t}\left(\tilde{c}_{m,t}, \tilde{h}_{m,t}\right)\right] \tag{8}$$

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). Aggregate consumption and hours worked are linked to their individual counterparts as $C_{j,t} = \theta_j \tilde{c}_{j,t}$ and $H_{j,t} = \theta_j \tilde{h}_{j,t}$. First-order conditions arising from the benevolent social planner's program are

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

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

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

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

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

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

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

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 AR(1) processes

$$\log(Z_t) = \rho_z \log(Z_{t-1}) + \nu_{z,t} \tag{17}$$
$$\log(B_{a,t}) = \rho_a \log(B_{a,t-1}) + \nu_{a,t} \tag{18}$$
$$\log(B_{r,t}) = \rho_r \log(B_{r,t-1}) + \nu_{r,t} \tag{19}$$
$$\log(B_{m,t}) = \rho_m \log(B_{m,t-1}) + \nu_{m,t} \tag{20}$$

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

2.1.3 Equilibrium and solution

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 $S = [K, Z, B_a, B_r, B_m]$ 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 $(Y, I, C_a, C_r, C_m, \Lambda_t, K, R, H_a, H_r, H_m, W_a, W_r, W_m, Z, B_a, B_r, B_m)_t$.

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 two sets of results displayed in Appendix A. On the one hand, 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. On the other hand, we exhibit the entire dynamics of the model's variables by displaying their impulse responses (Figures A.1 to A.3). We do so by log-linearizing the system around initial steady state. We solve the resulting system of linear expectational difference equations by using the generalized Schur decomposition method developed by Klein (2000).

2.2 Parametrization

We now parametrize the model. We set the discount factor β to .99 and the depreciation rate δ to .025. We set CES distribution parameters α_j to 1/3 and η to 1/2. 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 respectively .5 and 1.5. The AR(1) processes are parametrized such that persistence parameters ρ_j are set close to one (.9999) since we are looking at the effect of permanent shocks for $j = z, a, r, m$.

2.3 Main results

We now present the main results from the comparative statics analysis and impulse responses displayed in Appendix A. We mainly 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.

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

Table 1: Theoretical restrictions

Notes: We display signs of long-run responses to a positive 1% 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. We display those theoretically-grounded restrictions in Table 1. 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 $B_{a,t}$ or an increase in $B_{r,t}$. A negative shock in $B_{a,t}$ 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 $B_{r,t}$ shifts preferences of routine workers towards leisure. The abstract premium decreases while abstract to routine hours increases. 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. Therefore, task premiums and corresponding relative hours worked evolve in opposite directions whether task-supply shocks arise from $B_{a,t}$ or $B_{r,t}$. However, the change in labor productivity is ambiguous.

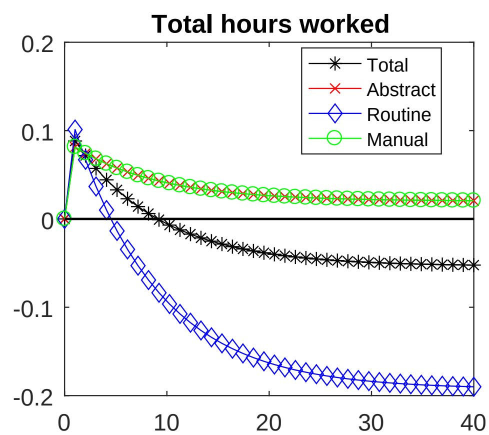

Figure 1: Impulse response of total hours worked to RBTC (Z_t)
Notes: Responses to a 1% shock. Variables are in percentage deviation from their initial steady state values.

In Figure 1, we display impulse responses of hours worked to RBTC from the model. RBTC decreases total hours worked in the long run through a strong fall in routine labor. However, hours worked initially increase in all tasks. The intuition is as follows. RBTC stimulates the diffusion of automation capital by increasing the efficiency at which investment is transformed into automation devices. At first, this incites households to save more, thus reducing their consumption and increasing their labor supply in all tasks. Quite rapidly, firms start to substitute automation capital for routine labor as it becomes available leading to a 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. Thus, a RBC model is able to capture the recessionary effects of technology shocks on hours worked 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. We seasonally adjust the resulting time series using the X-13 algorithm.

Sample. We build quarterly series of task premiums, relative employment, relative supply, hours, real wages and population from the IPUMS CPS[5] micro data from 1989Q1 to 2018Q1. 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 this series prior to the 1990 survey. 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

[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.

with a fixed factor method à la 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 .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[7] (CPI-U-RS) on all items in order to deflate hourly wages. For quarters where the CPI-U-RS is not available, we use the non-seasonally CPI-U[8] which is close to the CPI-U-RS after 2001 according to the BLS. 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[9] namely abstract, routine and manual, and control for change in gender, ethnicity, marital status, education and potential experience. 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 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

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

[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.

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 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 2 plots the abstract and routine wage premiums corrected for composition bias as well as logs of relative hours worked in efficiency units. The abstract premium increases significantly contrarily to the routine premium which decreased between 1989Q1 and 2016Q4. Indeed, the abstract premium is approximately equal to 0.47 log points at the end of the

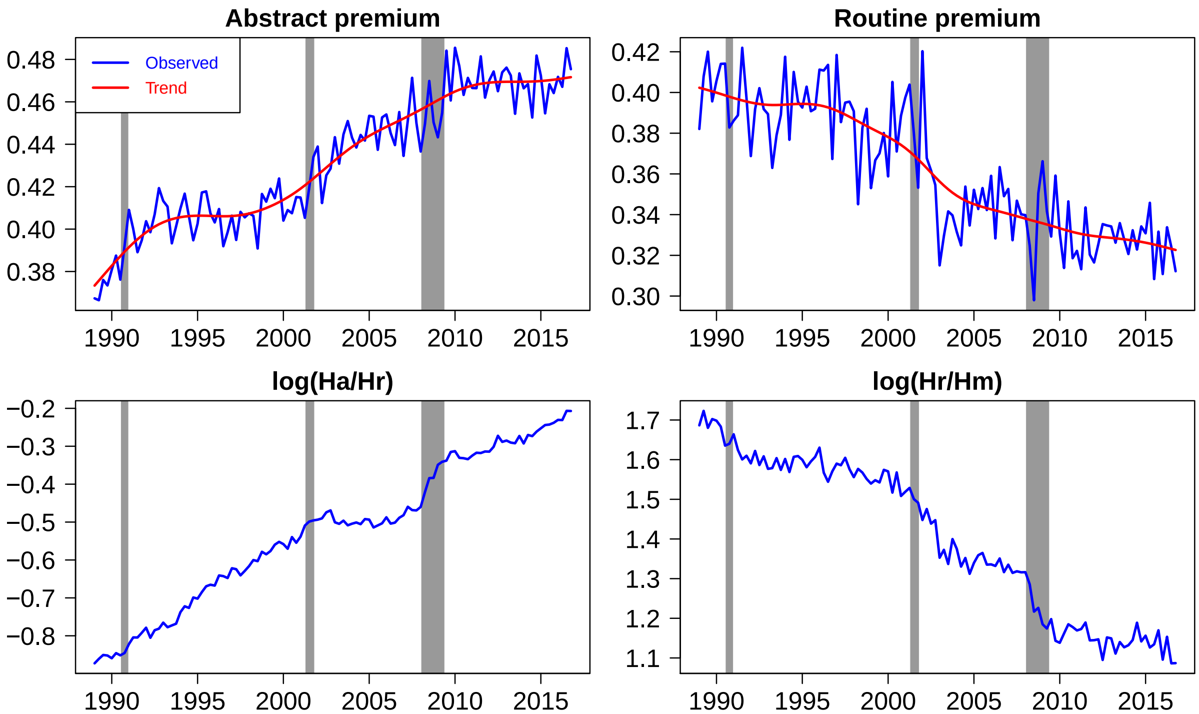

Figure 2: Job polarization, abstract premium and relative hours over the 1989-2017 period. *Notes*: Data are constructed as described in subsection 3.1. All time series are seasonally adjusted using x13. Measures of task premiums are controlled for changes in experience, gender and educational attainment while relative hours are expressed in efficiency units.

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

Figure 3 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

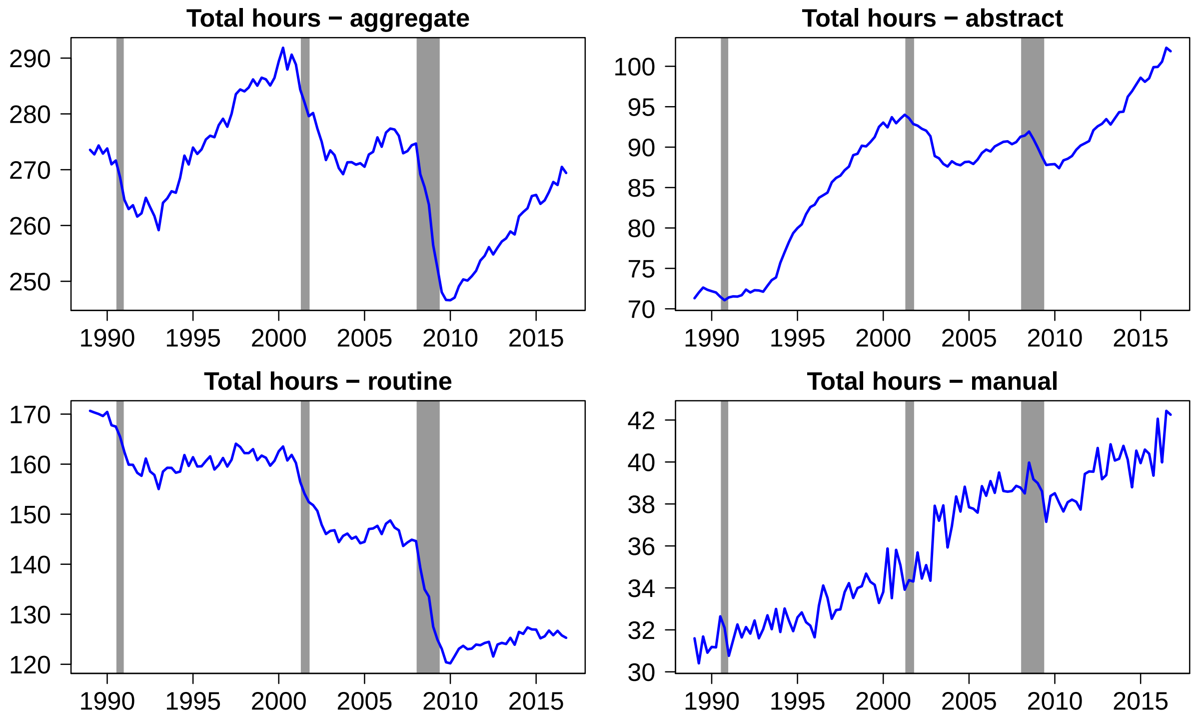

Figure 3: Total usual hours per capita by task over the 1989-2017 period.
Notes: Data are constructed as described in subsection 3.1. All time series is seasonally adjusted using x13.

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 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

		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: Data are constructed as described in subsection 3.1. Variables are in logs and HP-filtered with $\lambda = 1600$. Significance of at least *5%. Table B.2 displays the same business cycle moments for variables in first difference of their logarithm.

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.

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:

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

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 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 8 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 ε_t which are serially and contemporaneously uncorrelated by imposing meaningful economic restrictions. The structural VAR model can be written as follows:

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

with ω_t the matrix of structural shocks with covariance matrix $E\left(\omega_t \omega_t'\right) = I_N$ and A_k the matrices of structural parameters. 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

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

[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.

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

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

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

In this paper, we employ three specifications summarized in Table 3. Hence, we grasp the implication of each identification restriction progressively. 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 and third specifications combine 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, Rubio-Ramirez, and Waggoner (2014). We provide details on the algorithm in Appendix C.

The algorithm employed in specifications II and III 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

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

Specification I					
Order/Shock	Shock 1	Shock 2	Shock 3	Shock 4	Shock 5
	Gali	-	-	-	-
$\log(Y/L)$	$*$	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
	RBTC	Neutral	-	-	-
$\log(w_{a,t}/w_{r,t})$	>0	0	0	0	0
$\log(Y/L)$	>0	>0	0	0	0
$\log(H)$	$*$	$*$	$*$	$*$	$*$
$\log(H_{a,t}/H_{r,t})$	$*$	$*$	$*$	$*$	$*$
$\log(H_{r,t}/H_{m,t})$	$*$	$*$	$*$	$*$	$*$
Specification III					
Order/Shock	Shock 1	Shock 2	Shock 3	Shock 4	Shock 5
	Supply	RBTC	Neutral	-	-
$\log(H_{a,t}/H_{r,t})$	>0	>0	0	0	0
$\log(w_{a,t}/w_{r,t})$	<0	>0	0	0	0
$\log(Y/L)$	$*$	>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.

(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, Rubio-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 and a routine-biased technology shock that captures shifts in the task composition of labor demand. We order growth rates of abstract premium followed by labor productivity first and other variables subsequently. Both shocks raise labor productivity in the long run. In addition, we add restrictions on the long-run response of the abstract premium to discriminate between the two shocks. In particular, it is assumed that RBTC is the only shock raising permanently the abstract premium. Hence, we impose a zero long-run response of the abstract premium to shocks originating from labor productivity. As these shocks do not shift the task composition of labor demand, we label it neutral technology shock.

In specification III, we recognize the possibility that another shock could induce long-run variations of the abstract premium, namely task-supply shocks. This could potentially modify results based on the second specification. 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. Task-supply shocks affect relative hours and the premium in opposite directions while RBTC affect those variables in the same direction in the long run. Neutral shocks have no permanent effect on those variables. By definition, the relative amount of hours worked should not change because the demand for each type of task should vary in the same direction and in equal proportion. As previously, both RBTC and neutral technology 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 individual inputs. In contrast, a negative routine supply shock could increase it due to the higher efficiency of abstract workers.

5 Results

In this section, we present results obtained from the structural VAR analysis. We display results for all three 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 turn to the responses of RBTC and neutral shocks as described by specification II. Finally, we look at the effects of RBTC, neutral and task-supply shocks as presented in specification III.

5.1 Specification I - Is Gali's technology shocks neutral?

We present results 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.

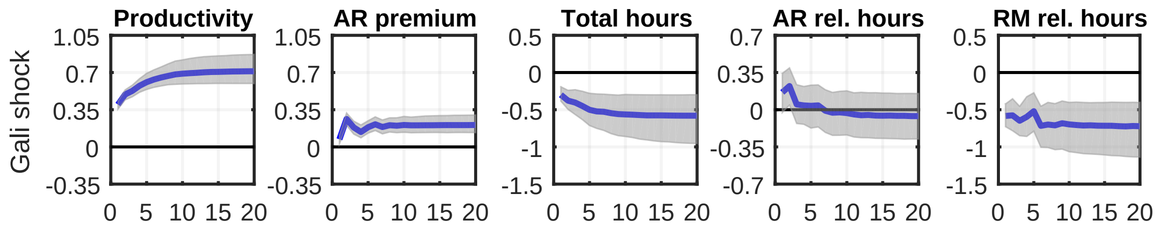

Figure 4: Impulse response functions to Gali's technology shocks.
Notes: Impulse responses to a one-standard deviation shock are reported. Solid lines represent the median of impulse responses. Dashed lines correspond to the 68% of the posterior distribution.

Figure 4 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 of variables mirroring the 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 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.

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 responses of hours worked by task. Figure 5 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. Abstract hours decrease similarly to routine hours 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.

We now assess the importance of technology shocks in explaining cyclical fluctuations in the variables of interests. In that respect, Table 4 displays a Decomposition of the Forecast Error Variance (FEVD) of the VAR at business cycle frequencies after 1 to 32 quarters. Technology shocks explain a significant share of the business cycle variance of labor productivity from 93% to 99% after respectively 8 and 32 quarters. On the contrary, they explain a low share of the abstract premium volatility at first, that progressively increases with time

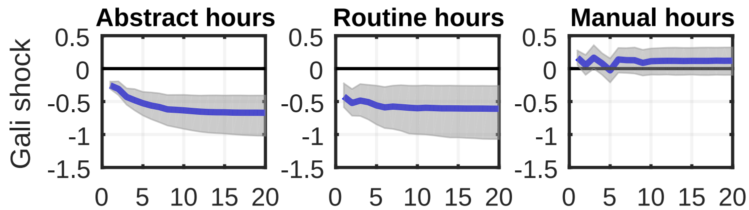

Figure 5: Impulse response functions to Gali's technology shocks - Hours by task.
Notes: Impulse responses to a one-standard deviation shock are reported. Solid lines represent the median of impulse responses. Dashed lines correspond to the 68% of the posterior distribution.

from 15% to 24% after 8 and 32 quarters. Furthermore, they explain almost none of the abstract to routine hours worked volatility with a share of around 2% at any horizon. They explain a larger share of fluctuations in routine to manual hours from 19% to 21% after 8 and 32 quarters. Concerning total hours worked, they account for 23% of their volatility over all horizons. In Table 5, we provide the FEVD for hours worked by task. We find that technology shocks explain from 28% to 31% of abstract hours fluctuations and approximately 16% for routine hours after 8 and 32 quarters. On the contrary, manual hours fluctuations explained by technology shocks reach at most 3% after 32 quarters.

It appears that fluctuations in aggregate variables seem relatively well explained by technology shocks identified as in Gali contrarily to task-related variables. As shown afterwards, this is partly because the technology shock entangles a variety of neutral and task-biased disturbances that have different effects on those variables. This partly hides the real contribution of each type of disturbances to the business cycle volatility of those variables.

5.2 Specification II - RBTC and neutral shocks

Previous results strongly indicate that technology shocks, identified as in the previous subsection, are actually biased towards replacing routine occupations. Therefore, we ask if the recessionary effect of technology shocks on hours worked is the result of a reallocation process of labor away from routine jobs? We answer that question by disentangling neutral technology shocks from RBTC. To do so, we propose a new specification based on long-run exclusion and sign restrictions. As described in subsection 4.2, we order the growth rates of abstract premium followed by labor productivity and then other variables. We restrict both shocks to affect positively labor productivity in the long run while RBTC is the only shock raising the abstract premium in the long run.

The first row of Figure 6 draws estimated responses to RBTC. Consistently with our identifying assumption, RBTC induces long-run increases in the abstract premium and labor productivity. The rise in the premium is entirely realized at impact while the one of labor

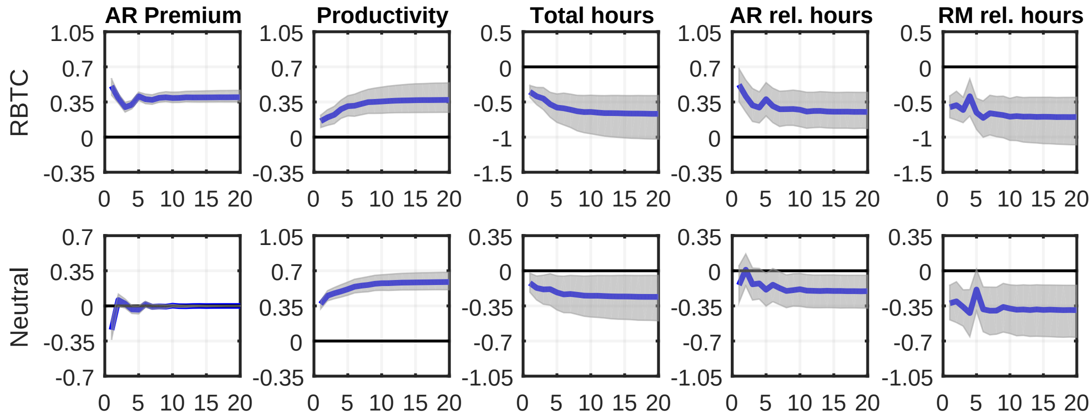

Figure 6: Impulse response functions to RBTC and neutral technology shocks
Notes: Impulse responses to a one-standard deviation shock are reported. Solid lines represent the median of impulse responses. Dashed lines correspond to the 68% of the posterior distribution.

productivity is more gradual. Abstract to routine hours increase after RBTC suggesting that relatively less routine hours are used in the production process. By contrast, routine to manual hours decline. Such variations in relative hours are translated into a fall in hours worked spent in each type of task as shown in Figure 7. As in specification I, both abstract and routine hours decrease but now the former decline is weaker than the latter. Our finding is a first piece of evidence indicating that shocks at the root of job polarization do not necessarily increase the amount of hours spent in non-routine jobs over the business cycle.

The dynamic responses after neutral technology shocks are reported in the bottom panel of Figure 6. In line with our identifying assumption, the dynamic response of the abstract premium is close to zero in the long run but also in the short and medium runs. Gali (1999)'s evidence seems robust at first sight. Total hours still drop when the economy is hit by neutral technology shocks. However, the fall in total hours is much sharper for RBTC. This reinforces our initial intuition: part of the fall in total hours arises from a shift in the task composition of labor demand away from routine labor casting doubts on the nominal rigidities explanation. Both abstract and routine hours tend to fall after neutral shocks. The response of the latter however is not significant.

Table 6 displays a decomposition of the forecast error variance of the VAR based on the second specification. As expected, disentangling RBTC from neutral shocks leads to a sizable increase in the share of the business cycle volatility explained by structural shocks of most variables especially for task-related variables. For instance, structural shocks now explain 86% to 96% of the abstract premium volatility against 20% to 25% in the Gali specification after 8 to 32 quarters. This is also the case for total hours with a share of 35% to 34% against approximately 23%.

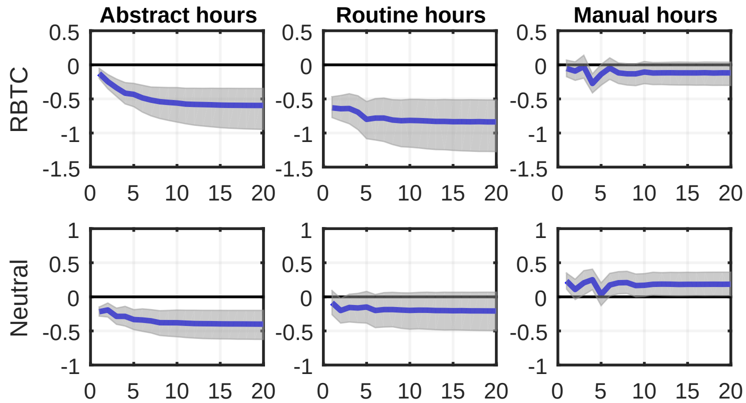

Figure 7: Impulse response functions to RBTC and neutral technology shocks - Hours by task.
Notes: Impulse responses to a one-standard deviation shock are reported. Solid lines represent the median of impulse responses. Dashed lines correspond to the 68% of the posterior distribution.

However, the contribution of each shock varies substantially across variables. Neutral shocks account for a large 72% of the volatility of labor productivity after 4 to 32 quarters. They explain a very small share of the business cycle volatility of total hours worked and task related variables. For example, they explain only 5% of the volatility in total hours worked and the abstract premium after 8 quarters. We obtain similar results for relative hours and hours worked by task. On the contrary, RBTC accounts only for 23% to 27% of the volatility of labor productivity but for a large 81% to 95% of the abstract premium volatility between 8 and 32 quarters. It also explains a larger share of total hours' volatility with around 30% after 4 quarters. As depicted in Table 7, this translates across hours worked by task with the exception of manual hours. For instance, RBTC accounts for 20% of the volatility of abstract hours and 28% for routine hours while only for 2% regarding manual hours after 8 quarters. RBTC also explains around 18% to 32% of routine to manual hours business cycle fluctuations. Surprisingly, the volatility of abstract to routine hours worked explained by RBTC remains quite low with a share of 10% to 8% after 8 to 32 quarters.

In the next section, we show that this is partly because RBTC is misidentified potentially discrediting some of the results obtained with the second specification. RBTC is entangled with task-supply shocks since they both affect task premiums in the long run. This could bias impulse responses and underestimate the contribution of currently identified shocks to the business cycle volatility of variables.

5.3 Specification III - RBTC, neutral and task-supply shocks

Finally, we present results derived from the third specification. In addition to RBTC and neutral technology shocks, we identify task-supply shocks. We order in the VAR growth rates of abstract to routine hours followed by abstract premium, productivity and then other variables. 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.

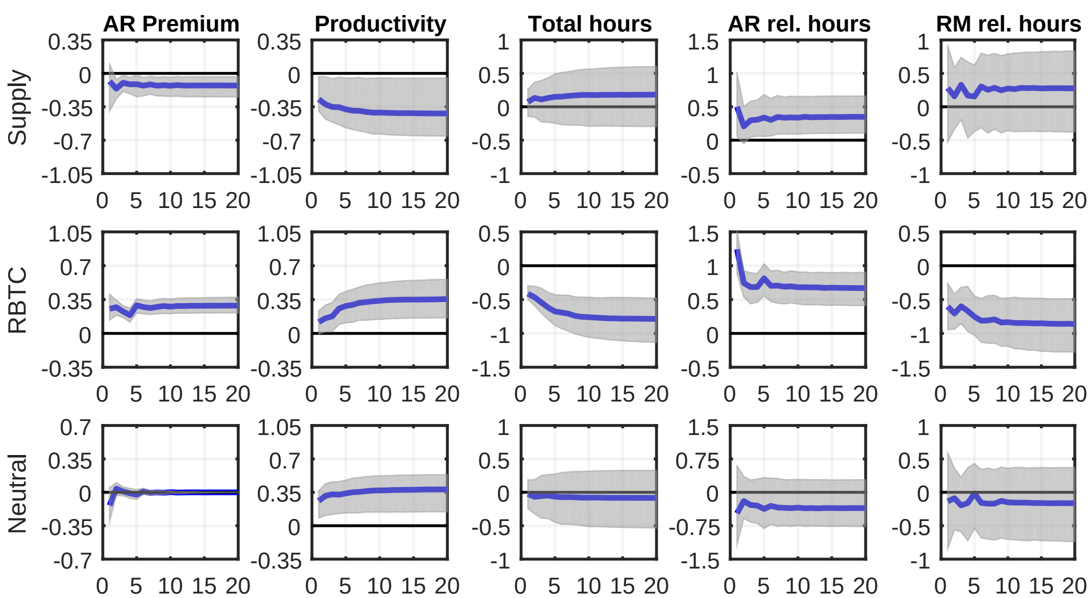

Figure 8: Impulse response functions to task-supply, RBTC, and neutral technology shocks.
Notes: Impulse responses to a one-standard deviation shock are reported. Solid lines represent the median of impulse responses. Dashed lines correspond to the 68% of the posterior distribution.

Figure 8 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 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 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 drop in hours worked.

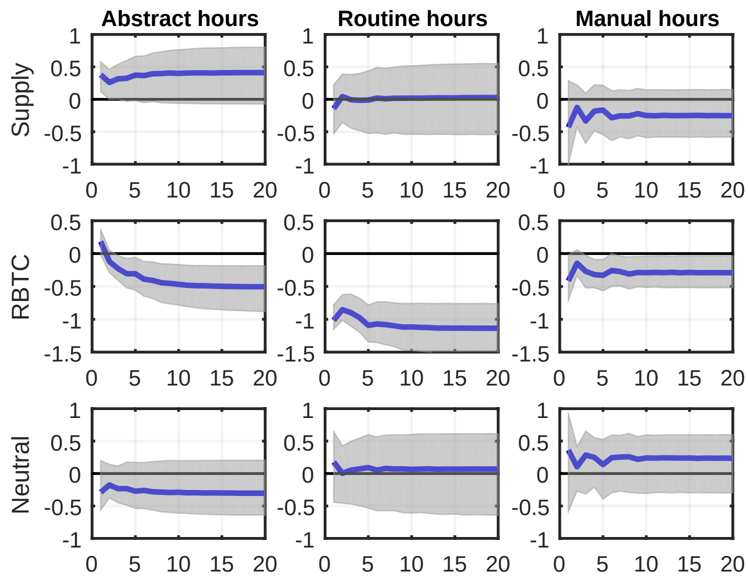

Figure 9: Impulse response functions to task-supply, RBTC, and neutral technology shocks - Hours by task.

Notes: Impulse responses to a one-standard deviation shock are reported. Solid lines represent the median of impulse responses. Dashed lines correspond to the 68% of the posterior distribution.

We now scrutinize the dynamics of total hours by task displayed in Figure 9. Except for an increase in abstract hours after task-supply shocks, impulse responses of hours worked by 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 declines in abstract and manual hours are weaker but significant. 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. In appendix D, we present a set of robustness checks and confirm that this finding holds. Hence, most of the drop in hours worked mainly stems from a shift in the task composition of labor demand due to RBTC. However, Gali (1999)'s interpretation holds to the extent that abstract and manual hours slightly decline after RBTC. We conclude that the effect of RBTC on hours worked reflects a mixture of compositional shifts in labor demand and nominal rigidities. However, the compositional shift in labor demand appear predominant since the responses of hours worked by task are of smaller magnitude and even inconclusive about the sign.

Table 8 displays a decomposition of the forecast error variance of the VAR based on the third specification. 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 25% in specification I after 8 to 32 quarters. This is also the case for total hours worked with a share of about 50% to 60% against approximately 23%.

However, the contribution of each shock varies substantially across variables. RBTC accounts for 19% of the volatility of productivity after 8 quarters against 31% for neutral shocks and 38% for task-supply shocks. Furthermore, it captures most of the volatility of task-related variables. For example, it explains 37% of the volatility of the abstract premium against 3% for neutral shocks and 11% for task-supply shocks. For total hours worked, RBTC captures around 41% of its volatility against 5% for neutral shocks and 7% for task-supply shocks after 8 quarters. As shown in Table 9, this is primarily stemming from routine hours since RBTC accounts for 57% of their volatility after 8 quarters while only for 13% and 8% 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.

6 Conclusion

During the last four decades, the U.S. have 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 argue that such shifts in labor demand are able to generate a fall in hours worked within a Real Business Cycle model with capital-routine substitutability. We also derive some identification restrictions from the comparative statics analysis and the impulse responses that allow us subsequently to disentangle structural shocks from one another.

Then, 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 in 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 bridge the gap between theory and data by relying on a VAR model. We identify structural shocks by combining theoretically grounded long-run exclusion and sign restrictions. Our results show that technology shocks identified as in Gali (1999) are biased towards replacing routine labor. Then, we disentangle a neutral shock from a routine-biased technology shock and a task-supply shock. 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. Nevertheless, Gali (1999) is robust to the extent that abstract and manual hours slightly decline. This type of shock accounts for almost half of the volatility of total hours worked highlighting its potential relevance over the business cycle.

While we have looked at some business cycle properties of routine-biased technological change, we did not study its role during economic recessions. This is particularly relevant since drops in routine employment seem to occur especially during such events as documented by Jaimovich and Siu (2018). One might argue that recessions purge the economy from the least profitable firms which might be those relying intensively on routine labor. This raises the question of the interaction between economic and financial turmoil, and technological change. One might ask how and to which extent economic and financial turmoil shapes employment outcomes in jobs inclined to technological disruption compared to other jobs. Such questions are left for future research.

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Table forecast error variance decomposition

Horizon	1	4	8	16	32
AR Premium	1.14	15.38	20.04	23.59	25.42
	[0.21,2.84]	[10.07,21.33]	[12.30,28.51]	[13.20,35.24]	[13.53,40.05]
Productivity	80.04	89.45	95.10	97.84	99.02
	[62.28,92.11]	[77.96,95.94]	[89.40,98.18]	[95.46,99.19]	[98.00,99.63]
Total hours	23.52	23.18	23.23	23.15	23.07
	[10.22,41.69]	[9.22,41.00]	[8.39,41.41]	[7.68,42.77]	[7.53,43.14]
AR rel. hours	1.03	2.45	2.42	2.43	2.34
	[0.09,4.01]	[0.89,6.72]	[0.92,6.50]	[0.85,7.22]	[0.65,7.78]
RM rel. hours	8.69	15.92	18.65	20.41	21.30
	[4.77,14.05]	[7.96,27.03]	[8.05,32.74]	[8.35,36.81]	[8.28,39.76]

Table 4: 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	10.48	22.70	27.90	30.17	31.17
	[5.90,15.70]	[11.71,36.45]	[13.75,44.03]	[13.78,47.56]	[13.28,49.32]
Routine hours	10.87	15.69	16.43	16.25	16.37
	[3.19,22.49]	[5.04,31.18]	[4.43,32.40]	[4.09,33.38]	[3.93,34.24]
Manual hours	0.84	1.91	2.20	2.40	2.65
	[0.11,2.50]	[0.75,4.40]	[1.06,5.47]	[0.85,7.20]	[0.61,8.70]

Table 5: 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					
RBTC	53.84	70.22	81.22	89.75	94.69
	[36.10,69.89]	[59.55,78.68]	[74.96,86.29]	[86.79,92.31]	[93.34,95.96]
Neutral	11.76	7.76	4.88	2.68	1.39
	[3.98,23.52]	[3.85,13.95]	[2.51,8.49]	[1.38,4.60]	[0.71,2.37]
Productivity					
RBTC	12.55	17.06	22.65	25.80	27.35
	[4.50,23.64]	[7.47,28.87]	[11.07,35.30]	[13.16,40.06]	[14.16,42.93]
Neutral	67.19	72.21	72.36	72.15	71.76
	[50.98,80.13]	[57.46,84.08]	[57.87,84.46]	[57.01,84.87]	[55.87,84.89]
Total hours					
RBTC	34.72	30.38	30.06	29.89	29.74
	[19.25,51.78]	[15.39,47.85]	[14.37,47.74]	[13.91,48.33]	[13.87,48.60]
Neutral	4.10	4.48	4.59	4.67	4.76
	[0.48,12.64]	[0.71,13.36]	[0.76,13.48]	[0.72,13.68]	[0.66,13.79]
AR rel. hours					
RBTC	9.09	10.72	10.05	8.78	7.86
	[4.14,15.51]	[4.89,19.08]	[4.12,18.98]	[3.02,18.00]	[2.14,17.51]
Neutral	0.90	1.79	2.48	3.16	3.79
	[0.08,3.47]	[0.66,4.70]	[0.80,6.78]	[0.78,9.10]	[0.71,10.95]
RM rel. hours					
RBTC	8.76	13.34	17.54	19.63	20.61
	[4.55,13.90]	[6.73,22.58]	[8.59,29.25]	[9.15,33.93]	[9.28,36.08]
Neutral	2.78	6.08	6.07	6.31	6.41
	[0.57,6.33]	[2.09,12.58]	[1.80,13.23]	[1.54,14.02]	[1.36,14.68]

Table 6: Forecast error variance decomposition with 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					
RBTC	2.52	14.94	19.92	22.82	23.87
	[0.44,6.34]	[6.25,26.60]	[8.65,35.25]	[9.76,40.19]	[10.29,42.05]
Neutral	7.59	10.25	11.20	11.07	10.98
	[3.59,12.77]	[3.79,19.30]	[3.71,21.44]	[3.42,21.96]	[3.11,22.39]
Routine hours					
RBTC	25.57	27.79	28.29	28.40	28.50
	[14.01,38.52]	[14.40,43.61]	[13.92,45.50]	[13.31,46.02]	[13.23,46.71]
Neutral	1.10	2.21	2.21	2.31	2.38
	[0.09,4.98]	[0.47,7.80]	[0.40,8.01]	[0.35,8.48]	[0.30,8.69]
Manual hours					
RBTC	0.25	2.17	2.10	2.07	2.08
	[0.02,1.11]	[0.97,4.39]	[0.97,5.21]	[0.77,6.49]	[0.54,7.51]
Neutral	1.65	3.46	3.46	3.53	3.57
	[0.41,3.68]	[1.44,7.05]	[1.45,8.00]	[1.11,9.65]	[0.81,10.93]

Table 7: Forecast error variance decomposition with RBTC and neutral technology shocks - 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	4.66	10.38	10.64	10.62	10.36
	[0.29,32.54]	[3.80,31.20]	[3.20,30.68]	[2.53,31.41]	[1.76,32.44]
RBTC	13.39	27.26	36.97	44.61	48.48
	[4.01,33.96]	[15.56,45.20]	[22.09,55.53]	[26.83,63.91]	[29.87,69.61]
Neutral	5.24	4.24	2.74	1.52	0.79
	[0.61,20.69]	[1.35,13.00]	[0.98,8.04]	[0.55,4.37]	[0.28,2.17]
Productivity					
Supply	37.69	38.08	38.42	37.29	36.54
	[5.32,77.32]	[5.63,78.90]	[5.14,79.04]	[5.06,78.30]	[4.92,77.79]
RBTC	7.18	12.16	18.64	23.18	25.33
	[0.64,26.97]	[1.83,34.76]	[3.05,43.20]	[3.95,48.26]	[4.50,51.25]
Neutral	33.88	33.85	30.79	28.89	27.66
	[4.62,65.54]	[5.63,65.08]	[5.12,61.93]	[4.51,60.35]	[4.19,59.39]
Total hours					
Supply	6.16	7.05	7.33	7.21	7.28
	[0.51,26.99]	[0.88,28.06]	[0.84,27.89]	[0.85,27.68]	[0.81,27.77]
RBTC	47.28	41.77	41.34	41.48	41.55
	[24.21,67.80]	[18.38,61.83]	[17.73,62.17]	[17.47,62.31]	[17.59,62.36]
Neutral	6.24	5.56	5.36	5.24	5.18
	[0.53,24.70]	[0.74,26.55]	[0.65,26.31]	[0.62,26.09]	[0.54,25.81]
AR rel. hours					
Supply	8.60	8.45	9.02	10.46	11.21
	[0.71,33.84]	[1.43,32.30]	[1.43,35.14]	[1.42,38.76]	[1.29,40.75]
RBTC	51.38	53.02	51.29	49.07	47.23
	[25.63,76.73]	[26.97,77.00]	[25.39,76.40]	[22.15,75.88]	[20.05,74.68]
Neutral	18.75	18.35	19.78	20.69	21.31
	[1.90,52.25]	[2.49,51.40]	[2.68,53.33]	[2.47,55.34]	[2.51,57.68]
RM rel. hours					
Supply	7.90	9.89	9.34	8.92	8.77
	[0.90,29.88]	[2.54,28.83]	[2.18,28.84]	[1.65,29.72]	[1.34,29.60]
RBTC	9.72	19.25	23.96	27.43	28.84
	[2.00,23.62]	[6.88,35.60]	[9.27,42.97]	[10.13,47.84]	[10.52,49.99]
Neutral	5.59	7.17	6.37	5.86	5.60
	[0.42,31.29]	[1.65,28.25]	[1.49,27.54]	[1.12,27.20]	[0.83,26.77]

Table 8: 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	23.04	19.45	17.91	16.66	15.62
	[3.52,53.27]	[4.70,45.46]	[3.38,42.74]	[2.55,41.15]	[2.22,40.48]
RBTC	6.03	10.41	12.50	15.31	16.87
	[0.63,21.51]	[5.48,21.75]	[4.26,30.43]	[3.47,36.24]	[3.32,38.91]
Neutral	22.63	15.66	12.42	10.86	10.19
	[2.69,53.35]	[4.59,35.34]	[3.24,32.45]	[2.21,31.54]	[1.58,30.77]
Routine hours					
Supply	4.51	5.05	5.05	5.26	5.41
	[0.44,21.15]	[1.22,20.67]	[0.91,20.65]	[0.76,21.30]	[0.60,21.42]
RBTC	66.11	58.85	56.84	55.52	54.78
	[39.25,85.42]	[32.72,76.11]	[30.82,74.76]	[29.61,73.92]	[28.67,73.24]
Neutral	10.84	9.13	7.98	7.43	7.09
	[1.25,36.66]	[1.70,29.43]	[1.27,28.94]	[0.98,28.08]	[0.84,27.88]
Manual hours					
Supply	9.36	10.83	10.84	10.78	10.70
	[1.16,33.93]	[2.72,31.93]	[2.54,32.43]	[1.99,33.19]	[1.64,34.25]
RBTC	5.71	7.30	8.20	8.63	8.86
	[0.70,15.31]	[1.94,18.12]	[1.99,20.82]	[1.82,22.02]	[1.51,23.24]
Neutral	10.95	12.41	13.00	13.13	13.43
	[1.46,37.83]	[3.20,37.77]	[3.09,38.49]	[2.58,40.59]	[2.22,42.02]

Table 9: 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.

Appendices

A RBC results

A.1 Comparative statics analysis

		Percent deviation from SS0		
Relative variables	SS0	Z_t	$B_{a,t}$	$B_{r,t}$
Y/H	0.3274	0.1490	0.0496	0.1021
H_a/H_r	1.2816	0.2123	-0.2681	0.3363
H_r/H_m	1.6019	-0.2119	0.0197	-0.3352
W_a/W_r	1.9515	0.4251	0.4592	-0.3230
W_r/W_m	0.0729	-0.4233	0.0394	0.3240
Aggregate variables				
Output	0.2513	0.0960	-0.0718	-0.0146
Consumption	0.2325	0.1121	-0.0695	-0.0245
Investment	0.0188	-0.1029	-0.0995	0.1081
Capital	0.7533	0.8960	-0.0995	0.1081
Rental rate	0.0351	-0.9901	0.0000	-0.0000
Total hours	0.7676	-0.0530	-0.1213	-0.1165
Abstract hours	0.3385	0.0200	-0.2669	-0.0012
Routine hours	0.2642	-0.1920	0.0012	-0.3364
Manual hours	0.1649	0.0200	-0.0185	-0.0012
Abstract wage	0.1378	0.1521	0.3917	-0.0268
Routine wage	0.0706	-0.2719	-0.0671	0.2971
Manual wage	0.9677	0.1521	-0.1065	-0.0268

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 1% change in corresponding shocks.

A.2 Log-linearized equilibrium conditions

The following system of equations describes the log-linearized equilibrium conditions around the initial steady state values for which shocks are normalized to one. Small case letters represent the log-deviation from the initial steady state of variables in capital letters. Variables without time subscripts capture their initial steady state values.

$$
\begin{aligned}
y_t &= \Omega_a h_{a,t} + \Omega_{ces}\Omega_k k_t + \Omega_{ces}\Omega_r h_{r,t} + \Omega_m h_{m,t} && \text{(A.1)}\\
w_{a,t} &= \frac{\Omega_a - 1}{\varepsilon} h_{a,t} + \frac{\Omega_m}{\varepsilon} h_{m,t} + \frac{\Omega_{ces}\Omega_r}{\varepsilon} h_{r,t} + \frac{\Omega_{ces}\Omega_k}{\varepsilon} k_t && \text{(A.2)}\\
w_{m,t} &= \frac{\Omega_m - 1}{\varepsilon} h_{m,t} + \frac{\Omega_a}{\varepsilon} h_{a,t} + \frac{\Omega_{ces}\Omega_r}{\varepsilon} h_{r,t} + \frac{\Omega_{ces}\Omega_k}{\varepsilon} k_t && \text{(A.3)}\\
w_{r,t} &= \left(-\frac{1}{\mu} + \frac{\Omega_{ces}\Omega_r}{\varepsilon} + \frac{(\varepsilon-\mu)}{\varepsilon\mu}\Omega_r\right) h_{r,t} + \frac{\Omega_a}{\varepsilon} h_{a,t} + \frac{\Omega_m}{\varepsilon} h_{m,t} && \text{(A.4)}\\
&\quad + \left(\frac{\Omega_{ces}}{\varepsilon} + \frac{\varepsilon-\mu}{\varepsilon\mu}\right)\Omega_k k_t &&\\
r_t &= \left(-\frac{1}{\mu} + \frac{\Omega_{ces}\Omega_k}{\varepsilon} + \frac{(\varepsilon-\mu)}{\varepsilon\mu}\Omega_k\right) k_t + \frac{\Omega_a}{\varepsilon} h_{a,t} + \frac{\Omega_m}{\varepsilon} h_{m,t} && \text{(A.5)}\\
&\quad + \left(\frac{\Omega_{ces}}{\varepsilon} + \frac{\varepsilon-\mu}{\varepsilon\mu}\right)\Omega_r h_{r,t} &&\\
\delta i_t &= -\delta z_t + k_{t+1} - (1-\delta) k_t && \text{(A.6)}\\
y_t &= \phi_a c_{a,t} + \phi_r c_{r,t} + \phi_m c_{m,t} + \phi_i i_t && \text{(A.7)}\\
\lambda_t - z_t &= \mathbb{E}_t\lambda_{t+1} + (1-\beta(1-\delta))\mathbb{E}_t r_{t+1} - \beta(1-\delta)\mathbb{E}_t z_{t+1} && \text{(A.8)}\\
\lambda_t &= -\sigma c_{a,t} && \text{(A.9)}\\
\lambda_t &= -\sigma c_{r,t} && \text{(A.10)}\\
\lambda_t &= -\sigma c_{m,t} && \text{(A.11)}\\
w_{a,t} &= b_{a,t} + \psi h_{a,t} + \sigma c_{a,t} && \text{(A.12)}\\
w_{r,t} &= b_{r,t} + \psi h_{r,t} + \sigma c_{r,t} && \text{(A.13)}\\
w_{m,t} &= b_{m,t} + \psi h_{m,t} + \sigma c_{m,t} && \text{(A.14)}\\
z_t &= \rho_z z_{t-1} + \nu_{z,t} && \text{(A.15)}\\
b_{a,t} &= \rho_a b_{a,t-1} + \nu_{a,t} && \text{(A.16)}\\
b_{r,t} &= \rho_r b_{r,t-1} + \nu_{r,t} && \text{(A.17)}\\
b_{m,t} &= \rho_m b_{m,t-1} + \nu_{m,t} && \text{(A.18)}
\end{aligned}
$$

where $\Omega_a = \frac{\alpha_a H_a^{\frac{\varepsilon-1}{\varepsilon}}}{X_1}$, $\Omega_m = \frac{\alpha_m H_m^{\frac{\varepsilon-1}{\varepsilon}}}{X_1}$, $\Omega_{ces} = \frac{\alpha_r X_2^{\frac{\mu}{\mu-1}\frac{\varepsilon-1}{\varepsilon}}}{X_1}$, $\Omega_k = \frac{(1-\eta)K^{\frac{\mu-1}{\mu}}}{X_2}$, $\Omega_r = \frac{\eta H_r^{\frac{\mu-1}{\mu}}}{X_2}$, $\phi_i = \frac{I}{Y}$ and $\phi_j = \frac{C_j}{Y}$ for $j = a, r, m$.

A.3 Impulse responses

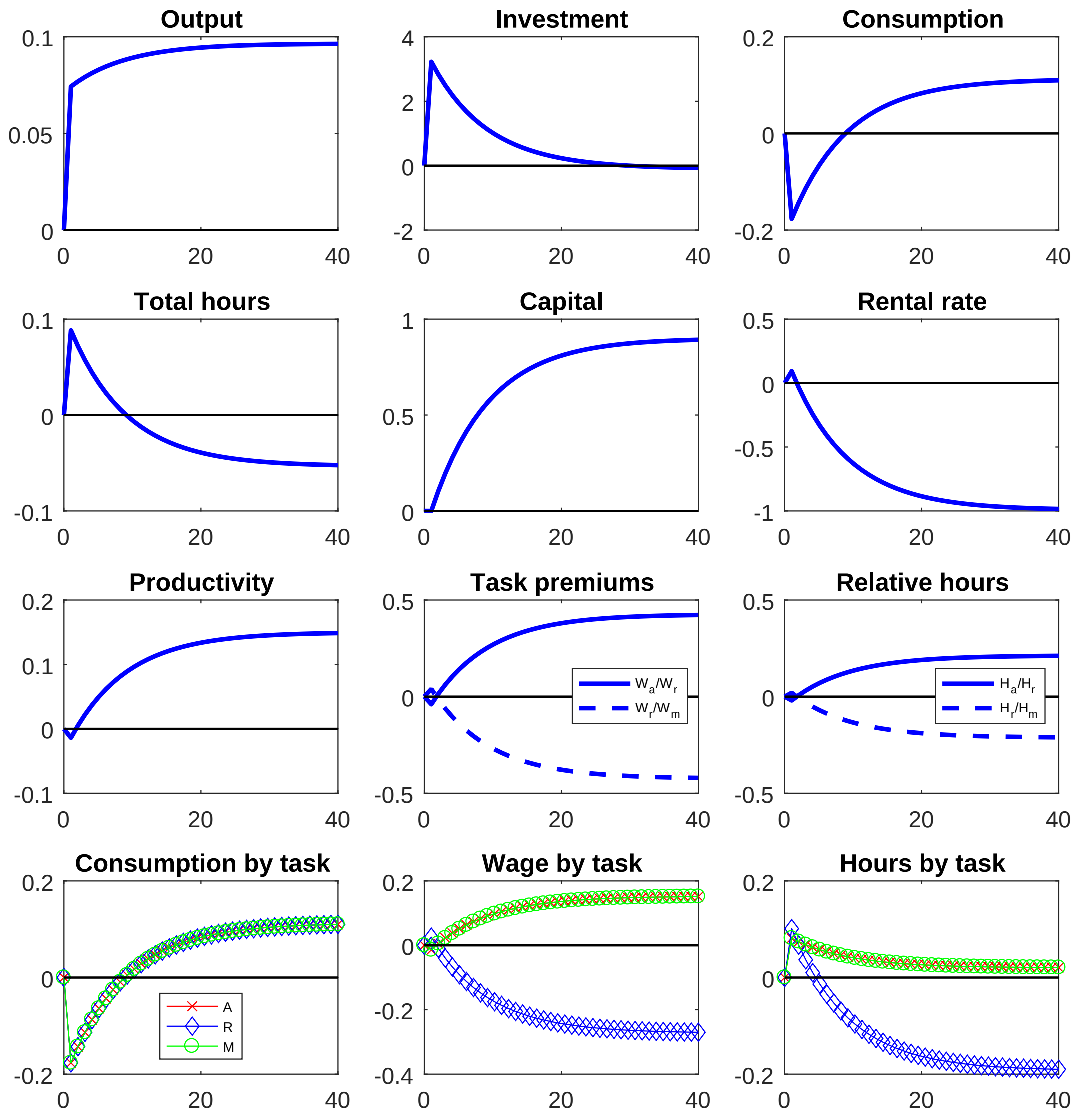

Figure A.1: Impulse responses to RBTC (Z_t)
Notes: Responses to a 1% shock. Variables are in percentage deviation from their initial steady state values.

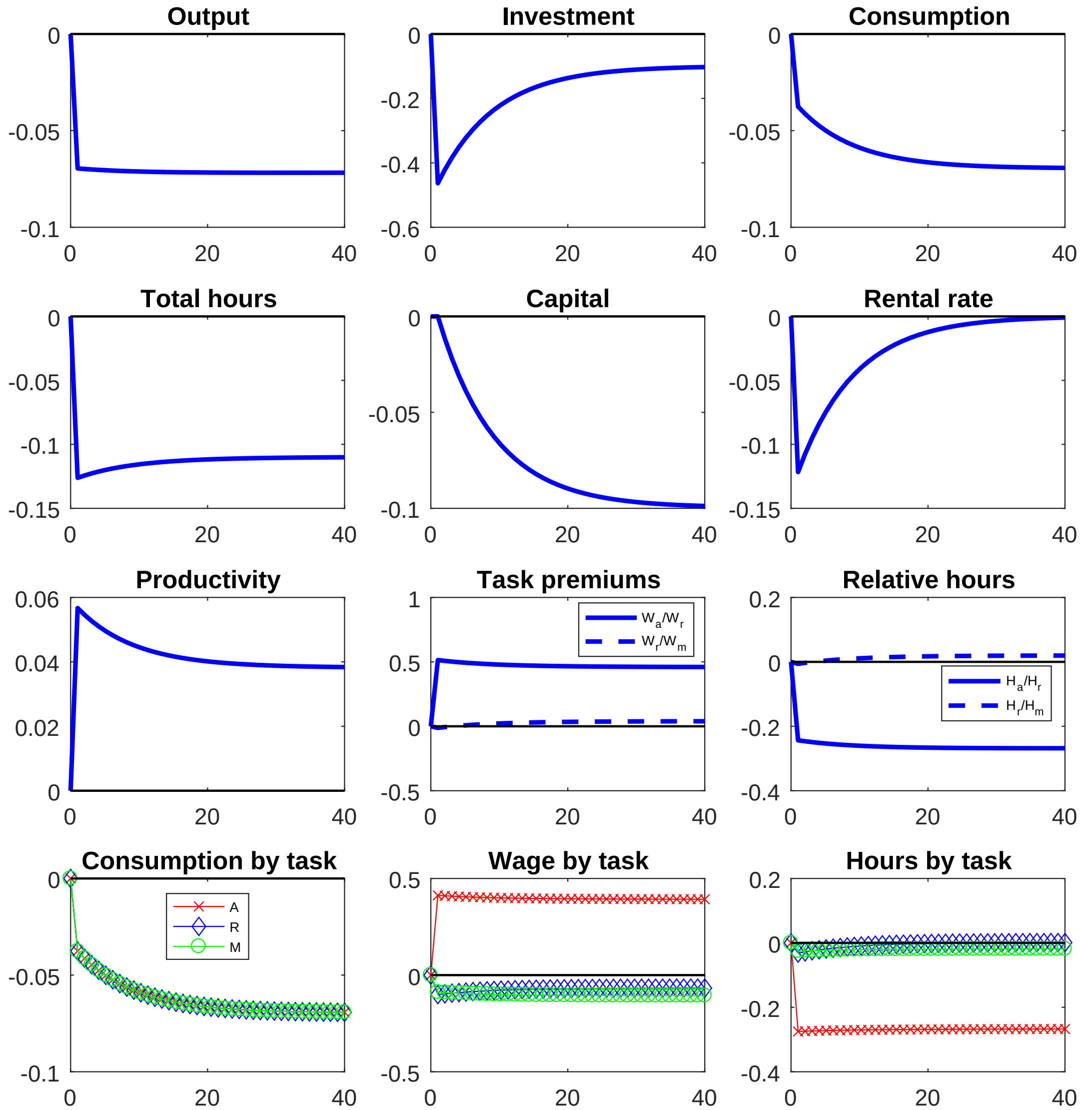

Figure A.2: Impulse responses to an abstract preference shock ($B_{a,t}$)
Notes: Responses to a 1% shock. Variables are in percentage deviation from their initial steady state values.

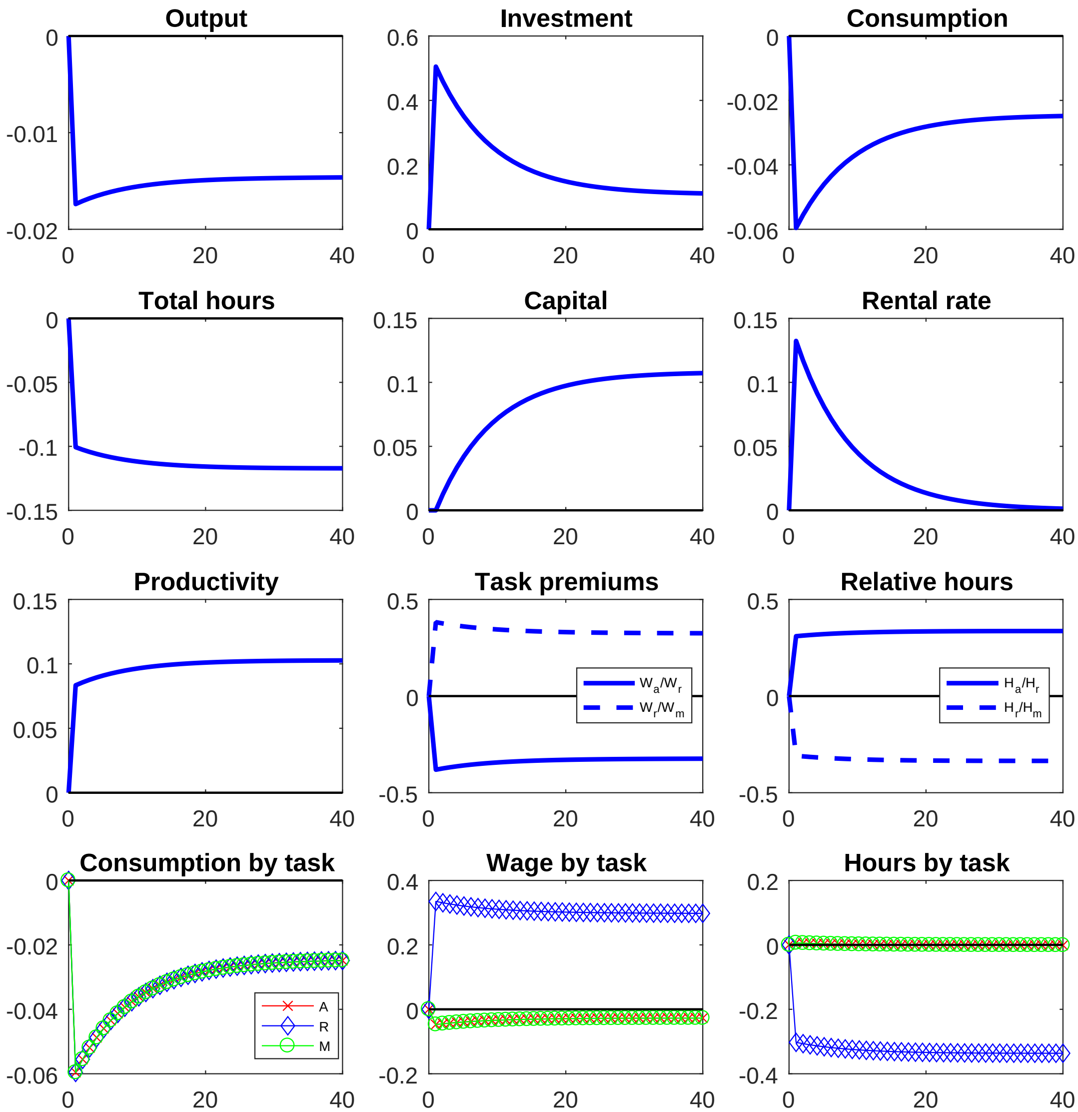

Figure A.3: Impulse responses to a routine preference shock ($B_{r,t}$)
Notes: Responses to a 1% shock. Variables are in percentage deviation from their initial steady state values.

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 5%. 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: Data are constructed as described in subsection 3.1. Variables are in first difference of their logarithm. Significance of at least *5%.

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, Rubio-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.[B.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.

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

D 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 III, namely the one that separately identifies RBTC from task-supply shocks and neutral technology shocks. Figures D.1 and D.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 similar when we change modelling 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 D.1 and D.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 D.1 and D.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.

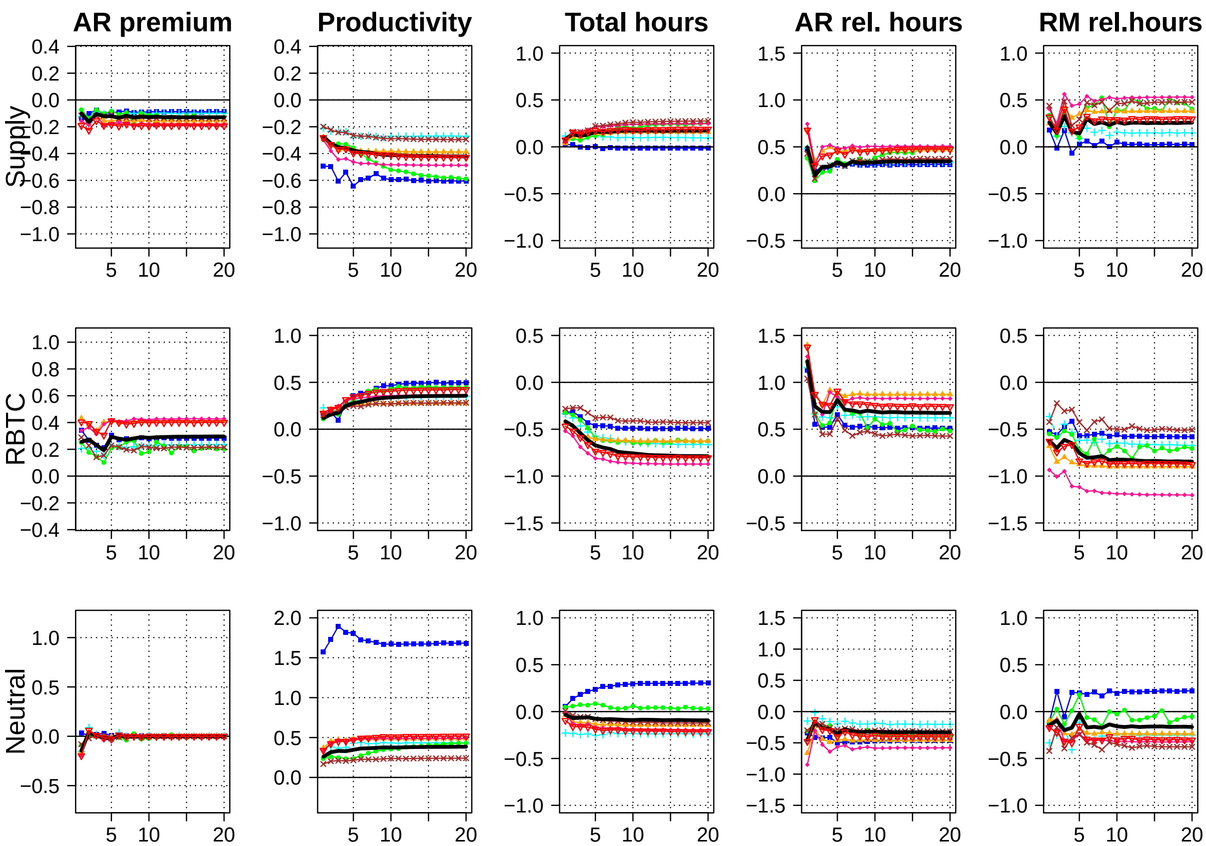

Figure D.1: Impulse response functions to task-supply, RBTC, and neutral technology shocks - Robustness.

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 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 5.3.

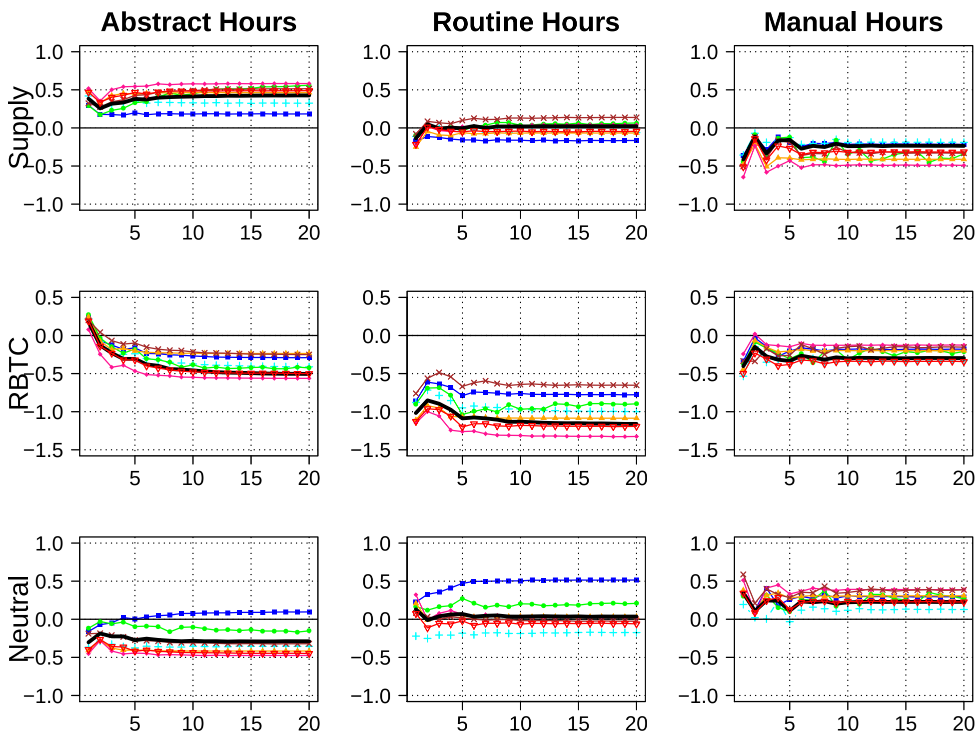

Figure D.2: Median impulse response functions of hours by task to task-supply, RBTC, and neutral technology shocks - Robustness.

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 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 5.3.