Short-Run Pain, Long-Run Gain? Recessions and Technological Transformation.

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Abstract

Recent empirical evidence suggests that skill-biased technological change that shifts labor demand towards non-routine jobs has accelerated during the Great Recession. We analyze the interaction between the gradual process of transition towards a skill intensive technology and business cycles in a standard neoclassical growth framework. In the model, periods of depressed economic activity are used by firms to deeply reorganize production and by routine workers to acquire new skills due to low opportunity costs. As a result, additional resources are diverted from production, amplifying the effect of a negative TFP shock. At the same time, recessions speed up technological transformation. For a reasonable parametrization, the model is able to match both the long-run trend in the routine employment share and the dramatic impact of the Great Recession on such jobs.

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1 Introduction

In recent decades, significant breakthroughs in information technology, electronics and robotics have made many routine jobs obsolete as they can now be easily preformed by machines. At the same time, employment in non-routine cognitive occupations (e.g., programmers or financial analysts) and non-routine manual jobs (mainly low-skill services), has been increasing. Both of these types of occupations are associated with tasks that have proved hard to automate and offshore, at least thus far. Routine jobs — those associated with repetitive but relatively simple tasks, like machine operators in manufacturing plans, bank tellers, office clerks — on the contrary, are disappearing. In the literature this process is known as job polarization (see Acemoglu (1999), Autor, Levy, and Murnane (2003), Goos and Manning (2007), Goos, Manning, and Salomons (2014) among others).

In a recent contribution, Jaimovich and Siu, 2015 (JS hereafter) emphasize that this job polarization process accelerates during recessions. They show that, over the last thirty years, employment in routine occupations experienced significant drops during economic downturns and that, unlike for other types of jobs, these drops were not followed by recoveries once the recessions ended. Strikingly, 88% of job losses in routine occupations since the mid 1980s happened during these downturns. In contrast, non-routine jobs experienced only small declines during these recessions, and rapidly recovered afterwards. Importantly, these patterns began during the mid 1980s, when the pace of innovation in automation technologies accelerated.[1] Before that time, routine employment bounced back quickly after the recoveries began.

To better understand these patterns, and to evaluate their importance for macroeconomic fluctuations and technology adoption, we build a theory in which a gradual process of routine-biased technological change (Autor, Levy, and Murnane, 2003) interacts with the business cycle. We do so by embedding transformative technological change into a standard neoclassical growth framework. In our model, the economy is populated by two types of agents, low-skilled and high-skilled, who work in the goods or the services sector. In the services sector, low-skill workers perform non-routine manual tasks. In the goods sector, non-routine cognitive tasks, performed by high-skill workers, are combined with routine tasks, which are performed by low-skill workers.[2] While only one technology is available to produce services, firms can choose either "old" or "new" technology

[1]See Eden and Gaggl (2016) for a time series of ICT capital stock and its price (Figures 8 and 9). In Appendix A we also show that worldwide shipment of industrial robots experienced a significant increase after the Great Recession.

[2]Thus, low-skill workers can be employed both in routine and non-routine manual jobs, while high-skill labor is performing non-routine cognitive tasks. This is similar to the framework of Autor and Dorn (2013).

to produce goods. The new technology is more skill intensive than the old technology. Critically, we assume an exogenous skill-biased technological progress alongside the standard (neutral) aggregate technology shocks. Over time, as the new technology becomes more productive, firms progressively switch to the new technology. When this happens, non-routine cognitive employment goes up. Moreover, if services and goods are sufficiently complementary, non-routine manual employment also increases, thus generating job polarization.

Adopting the new technology is costly, both in terms of factors of production that must be used to reorganize the firm, but also in terms of the profits that are lost during the reorganization. As a result, firms prefer to adopt the new technology during recessions, when factors of production are cheap and, because of the low productivity, the loss in foregone profits is minimized. While recessions are periods of intense transformation for firms, they are also periods of skill adoption for workers. Since wages are depressed, and since the adoption of the new technology will lead to an increased demand for high-skill workers once the recession is over, low-skill workers use the recession to invest in their human capital and, as a result, become high-skilled. While in the data these workers may exit from the labor force for a variety of reasons, we show that the dynamics of postsecondary education enrollment broadly correspond to the dynamics of the share of routine workers (with the opposite sign), which is consistent with the qualitative prediction of our model. Together, the technology adoption by firm and the skill adoption by workers take resources away from production during downturns and therefore amplify the effect of negative business cycle shocks. At the same time, this short-run pain creates long-lasting value in the form of a better production technology and higher skill level.

We parametrize the economy to match standard real business cycle moments and the overall decline in the employment share of routine workers. Importantly, for a reasonable level of complementarity between goods and services, the model is able to explain a recent growth in the employment share of non-routine manual labor. We demonstrate that by feeding into our model a large negative TFP shock that corresponds to the Great Recession in both its magnitude and its timing (relative to the process of technological transition), we can largely account for the sharp drop in the share of routine workers in the labor force that occurred between 2008 and 2010.

Literature

In the model, technology adoption requires both time and resources. In this regard, it is similar to Jovanovic and Macdonald (1994), Andolfatto and MacDonald (1998) and, especially, to Greenwood and Yorukoglu (1997) who assume that high-skill labor is essential to adopt new technologies.

Several other works (e.g., Cooper and Haltiwanger, 1993, Aghion and Saint-Paul, 1998 and Caballero and Engel, 1999) also use a "pit stop" model of technology adoption such that periods of depressed economic activity are used by firms to fundamentally reorganize their production technology.[3] In related works (e.g., Hall, 1991), recessions are viewed as periods of enhanced investment in organization capital. Recently, several studies have used these ideas to explain anemic employment recoveries following the three latest recessions (van Rens, 2004, Koenders and Rogerson, 2005, and Berger, 2012).

In the model, investment in human capital also increases during recessions. Counter-cyclical investment in education is a well established fact in the empirical literature (see, among many others, Betts and McFarland, 1995, Dellas and Sakellaris, 2003, Charles, Hurst, and Notowidigdo, 2015, and Barr and Turner, 2015). Schooling in our paper is modeled in the spirit of real business cycle models augmented with human capital accumulation (e.g., Perli and Sakellaris, 1998 and DeJong and Ingram, 2001).

The remainder of the paper is organized as follows. Section 2 discusses recent empirical evidence on the interaction between routine-biased technological change and recessions. Section 3 describes the model. In Section 4, we describe the calibration. Section 5 contains a numerical analysis of the model. Section 6 concludes.

2 Empirical evidence

Several empirical papers document that job polarization, induced by routine-biased technological change, was accelerated by the recent recessions, and especially the Great Recession. Hershbein and Kahn (2016), using job vacancies posting data, find that skill demand is elevated when the local employment growth is slow. This "upskilling" effect is long lasting and does not disappear even when then labor market recovers. Moreover, firms that upskill more actively also invest more.[4] Anghel, De la Rica, and Lacuesta (2014) document that the Great Recession sped up job

[3]This is reminiscent of the Schumpetarian view of recessions. Schumpeter (1934) considers recessions as "industrial mutation that incessantly revolutionizes the economic structure from within, incessantly destroying the old one, incessantly creating a new one." Caballero and Hammour (1994) study how the process of creative destruction interacts with business cycles.

[4]Interestingly, a large and very persistent drop in investment after the Great Recession is entirely driven by investment in structures. At the same time, as documented in Brynjolfsson and McAfee (2012), investment in equipment and software, which are presumably used more actively by skill intensive firms, actually recovered unprecedentedly rapidly, up to 95% of its historical peak by 2010. Total investment in intellectual property showed

polarization in Spain. Zhang (2015) finds that during crises routine labor intensive firms reduce their routine employment and invest more in machines. Using a panel of Spanish manufacturing firms, Aguirregabiria and Alonso-Borrego (2001) show that firms' decisions to reorganize production is counter-cyclical and lead to a significant shift in occupation structure towards white-collar jobs. These findings are in line with our model, where the adoption of a new skill intensive technology requires reorganization of production, which often takes time and is the most attractive during low opportunity cost periods.

Most relevant for our purpose, JS argue that the three recent recessions affected routine and non-routine workers in a dramatically different way.[5] They show that routine employment generally drops more during crises than non-routine employment. In addition, the three recent recessions are accompanied by no recovery in routine employment at all: since the 1980s per capita routine employment has been falling not only as a fraction of total employment but also in absolute terms. JS therefore refer to the mid 1980s as the start of the job polarization era.

The job polarization era is also marked by a drop in the labor force participation rate and an increase in the postsecondary education enrollment ratio, as shown in Figure 1. The labor force participation rate has been declining since at least the mid 1990s. The recession of 2001 and especially the Great Recession seem to trigger the downward shift in the the labor force participation rate from 67% in 2000 down to 66% in 2003 and from 66% in 2007 to 63% in 2013, respectively. At the same time, postsecondary education enrollment ratio was almost flat from the mid 1970s up to mid 1990s, but increased significantly afterwards.[6] In our model, both the decreasing labor force participation ratio and increasing education enrollment are driven by the process of adoption of the relatively more skill-intensive technology.

only a small 1.5% drop and also recovered quickly.

[5]Using FRED data, JS define routine occupations as "sales and related occupations", "office and administrative support occupations", "production occupations", "transportation and material moving occupations", "construction and extraction occupations", and "installation, maintenance, and repair occupations". Non-routine cognitive occupations include "management, business, and financial operations occupations", "professional and related occupations". "Service occupations" are non-routine manual. We use their classification in our numerical analysis. See their paper for more details about classification and robustness.

[6]Interestingly, correlation between the labor force participation and the postsecondary enrollment ratio seems to change sign around the start of the job polarization era. Between 1963 and 1984 the correlation is 0.84, while between 1985 and 2014 it is -0.63.

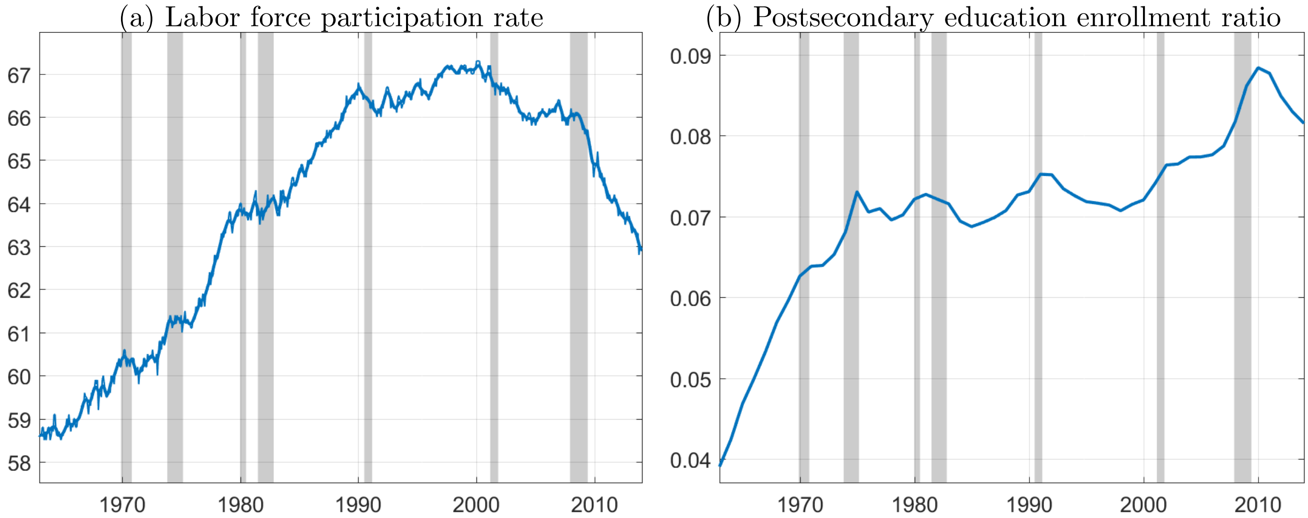

Figure 1: Labor force participation rate (from FRED) and and postsecondary education enrollment ratio (from National Center for Education Statistics). A smooth line in the left panel shows the series adjusted for seasonality with a 13-term Henderson filter (Henderson, 1916)

3 Model

Time is discrete and goes on forever, $t = \{0, 1, \dots\}$. The economy is populated by a representative household that consists of a unit measure of workers. A worker is either low-skill or high-skill, and a low-skill worker can become high-skill through schooling. Workers are employed by firms in a services and a goods sector. Firms in the services sector have a access to a single technology that uses only low-skill workers. Firms in the goods sector, however, can employ both types of workers and produce using one of two different technologies: the old technology that is low-skill-intensive and the new technology that is high-skill-intensive.[7] All firms begin by using the old technology and, as the productivity of the new technology slowly improves, progressively switch to it. Adopting the new technology requires capital and high-skill labor, and the firm must stop production while the workplace is being reorganized. Final goods producer combines services and goods into final consumption goods. Below we describe the agents in greater detail.

3.1 Representative household

The representative household values final consumption goods using a constant relative risk aversion utility function with coefficient γ and discounts future utility at a rate b. The household consists of a unit mass of atomistic workers, each endowed with one unit of labor. A fraction h of

[7]Our sectors definition follows Autor and Dorn (2013). This definition distinguishes between the two broad types of tasks implemented by low-skill workers. Routine tasks in the ‘goods’ sector are relatively easy to automate or offshore, while non-routine manual tasks in the ‘services’ sectors are not.

them are high-skill and the remaining $u = 1 - h$ are low-skill.[8] Low-skill workers can either work in production (u_p), in which case they earn wage w_u, or go to school as students in order to be retrained and eventually become high-skill workers (u_r). Similarly, high-skill workers can either produce (h_p) for a wage w_h, or teach at the school (h_r).[9] The household also owns the capital stock k and either uses it to retrain workers (k_r) or rents it out to firms for production (k_p) at rate r.

Each period, the abilities of a fraction δ_h of the high-skill workers are rendered obsolete and they become low-skill. The dynamics of the mass of high-skill workers is

$$h' = (1 - \delta_h)h + \phi(k_r, h_r, u_r),\ h' \in [0, 1] \tag{1}$$

where ϕ is the retraining technology. As in Perli and Sakellaris (1998), we assume that

$$\phi(k, h, u) = sk^{\beta_r} \left(\mu_r h^{\rho_r} + (1 - \mu_r)u^{\rho_r}\right)^{\frac{1-\beta_r}{\rho_r}}$$

where β_r is the capital intensity of the retraining sector, μ_r is the high-skill intensity and ρ_r relates to the elasticity of substitution between high-skill and low-skill workers.[10]

The household owns the firms and receives their profits Π every period. It also invests in new capital subject to quadratic adjustment costs $\varphi(i, k) = \frac{\chi}{2}\left(\frac{i}{k} - \delta_k\right)^2 k$. Capital depreciates at rate δ_k, so that its law of motion is

$$k' = (1 - \delta_k)k + i - \varphi(i, k). \tag{2}$$

Denoting by Ω the aggregate state of the economy (which will be fully described later), the dynamic problem of the household is

$$W(h, k, \Omega) = \max_{\substack{h', k', h_r, h_p, \\ u_r, u_p, k_s, k_p}} \frac{c^{1-\gamma}}{1 - \gamma} + b\,\mathbb{E}\left[W\left(h', k', \Omega' | \Omega\right)\right] \tag{3}$$

[8] Our definition of high skill is related to ability to implement non-routine cognitive tasks and not directly to the education level. Although the two are doubtlessly positively correlated, they are not the same (see JS for the discussion). Nevertheless, as discussed in Section 4, we use postsecondary education data for our calibration purposes.

[9] The only source of non-employment in the model is schooling: low-skill workers are out of the labor force while in schools. High-skill workers are always employed.

[10] This retraining process is reminiscent of Greenwood and Yorukoglu (1997), where acquisition of new skills requires staying out of the labor market. It also relates to RBC models with human capital as in Perli and Sakellaris (1998) and DeJong and Ingram (2001).

subject to the budget constraint

$$c + i = w_h(\Omega) \cdot h_p + w_u(\Omega) \cdot u_p + r(\Omega) \cdot k_p + \Pi(\Omega),$$

and the laws of motion (2) for capital and (1) for high-skill workers and to an aggregate law of motion $\Omega' = G(\Omega)$ for Ω.

3.2 Firms and technologies

On the production side, there are two intermediate inputs: goods and services. As in Autor and Dorn (2013), intermediate services are produced by a technology that only employs low-skill workers. We think about these jobs as of non-routine manual. Intermediate goods can be produced by either a new or an old technology that both employ low-skill and high-skill workers. High-skill/low-skill workers in the goods sector implement non-routine cognitive/routine tasks. The final goods producers combine both intermediate inputs into final goods, which are consumed by the household.

3.2.1 Final goods producer

There is a competitive final consumption goods industry which combines intermediate goods (from both old and new firms) as well as intermediate services into a consumption bundle. We normalize the price of this final good to 1. The static problem of a firm in this industry is

$$\max_{y_{g,n};y_{g,o};y_s} e^z \left[\left(y_{g,n}^{\theta} + y_{g,o}^{\theta} \right)^{\frac{\epsilon}{\theta}} + y_s^{\epsilon} \right]^{\frac{1}{\epsilon}} - P_o(\Omega) y_o - P_n(\Omega) y_n - P_s(\Omega) y_s, \tag{4}$$

where $y_{g,n}$ is the amount of intermediate goods produced with the new technology, $y_{g,o}$ is the amount of intermediate goods produced with the old technology and y_s is the amount of services. Aggregate total factor productivity z follows an AR(1) process such that

$$z' = (1-\rho)\bar{z} + \rho z + \sigma_z \epsilon_z', \text{ where } \epsilon_z \sim \mathcal{N}(0,1).$$

We allow some imperfect substitutability between the goods produced by the new and the old technology.

3.2.2 Intermediate goods producers

There is a unit mass of atomistic intermediate goods producers. These firms can operate using either an old or a new technology, which we index by $j = \{o, n\}$. The production functions are

$$F_j(A_j, h, u, k) = A_j \left[k^{\beta}(\mu_j h^{\rho} + (1-\mu_j)u^{\rho})^{\frac{1-\beta}{\rho}}\right]^{\alpha}, \ \ j = \{o, n\}.$$

where the inputs are the capital k, high-skill labor h and low-skill labor u. The parameter β captures the capital intensity, A_j is total factor productivity, ρ captures the degree of substitutability between low and high skill workers, and μ_j is the skill intensity of the production function. The corresponding profits for a firm that produces is

$$\pi_j(\Omega) = \max_{h,u,k} P_j(\Omega)F_j(A_j, h, u, k) - w_h(\Omega)\cdot h - w_u(\Omega)\cdot u - r(\Omega)\cdot k,$$

where $P_j(\Omega)$ is the price of the goods.

The old and the new technology differ in two ways. First, the new technology is relatively more high-skill intensive than the old one ($\mu_n > \mu_o$). Second, the productivities are different ($A_n \neq A_o$). At $t = 0$ the new technology is not available ($A_n = 0$) and all agents consider its arrival as a zero probability event. Therefore in the initial steady state all firms are using the old technology. Over time, exogenous technological progress favors the new technology, so that A_n grows relatively to A_o. This induces firms to switch from the old to the new technology.[11,12] Since the new technology is more skill intensive, the technological adoption process increases the demand for high-skill workers, which pushes their wages up. As a result, more low-skill workers enter the retraining process and the overall skill level in the economy increases. Without loss of generality, in what follows we assume that $A_o = 1$.

Switching from the old to the new technology is costly and risky. A firm that attempts to switch does not produce during the current period and successfully acquires the new technology with probability $\xi(h, k)$, $\xi \in [0, 1)$, $\xi_{hh}, \xi_{kk} < 0 < \xi_h, \xi_k$. A firm can increase its odds of switching to the

[11]The arrival of the new technology allows intermediate firms to produce a new variety of goods. This is reminiscent of the endogenous growth models in the spirit of Romer (1990) and Grossman and Helpman (1991).

[12]Technological progress is associated with a change in production function, redolent of general purpose technology literature (e.g., Helpman, 1998). The new technology is relatively more high-skill intensive, similar to Heckman, Lochner, and Taber (1998) and Goldin and Katz (1998). Buera, Kaboski, and Rogerson (2015) also hypothesize that the share of high-skill labor in the production function has increased as a result of the recent technological change. An alternative approach would be to use the notion of capital-skill complementarity, as proposed by Griliches (1969) and Krusell, Ohanian, Rios-Rull, and Violante (2000). There, technological progress makes capital equipment more productive and cheaper, causing increase in demand for the high skill.

new technology by hiring more high-skill workers h or by renting more capital k.[13,14] Following Andolfatto and MacDonald (1998) and Andolfatto and MacDonald (2006), we assume that

$$\xi(k,h) = 1 - \exp(-\eta k^{\beta_{tr}} h^{1-\beta_{tr}}).$$

Since a new firm never switches back to the old technology, its value is simply

$$V_n(\Omega) = \pi_n(\Omega) + \mathbb{E}\left[M(\Omega,\Omega')V_n(\Omega')|\Omega\right], \tag{5}$$

where $M(\Omega,\Omega')$ is the stochastic discount factor of the representative household and where $\Omega' = G(\Omega)$ is the law of motion of Ω.

In contrast, an old firm must decide each period whether to attempt a technological transition or not. As a result, its value is

$$V_o(\Omega) = \max\left\{V_o^p(\Omega); V_o^s(\Omega)\right\}, \tag{6}$$

where the value of production is

$$V_o^p(\Omega) = \pi_o(\Omega) + \mathbb{E}\left[M(\Omega,\Omega')V_o(\Omega')|\Omega\right],$$

and the value of switching technology is

$$\begin{aligned} V_o^s(\Omega) = \max_{h,k}\Big\{ & -w_h(\Omega)h - r(\Omega)k + \xi(h,k)\,\mathbb{E}\left[M(\Omega,\Omega')V_n(\Omega')|\Omega\right] \\ & + (1-\xi(h,k))\,\mathbb{E}\left[M(\Omega,\Omega')V_o(\Omega')|\Omega\right]\Big\}. \end{aligned}$$

[13] Importance of high-skill labor (e.g., management and IT consultants) for technology adoption is emphasized by Nelson and Phelps (1966) and Greenwood and Yorukoglu (1997).

[14] A potentially important aspect of technological adoption (e.g., Andolfatto and MacDonald, 1998) is diffusion externality. The idea is that the ease of technology learning is positively related to the mass of its users. In Appendix C we investigate how this externality affects both the shape of transition and interaction of adoption with business cycles.

3.2.3 Intermediate services producer

There is a representative firm producing low-skill intensive services using the production $F_s(u) = A_s u$ as in Autor and Dorn (2013). Its problem is simply

$$\max_u P_s(\Omega) F_s(u) - w_u(\Omega) u, \tag{7}$$

where $P_s(\Omega)$ is the price of services.

3.3 Competitive equilibrium

In this economy, the set of aggregate state variables Ω contains the aggregate capital stock K, the number of high-skill workers H, the mass of intermediate goods producing firms using the new technology m_n, the productivity of the new technology A_n and the productivity for the final goods producer ξ. We are ready to define a competitive equilibrium in this economy.

Definition 1 *A recursive competitive equilibrium is a collection of value functions for the firms V_o, V_o^p,V_o^s ,V_n and for the household W, and there associated optimal decisions; a collection of prices w_h, w_u, r, P_o, P_n, and aggregate laws of motion G, such that*

1. *the value functions and the optimal decisions solve problems 3, 4, 5, 6 and 7;*
2. *the markets for high-skill and low-skill labor and the market for capital clear;*
3. *the law of motion G is consistent with individual decisions.*

4 Parametrization

We parametrize the model to match features of the United States economy since the middle of the 1980s, the beginning of the job polarization era. One period is one year. Below, we explain how the parameters are picked and Table 1 summarizes their values. In Appendix B we conduct sensitivity analysis and verify that our results are robust to changes in the parameters.

Business cycle shocks

The persistence and the standard deviation of the business cycle shocks, ρ_z and σ_z, are set to match the first order autocorrelation and the volatility of HP-filtered real GDP per capita.[15] We find $\rho_z = 0.85$ and $\sigma_z = 0.025$. The persistence value is close to what is normally used in the RBC literature (Cooley and Prescott, 1995). The standard deviation σ_z is somewhat larger than usual values. Since, in the model, there is no labor-leisure choice, larger fluctuations in exogenous productivity are necessary to match aggregate output volatility.

Parameter	Value	Source/Target
Business cycle shock		
Aggregate shock persistence	$\rho_z = 0.85$	Autocorrelation of output
Volatility of aggregate shock	$\sigma_z = 0.025$	Volatility of output
Preferences		
Risk aversion	$\gamma = 1.0$	Log utility
Time discounting	$b = 0.96$	4% annual interest rate
Production sector		
DRS parameter	$\alpha = 0.9$	Basu and Fernald (1997)
Share of capital	$\beta = 0.3$	Average labor share
EoS between H and U	$\frac{1}{1-\rho} = 1.43$	Katz and Murphy (1992)
Share of H in old technology	$\mu_o = 0.50$	Routine employment in 1985
Share of H in new technology	$\mu_n = 0.77$	Cross-sectional dispersion in routine wage share
EoS between new and old goods	$\frac{1}{1-\theta} = 4$	Bernard, Eaton, Jensen, and Kortum (2003)
EoS between goods and services	$\frac{1}{1-\epsilon} = 0.33$	Buera, Kaboski, and Rogerson (2015)
Productivity of services	$A_s = 11.6$	Non-routine manual employment in 1985
Physical capital depreciation	$\delta_k = 0.1$	10% annually
Adjustment cost parameter	$\chi = 0.25$	Investment volatility
Retraining sector		
Share of capital	$\beta_r = 0.1$	Perli and Sakellaris (1998)
EoS between H and U	$\frac{1}{1-\rho_r} = 0.5$	Perli and Sakellaris (1998)
Share of H in education	$\mu_r = 0.0067$	Student-teacher ratio
Constant	$s = 0.249$	Postsecondary enrollment in 1985
High skill depreciation	$\delta_h = 0.05$	Heckman (1976)
Technology adoption		
Capital share	$\beta_{tr} = 0.3$	Same as in production sector
Ease of adoption	$\eta = 1.5$	Expected adoption lag is 3 years
Technological progress		
Initial impact	$A_n^0 = 0.1$	Trends in non-routine cognitive, non-routine manual and routine employment shares
Final value	$\bar{A}_n = 1.5$	
Length	$T_{finish} - T_{start} = 75$	

Table 1: Parametrization

Preferences

The time discount rate b is set to 0.96, which corresponds to 4% annual interest rate. The risk

[15] In particular, we match the moments (corresponding macro series are taken from FRED) implied by our economy at the initial steady state with the data counterparts, where the data between 1947 and 1985 is utilized. Recall that the job polarization era, associated in our model with the arrival of the new technology, started around the mid the 1980s, as argued by JS.

aversion γ is 1, corresponding to the log utility.

Production sector

The returns to scale parameter for goods producing firms is set to $\alpha = 0.9$, consistent with the estimates of Basu and Fernald (1997). The capital share parameter is $\beta = 0.3$. The elasticity of substitution between high and low-skill labor is set to 1.43, as in Katz and Murphy (1992), which corresponds to $\rho = 0.3$.[16] The relative weight of high-skill labor in the old production technology is $\mu_o = 0.50$. It is chosen to match the fraction of the routine employment in total employment at the beginning of the job polarization era. $\mu_n = 0.77$ is set in order to match a cross-sectional dispersion in routine wage share in total wage bill across goods producing firms to Zhang (2015).[17] The elasticity of substitution between the new and old goods is 4, so that $\theta = 0.75$.[18] The elasticity of substitution between services and goods to 0.33, which implies $\epsilon = -2$.[19] Productivity of low-skill services is $A_s = 11.6$ in order to match the employment share of non-routine manual labor in 1985. Physical capital depreciates at the rate of $\delta_k = 0.1$. Adjustment cost parameter χ is 0.25 to match volatility of private investment.

Retraining sector

The calibration of the retraining sector related parameters is not straightforward. To the best of our knowledge, there is no empirical estimates of an aggregate training function depending on low and high-skill labor as well as physical capital. Probably closest to our paper in this regard, Perli and Sakellaris (1998) consider a two-sector RBC economy with a human capital sector. Their human capital production technology is similar to ours. We follow this study and set the capital share to $\beta_r = 0.1$ and the elasticity of substitution between high and low-skill labor to $\frac{1}{1-\rho_r} = 0.5$. The latter value implies that high and low-skill labor are strong complements in the retraining sector. We set the relative weight of high-skill labor $\mu_r = 0.0076$ in order to roughly match the teacher-student ratio in the postsecondary education.[20] The constant $s = 0.249$ is set

[16]See Appendix B.1 for the sensitivity analysis.

[17]Zhang (2015) sorts firms based on this characteristic and finds that the spread between highest and lowest quintiles is 0.37. In our model, the goods sector features a trivial cross-section of firms, with old firms having a higher routine wage share. $\mu_n = 0.77$ implies that the difference in the routine wage share between new and old firms is close to 0.37. This value stays almost constant along the transition path.

[18]In the literature there is no consensus about the elasticity of substitution between intermediate goods. The estimates vary a lot and are usually not precisely identified. For example, Hsieh and Klenow (2014) use $\frac{1}{1-\theta} = 3$, Bernard, Eaton, Jensen, and Kortum (2003) and Christiano, Eichenbaum, and Trabandt (2015) report the value of roughly 3.8, Kuester (2010) estimates it at 22.7, and in the calibration of Altig, Christiano, Eichenbaum, and Linde (2011) it varies from 6 to 101 depending on the target. See Appendix B.3 for the sensitivity analysis.

[19]This is in line with estimates of Buera and Kaboski (2009) and Herrendorf, Rogerson, and Valentinyi (2013). See Appendix B.2 for the sensitivity analysis.

[20]According to the National Center for Education Statistics, this ratio was roughly 6% in the 1980s and has increased up to 8% by the 2010s. We set μ_r so that in the initial steady state $\frac{H_r}{U_r} = 0.07$. Due to absence of reliable

to match the number of low-skill agents in the retraining process U_r in the initial steady state to the fraction of civilian noninstitutional population in postsecondary education in 1985. Finally, the skill depreciation rate is $\delta_h = 0.05$.[21]

Technology adoption

An old firm attempting to switch to the new technology is successful with probability $\xi(k_{tr}, k_{tr}) = 1 - \exp(-\eta k^{\beta_{tr}} h^{1-\beta_{tr}})$. As for intermediate firms' production technology, we set $\beta_{tr} = 0.3$. The parameter $\eta > 0$ governs the importance of capital and high-skill labor for the technology adoption. If η is large, then only few workers and small amounts of capital are required to get the transition probability close to its maximum level of 1. On the contrary, a small value of η implies a large demand for high-skill labor and capital among adopting firms. Thus, smaller η's are associated with larger adoption costs. We set $\eta = 1.5$. Along the transition path, the resulting probability of successful technology adoption is around 0.33.[22]

Technological progress

In the model technological innovation is associated with the arrival of the new high-skill intensive production technology. The productivity of the old technology is held constant at $A_o = 1$. We are interested in understanding when firms adopt a new technology as the technological frontier evolves exogenously. We therefore parametrize $A_n(t)$ as follows

$$A_n(t) = \begin{cases} 0, & t < T_{start}, \\ A_n^0 + (\bar{A}_n - A_n^0)\dfrac{1 - \exp(T_{start} - t)}{1 - \exp(T_{start} - T_{finish})}, & t \in [T_{start}, T_{finish}], \\ \bar{A}_n, & t > T_{finish}. \end{cases}$$

where T_{start} denotes the beginning of the technological transition of the economy (the mid 1980s in our case, corresponding to the start of the job polarization era in JS) and T_{finish} denotes the end to the transition.[23]

data, we ignore other forms of training besides higher education. However, as argued by Perli and Sakellaris (1998), higher education is responsible for up to 90% of total investment in human capital.

[21]In our model δ_h can be interpreted as the retiring rate, which is currently around 3% in the USA. One can assume that every period fraction δ_h of the total labor force $\bar{L}$ retires and is immediately replaced by low-skill workers. At the same time, δ_h should include the rate of skill obsolescence. In the related literature, the depreciation rate of human capital is estimated. Despite a large variation, $\delta_h = 0.05$ is close to what is normally found (Heckman, 1976 and Mincer and Ofek, 1982).

[22]Consistent with this number, Brynjolfsson, Malone, Gurbaxani, and Kambil (1994) and Brynjolfsson and Hitt (2003) find that it normally takes several years for a firm to fully adopt computer technology. See Appendix B.4 for the sensitivity analysis.

[23]Another approach to modelling the process A_n would be to incorporate insights from the general purpose technology (GPT) literature (Helpman and Trajtenberg, 1994, Bresnahan and Trajtenberg, 1995), where arrival of

In our baseline analysis, we set $A_n^0 = 0.1$, $\bar{A}_n = 1.5$, $T_{finish} - T_{start} = 75$.[24] These parameters are chosen to match the trends in the employment shares of non-routine cognitive, non-routine manual and routine jobs reasonably well.[25]

5 Numerical results

This section presents our main numerical results.[26] Section 5.1 illustrates economic forces at work. In Section 5.1.1, we discuss the transition between the steady states induced by the new technology arrival. Section 5.1.2 describes the differential impacts of business cycles on the economy in the pre- and during transition periods. Finally, Section 5.2 investigates whether the model can rationalize job polarization and specifically its interaction with recessions.

5.1 Economic forces at work

5.1.1 Transition paths

We begin by investigating how the arrival of the new technology affects the economy without business cycle shocks. The path for the exogenous process A_n is shown in Figure 2. The initial shock is small, representing the idea that a new fundamental technology is hardly productive right after the arrival. As the new technology gradually becomes better, A_n increases and reaches its steady state level after 75 years.

Figure 3 shows the impact of the arrival of the new technology on the types of firms in the economy as well as on the types of workers. Over time, firms adopt the new technology as its

GPT is followed by a sequence of smaller innovations. This could pin down the A_n process endogenously. However, such an extension lies beyond the scope of our paper. Nonetheless, our exogenous process $A_n(t)$ captures the idea that the initial impact of the new technology A_n^0 can be small. Later on, a sequence of smaller innovations enhance the productivity of the new technology. As a result, the technology reaches its peak $\bar{A}_n$ after a (potentially long) lag $T_{finish} - T_{start}$. This is typical of GPTs (Helpman, 1998), including ICT (Jovanovic and Rousseau, 2005).

[24] GPTs are known to become fully productive only after a significant lag. For example, David (1990) argues that electricity delivered a major economic boost only in the 1920s, 40 years after the first generating station came into being. Crafts (2004) finds a lag of almost 100 years for the steam related technologies. Using asset prices, Ward (2015) predicts that it will take around 50 years for the IT to be fully absorbed by the economy.

[25] Our choice of $\bar{A}_n$ and $T_{finish} - T_{start}$ is not unique to match the employment shares. In Appendix B.5 we verify that our results are unchanged if we simultaneously change these parameters.

[26] Since the competitive economy is efficient, we solve the problem of a social planner that maximizes the welfare of the representative household. Given the complexity of the economy, we solve the model using a perfect foresight approach. In particular, we assume that all business cycle shocks are completely unexpected. To verify the validity of this approach, we have also solved a simpler version of the fully stochastic model globally. The perfect foresight approach does not matter much for the predictions of the model but significantly decreases the complexity of the computations.

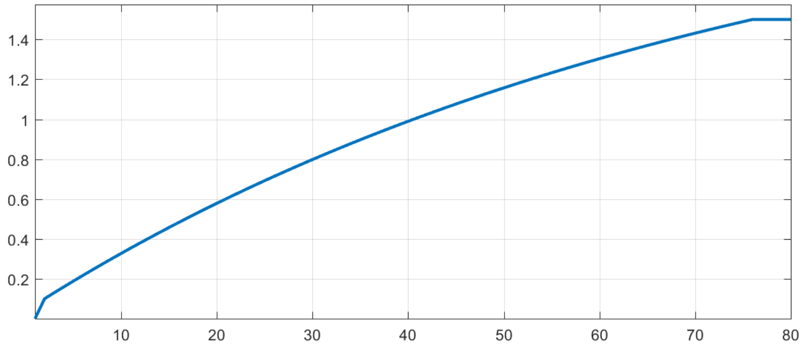

Figure 2: The productivity $A_n(t)$ of the new technology

productivity increases. To do so, old firms temporarily halt production and adopt the innovation (left panel). Since the new technology is relatively more skill intensive, low-skill workers respond accordingly and start to retrain actively (right panel). As a result, low-skill employment in the goods sector declines. At the same time, employment in low-skill intensive services increases gradually. This is due to the high degree of complementarity between goods and services in the final consumption bundle. Thus, the model is able to generate job polarization. As discussed in more details in Section 5.2, for our parametrization the model does a fairly good job in explaining the job polarization phenomenon quantitatively.

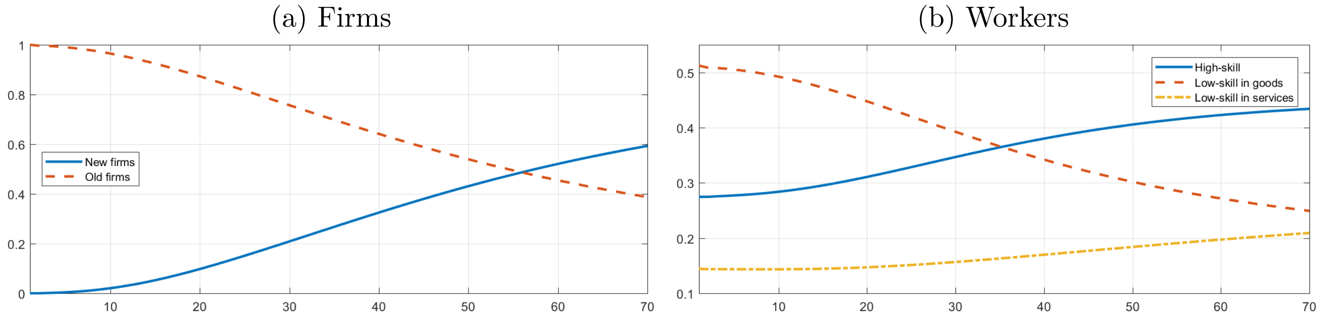

Figure 3: Transition upon arrival of the new technology

Figure 4 illustrates other aspects of the technology adoption process. The top-left panel shows the dynamics of the final good output Y_f. Despite the positive technological surprise at $t = 0$, Y_f does not respond immediately. For roughly 15 years Y_f is almost unchanged and starts to grow only afterwards. This is due to the GPT nature of the new technology. Adoption of such a technology requires significant investment in reorganization and accumulation of required production factors.[27] This is illustrated by the top-right and bottom panels of Figure 4. The top-right panel shows the ratio of total adoption costs Y_a to final output Y_f. We use two measures of Y_a. The first measure, $Y_{a,1}$, includes capital and high-skill labor rents in the schooling and adoption sectors. The second measure, $Y_{a,2}$, also takes into account forgone profits due to firms

[27]This is reminiscent of the infamous Solow productivity paradox. In the model, the long lag between the technology arrival and its resulting output growth is due to large reorganization costs, to the large extent not measured properly and thus not reflected in the GDP calculations. See also Brynjolfsson (1993).

being in the restructuring stage.

$$Y_{a,1} = w_h(H_{tr} + H_s) + r(K_{tr} + K_s),$$
$$Y_{a,2} = Y_{a,1} + \frac{\partial Y_f}{\partial m_o}(\bar{m} - m_n - m_o).$$

The calibration implies that $Y_{a,1}$ becomes as high as 2.7% of Y_f around year 30. Arount the same time, unmeasured reorganization investment, captured in our model by foregone output due to old firms in the process of technology adoption, account for about 0.25% of Y_f.

The bottom panel of Figure 4 further illustrates that periods after the new technology arrives are marked by diversion of resources away from final good production. The total mass of active firms and the overall number of workers in the production sector are shrinking during around 30 years (the yellow dot-dashed and red dashed lines, respectively). High-skill labor is required for the reorganization of the firms and the retraining of the low-skill workers. At the same time, low-skill workers go to school in larger numbers which contributes to the drop in labor force participation (the blue line) and to an increase in school enrollment. These two phenomena are salient for the U.S. during the last two decades.

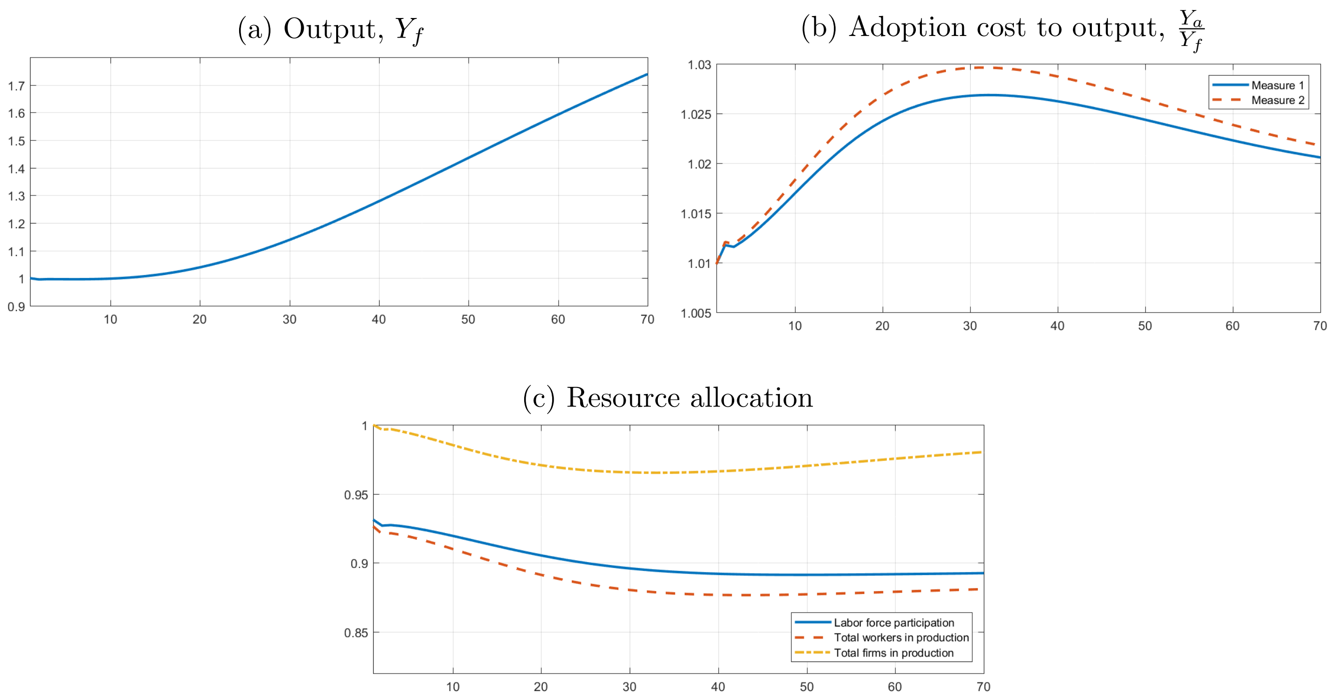

Figure 4: Top-left panel shows output of the final good sector Y_f. Top-right panel shows two measures of adoption costs Y_a (see text) as a fraction of the final good sector production Y_f. The bottom panel illustrates how the allocation of resources vary over time

In particular, the model predicts that the labor force participation drops by around 4 p.p. between 1985 and 2017, which is comparable to the number observed in the data (Figure 1, left panel). At the same time, the model-implied school enrollment ratio increased from 6.9% in 1985 up to 10.2%

in 2014. This is larger than in the data, where the ratio increased from 6.9% up to 8.2% (Figure 1, right panel). There are two reasons why the model-implied increase is higher. First, in the model schooling represents all types of retraining, including on-the-job training and various job training programs, while the data counterpart takes into account only formal higher education. Second, in the model all workers are either employed or in schools, and a decrease in the number of employed low-skill workers necessarily leads to an increase in number of employed high-skill workers (with a time lag). This approach misses a recent increase in non-employment probability among low-skill workers (Cortes, Jaimovich, Nekarda, and Siu, 2014 and Cortes, Jaimovich, and Siu, 2016), unrelated to education.[28] Demographic changes, such as population aging, might also play a role (Autor and Dorn, 2009).

In our paper, job polarization is driven by two main forces. First, the number of low-skill workers goes down along the transition path. As a result, the supply of routine workers diminishes. Second, at each point in time, the propensity of a low-skill worker to take a routine job (i.e., a job in the goods sector) goes down. On the one hand, she is more likely to attend school. Conditional on not attending school, on the other hand, she is more likely to be employed in the services sector. Formally, the routine employment R can be written as

$$R = U(1 - p_{sc} - p_{nrm}),$$

where U is total supply of low-skill workers in the economy, p_{sc}/p_{nrm} is the probability that a low-skill worker is in the retraining process/employed in the services sector. Change in routine employment therefore can be decomposed into composition and propensity effects:

$$\Delta R = \underbrace{\Delta U(1 - p_{sc} - p_{nrm})}_{\text{Composition}} - \underbrace{U\Delta(p_{sc} + p_{nrm})}_{\text{Propensitiy}} - \underbrace{\Delta U \Delta(p_{sc} + p_{nrm})}_{\text{Interaction}}$$

Table 2 presents the decomposition of the overall decline of R between changes in U, p_{sc} and p_{nrm}.

	R_{1989}	R_{2014}	ΔR	Composition	Propensity		Interaction
					Schooling	NRM	
R	50.64%	38.55%	−12.02%	−5.41%	−4.13%	−3.27%	0.79%

Table 2: Model-implied change in routine employment R between 1989 and 2014. The years are chosen as in Cortes, Jaimovich, and Siu (2016).

[28] Aguiar, Crossley, Charles, and Hurst (2017) emphasize importance of video gaming and other recreational computer activities in reducing labor supply of young males.

The model implies that both composition and propensities change are important for job polarization, with the latter force being more significant. This is consistent with the micro evidence provided by Cortes, Jaimovich, Nekarda, and Siu (2014) and Cortes, Jaimovich, and Siu (2016).

5.1.2 Business cycles

We now compare the response of the economy to business cycle shocks before and during the adoption of a technology. We investigate this question by first shocking the economy with an adverse z shock along the transition path. We consider a large 2.5 standard deviation z shock happening 23 years after the new technology arrival. Assuming that the technology arrived around 1985, the timing and the magnitude of the recession in the model corresponds to the Great Recession in the data. We then compare the outcome of this first experiment with the response of the economy to the same shock but before the new technology was available.[29]

The results are shown in Figure 5. We see that before the arrival of the new technology, when firms are not expecting any future change in technology, retraining of workers is counter-cyclical (the red dashed curves in Panels (f)-(h)), as is typical of RBC models with human capital (e.g., Perli and Sakellaris, 1998). The intuition is straightforward. During recession, workers are relatively inefficient in production and the economy therefore uses these periods to accumulate human capital. This process is however amplified along the transition path. In this case, in addition to the mechanism highlighted above, the household understands that, since firms also use the recession to adopt the new technology, the future demand for high-skill workers will increase. The recession is therefore the perfect period to retraining the workforce to use the new technology. In addition, since firms need high-skill workers to adopt the new technology, even more workers are taken away from production. As a result, an adverse productivity shock to the final good sector leads to a more active factors reallocation during the technological transition than before the arrival of the new technology. In particular, Panels (g) and (h) show that retraining is now absorbing more resources. Reallocation towards the adoption sector (Panel (i)), which is completely absent in the initial steady state, is responsible for roughly half of the additional drop in total production employment (Panel (f)).

Panels (j)-(l) of Figure 5 show the production-adoption decisions of the firms. Since the technology

[29] The arrival of the new technology changes the structure of the production technology. In general, this can affect the economy's response to business cycle shocks by itself. We verify that our results are driven by the interaction between the adoption and business cycle rather than a different production technology. In Appendix D we consider the impulse response functions to the same z shock in the new steady state. We find that the responses are much closer to their pre-transition counterparts than to the ones observed along the transition path.

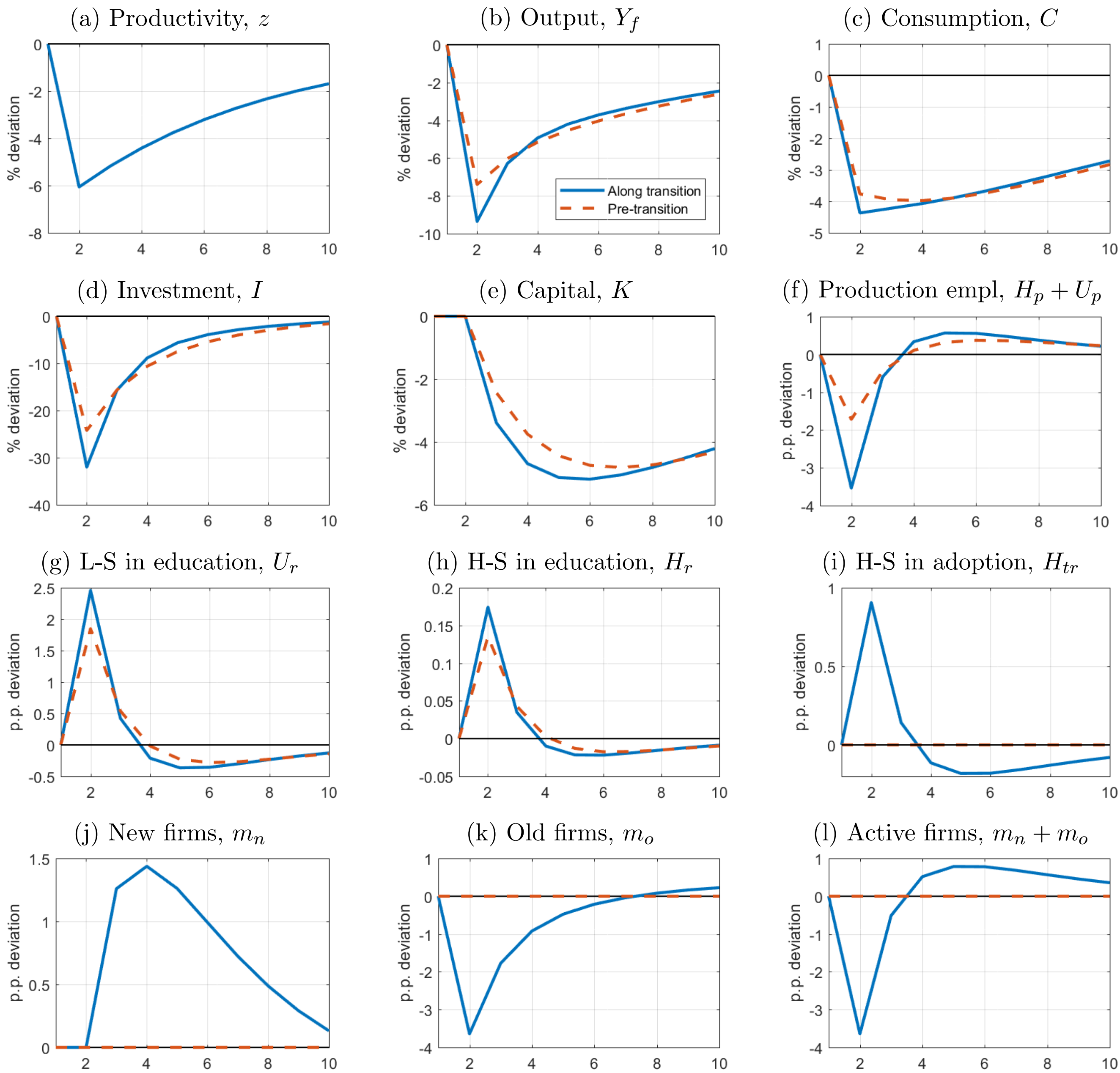

Figure 5: IRFs after a negative z shock. Graphs are plotted relative to no z shock scenarios

change requires a temporary halt to production, it is more attractive during economic downturns. A negative TFP surprise leads to a sharp drop in current profits. At the same time, due to mean reversion of the z process, future cashflows are less affected by a contemporaneous shock. Therefore, the new technology adoption is relatively more attractive during downturns because, if successful, it increases profits in all future periods. The counter-cyclical adoption incentive is mitigated (and in general can be even overturned for a large enough value of the risk aversion parameter γ) by consumption smoothing of the representative household. However, this effect turns out to be relatively small for a conventional value of $\gamma = 1$. Panel (k) shows that the mass of old firms drops by 3.5 p.p. as a result of the negative z shock. This drop leads to a lagged increase in the mass of firms operating the new technology, as shown in Panel (j).

As a result of the technological adoption and the workers retraining triggered by the recession, the drops in output, consumption and investment are all significantly more pronounced during the technological transition than before the arrival of the technology (Panels (b)-(d) in Figure 5).[30]

5.2 Routine-biased technological change and the Great Recession

We now investigate whether the model can rationalize both the long-run trend in the employment shares induced by routine-biased technological change and the importance of recessions in generating job polarization. We use the same definitions and data sources as JS. Particularly, non-routine cognitive/non-routine manual/routine jobs in their definition correspond to high-skill/low-skill services/low-skill goods jobs in the model. Figure 6 shows the results.

We consider the impact of a negative 2.5 standard deviation z shock 23 years after the technology arrival for the model-implied employment shares. Again, given our timing, this shock corresponds to the Great Recession in the data.[31] The top panel of the figure shows the employment share of high-skill (model) versus non-routine cognitive (data) workers. Since the technological progress favors the high-skill intensive technology, the corresponding employment share is gradually growing. At the same time, the recession induces more active retraining, resulting in an upward shift of the curve. Similarly, low-skill goods employment share (bottom panel) is declining and discontinuously jumps down during the downturn. Finally, low-skill services employment share (middle panel) stays almost constant for the first 15 years. Since goods and services are strong complements, during the initial transition stage, when the goods sector output is barely changed, it is optimal not to increase the service sector output as well. Later on, low-skill employment starts to grow.[32]

Recent empirical evidence (e.g., JS and Hershbein and Kahn, 2016) emphasize the acceleration of the routine employment loss during the Great Recession. Figure 7 takes a closer look at this phenomenon. In the data, the routine employment share dropped by 1.90 p.p. between 2007Q4

[30]In Appendix E we verify that recessions during technological transitions are still deeper, even after adjusting the output measure for learning costs.

[31]The size of the shock is picked in order to match an almost 10% drop in output in the Great Recession (Fajgelbaum, Schaal, and Taschereau-Dumouchel, 2017).

[32]The model does not match an increase of the non-routine manual employment share during the Great Recession. A negative TFP surprise induces reallocation of high-skill workers towards adoption and teaching. As a result, the goods sector's production drops. Due to complementarity between goods and services, marginal productivity of low-skill workers in the services sectors declines. The planner therefore moves them to schools.

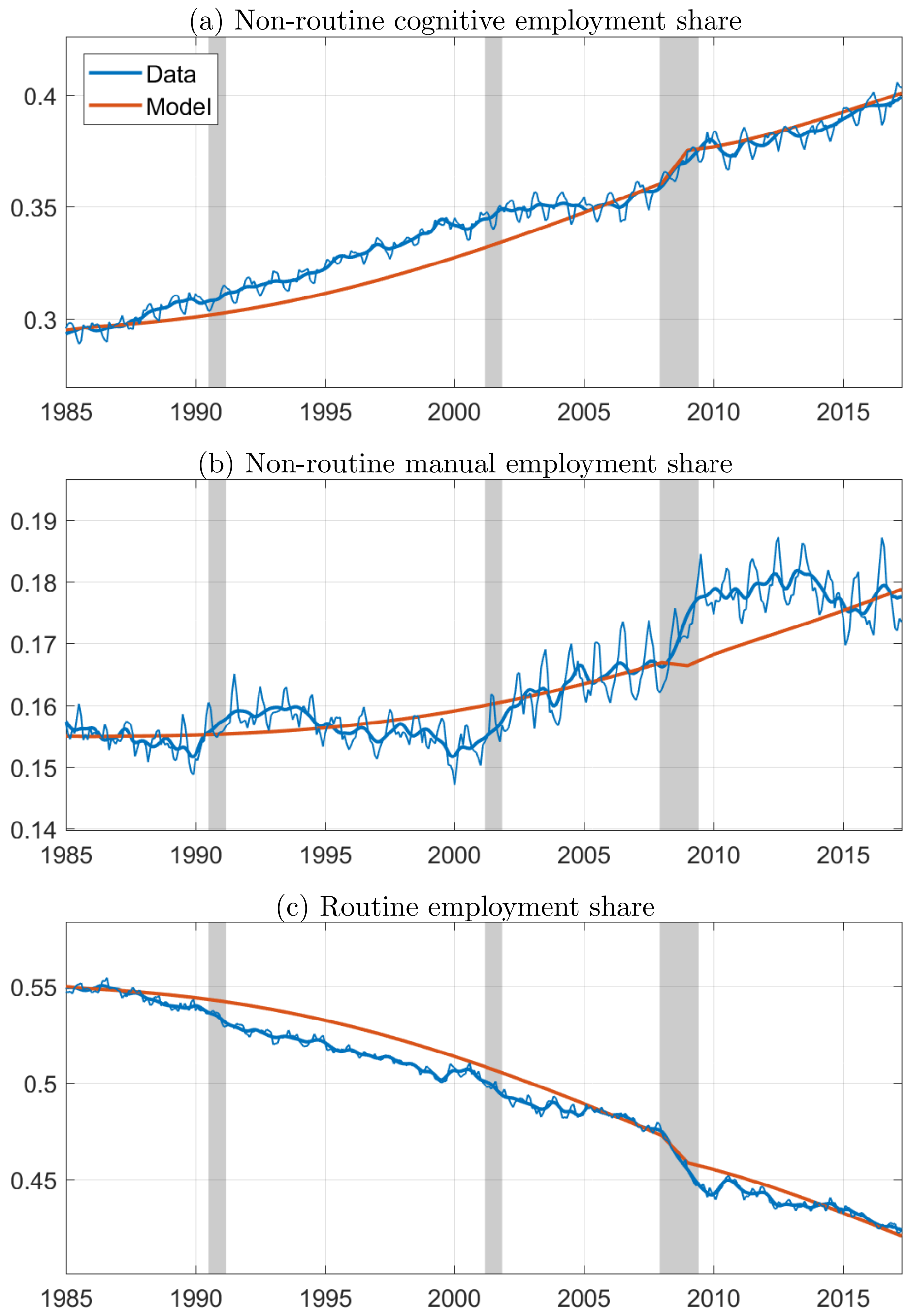

Figure 6: Employment shares by type of jobs. Definitions are from JS. Smooth blue lines show the series adjusted for seasonality with a 13-term Henderson filter (Henderson, 1916)

and 2008Q4.[33] Thus, 15% of the overall drop observed between January of 1985 and April of 2017 happened during only 1 year, or 3% of the total time span. In the model, a 2.5 standard deviation negative z shock implies a drop of 1.42 p.p., or nearly 75% of what is observed in the data. In the absence of the z shock, the model-implied routine employment share would have declined by only 0.57 p.p. because of the gradual transition between the steady states. The model is therefore able to replicate a substantial fraction of the routine employment loss during the Great Recession.

[33] We consider 1 year after the start of the Great Recession, since in our model we approximate the Great Recession by 1 large negative z shock. An alternative approach would be to extract a sequence of TFP shocks to match a cumulutive drop in output in the data and in the model, feed these shocks to the model, and then compare the overall drop during the Great Recession.

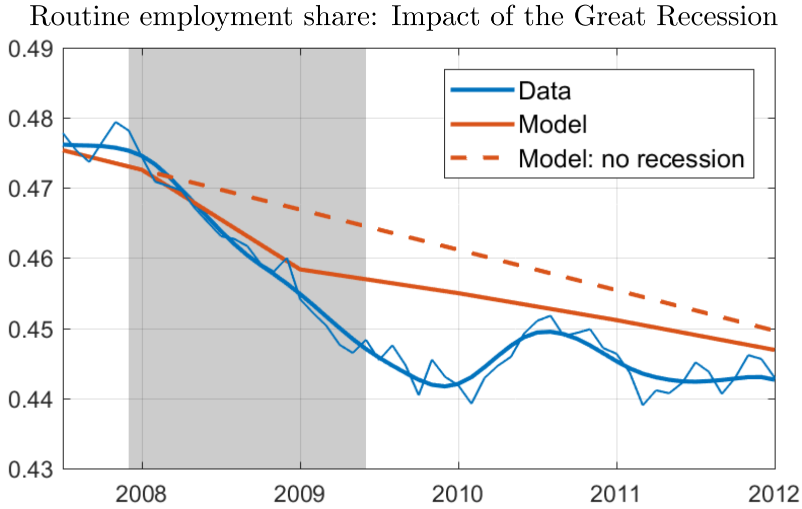

Figure 7: Routine employment share (defined as in JS) around the Great Recession. Red dashed line shows the model-implied path holding z at the steady state level. Smooth blue line shows the series adjusted for seasonality with a 13-term Henderson filter (Henderson, 1916)

Overall, Figure 6 and 7 show that the model does a rather good job in matching several important aspects of the job polarization phenomenon. First, the model is able to replicate the steady decline, since at least the start of the job polarization era, of the fraction of routine workers while, at the same time, replicating the increase in both non-routine cognitive and manual jobs. To do so, the model relies only on changes in the A_n process and complementarity between goods and services. Second, the model is also able to generate the acceleration of the job polarization process during recessions and, specifically, during the Great Recession. The counter-cyclical restructuring incentives are responsible for these rapid movements during recessions.

6 Conclusion

In this paper, we analyze the interaction between routine-biased technological change and business cycles. Since economic downturns are periods of low opportunity costs, they are used by firms to optimize their production technology and by workers to adjust their skill set to a changing economic environment. Restructuring incentives are enhanced during technological transitions, associated with higher than usual demand for new skills. As a result, recessions during transitions are marked by high scarcity of factors in the production of the final good. At the same time, routine-biased technological change is accelerated, consistent with the recent empirical evidence.

The paper provides a theoretical rationale for two major features of job polarization. First, the fraction of routine workers has been declining since at least the mid 1980s, while both non-routine cognitive and non-routine manual employment shares have been growing. Second, job polarization is concentrated in recessions. In our model, a gradual technology adoption generates the trend, while large downturns speed up the transition due to counter-cyclical restructuring incentives.

The model can be extended along several important directions. First, as discussed in Section 5.1.1, one could allow workers to permanently stay out of labor force, for example, by introducing a home production sector. It would be interesting to investigate, both theoretically and empirically, how routine-biased technological change and recessions along the transition path affect labor adjustments along this margin. Another potential direction would be enriching the model with labor-leisure choice. If the value of leisure is affected by new technologies, as suggested by Aguiar, Crossley, Charles, and Hurst (2017), then the model can rationalize declining labor force participation, as well as job polarization.

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Appendix

A Industrial robots

Figure A1 shows the worldwide shipment of industrial robots. After a temporary drop in 2009, the series recovered quickly and has been growing at a faster rate afterwards. The model interprets this data as an increase in technology adoption in the aftermath of the recession.

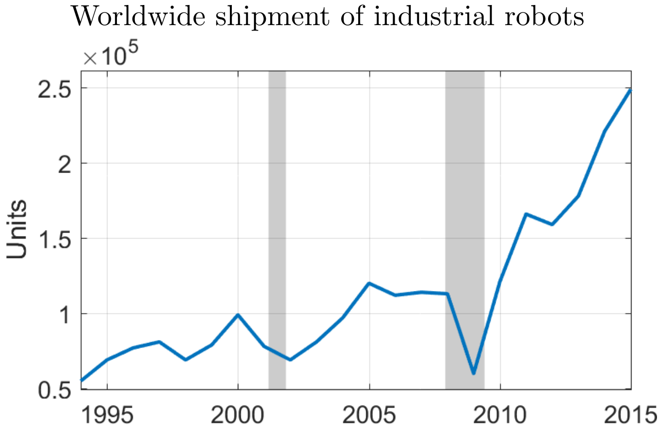

Figure A1: Data source: International Federation of Robotics

B Sensitivity analysis

B.1 Role of ρ

In the main text, we use $\rho = 0.3$, implying the elasticity of substitution between high and low-skill labor in the production sector of 1.43, as in Katz and Murphy (1992). Despite this value is standard in the literature, it is not necessarily applicable in our setting. First, in our model the aggregate production function is different from the one assumed in Katz and Murphy (1992). Second, our definition of skill is related to ability to implement non-routine cognitive tasks rather than to education. We therefore do a sensitivity analysis with respect to the value of ρ, varying the parameter from -0.3 to 0.6, which correspond to the elasticity of substitution of 0.77 and 2.50, respectively.

Holding all other parameters fixed, we redo the exercise from the main text and consider the impact of a large negative z shock on the time series of the employment shares. Figure A2 demonstrates the results. Naturally, the same skill-biased technological innovation implies a larger number of

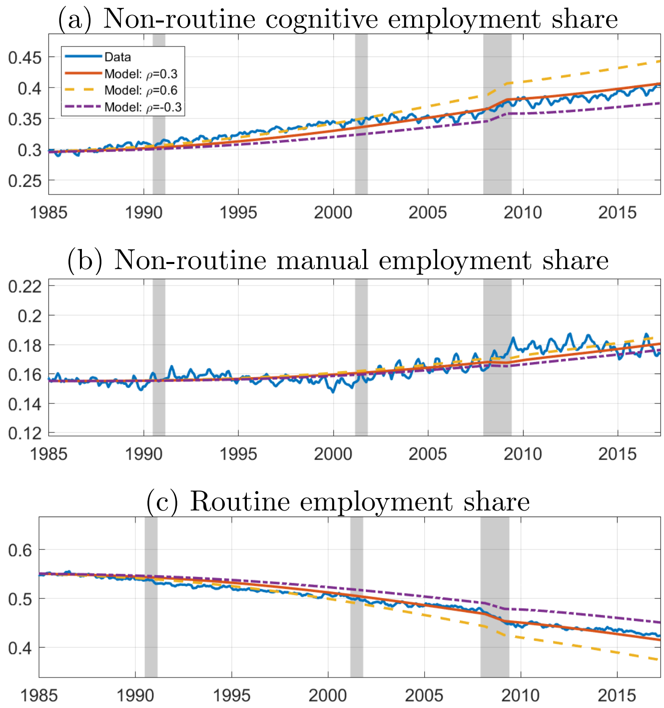

Figure A2: Employment shares by type of jobs: role of ρ

high-skill workers in the new steady state if the two types of labor are more substitutable in the production sector. As a result, the model-implied employment share of non-routine cognitive workers is increasing in ρ (top panel of Figure A2). Since goods and low-skill services are strong complements, it also leads to more low-skill workers employed in the service sector (middle panel of Figure A2).

As discussed above, higher values of ρ in general implies more reorganization needs for the same technological shock. Therefore, recessions are in general associated with more restructuring. However, the effect is marginal for a large range of ρ we consider. Importantly, the value of ρ does not affect the interaction between the technological adoption and business cycles qualitatively: recessions during technological transitions are still deeper and are associated with more reorganization. Corresponding graphs are omitted for brevity.

B.2 Role of ϵ

ϵ governs the degree of substitutability between goods and low-skill services. Our benchmark calibration uses $\epsilon = -2$. Normally, the literature (e.g., Buera and Kaboski, 2009 and Herrendorf, Rogerson, and Valentinyi, 2013) aims to estimate the degree of substitutability between goods and all, rather than just low-skill, services. For this reason, we try a wide range of ϵ from -5 to 0.5. Corresponding results are given in Figure A3.

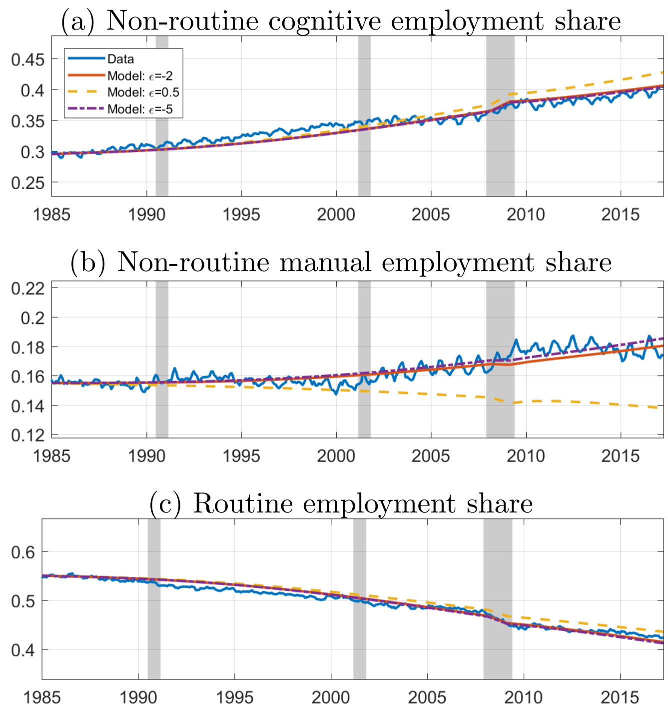

Figure A3: Employment shares by type of jobs: role of ϵ

Higher values of ϵ imply a higher level of substitutability between goods and services. If goods and services are strong complements ($\epsilon = -2$ and especially $\epsilon = -5$), enhanced productivity of the goods sector due to routine-biased technological change is also associated with an elevated demand for services. Thus, for these values of ϵ the employment share of non-routine manual labor goes up (middle panel of Figure A3). However, for sufficiently high ϵ, it becomes optimal to move resources towards more productive goods sector, and employment in low-skill services decreases.

As with ρ, we verify that the value of ϵ does not affect the interaction between technology adoption and business cycles in any important way.

B.3 Role of θ

In our benchmark calibration $\theta = 0.75$. This implies the elasticity of substitution between new and old goods of 4. While this is in line with some of the existing estimates (e.g., Hsieh and Klenow, 2014, Bernard, Eaton, Jensen, and Kortum, 2003, Christiano, Eichenbaum, and Trabandt, 2015), other studies report much larger values (e.g., Kuester, 2010, Altig, Christiano, Eichenbaum, and Linde, 2011). Figure A4 shows the results for our benchmark calibration and $\theta = 0.9$.[1]

[1] We also increase the initial technological shock A_n^0 from 0.1 to 0.5. For smaller values of A_n^0 the numerical algorithm fails to converge since at the initial stages of the transition marginal benefit from adding a new firm is infinitesimal. The Matlab solver has problems when solving Euler equations under these circumstances.

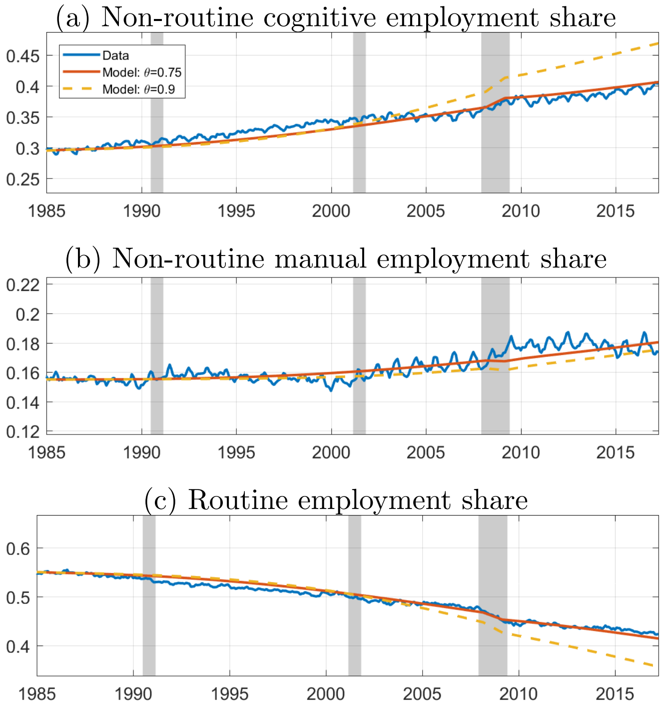

Figure A4: Employment shares by type of jobs: role of θ

Higher θ affects the transition paths in two ways. First, for high θ there is more firms producing new goods and thus more workers are high-skill in the new steady state, since the new technology is skill-intensive. Second, the transition is more concentrated in time. If goods are easily substitutable, it is optimal to produce both of them only if productivities are sufficiently close. Hence, the adoption tends to start later, when productivity of the new sector is high enough, but takes less time. A more concentrated transition leads to more active interaction between business cycles and adoption. In particular, we find that in the economy with $\theta = 0.9$ and all other parameters at the benchmark values, right after the Great Recession-like shock, the number of reorganizing old firms increases by more than 1 p.p. Employment in production drops by additional 0.7 p.p. As a result, output drops more by almost 1%.[2]

B.4 Role of η

The parameter η governs the importance of capital and high-skill labor for the technology adoption. In the benchmark calibration $\eta = 1.5$, which implies the probability of successful technology adoption is about 0.3, in line with Brynjolfsson, Malone, Gurbaxani, and Kambil (1994) and Brynjolfsson and Hitt (2003). We also try $\eta = 0.1$ and $\eta = 10$, corresponding to the probabilities around 0.1 and 0.64, respectively. As documented in Figure A5, lower η generally slows down the

[2]These numbers are not immediately comparable to our benchmark results. In the main text, we pick the exogenous path of A in order to match the time series behavior of the routine and non-routine employment shares. Therefore, for $\theta = 0.9$ one should reparametrize the A process accordingly.

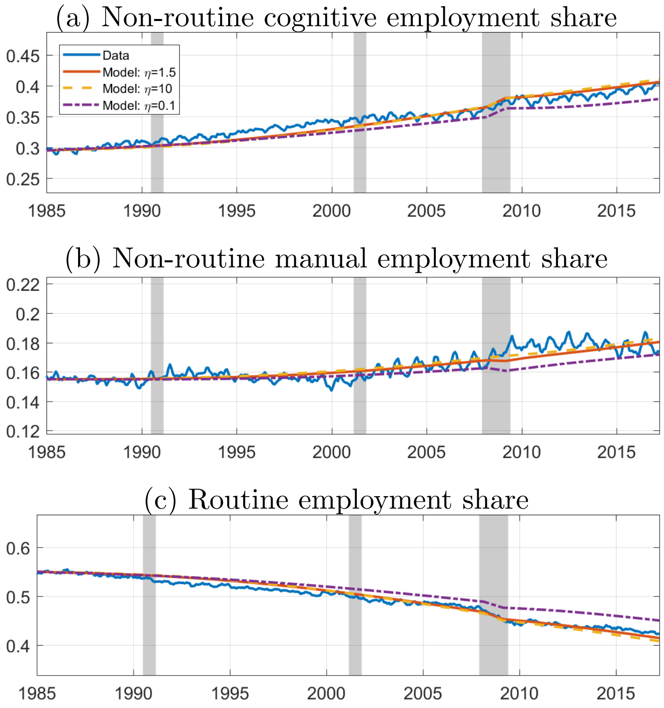

Figure A5: Employment shares by type of jobs: role of η

adoption process. This result is natural: for low levels of η learning costs are high.

The value of η also importantly affects the interaction between the adoption process and business cycles (Figure A6). For high η the adoption process does not require much resources. Thus, impact of a negative z shock on H_{tr} is minimal (the red dashed line in Panel (d) of Figure A6). Since high-skill workers stay in the production sector, it is not optimal to move many low-skill workers to the retraining sector, as shown in Panel (c). As a result, the production sector employment and output does not drop that much (Panels (b) and (a), respectively). Finally, the response of mass of restructuring firms is nonlinear in η (Panel (f)). For low η, the probability of successful switching is low and it's too costly to send many firms to the reorganization process. For high η, on the contrary, successful switching is much more likely. There is no need to temporarily shut down production of many old firms. For moderate levels of η, these two forces are balanced and m_o drops the most after an adverse TFP surprise.

B.5 The $A_n(t)$ process

In the main text we assume that the technological transition takes $T_{finish} - T_{start} = 75$ years and the terminal value is $\bar{A}_n = 1.5$. We verify that our main results are robust to a simultaneous change of these parameters. For example, if we consider a shorter transition period of 50 years, we can match the employment shares by setting $\bar{A}_n = 1.15$. Interaction of the technology adoption

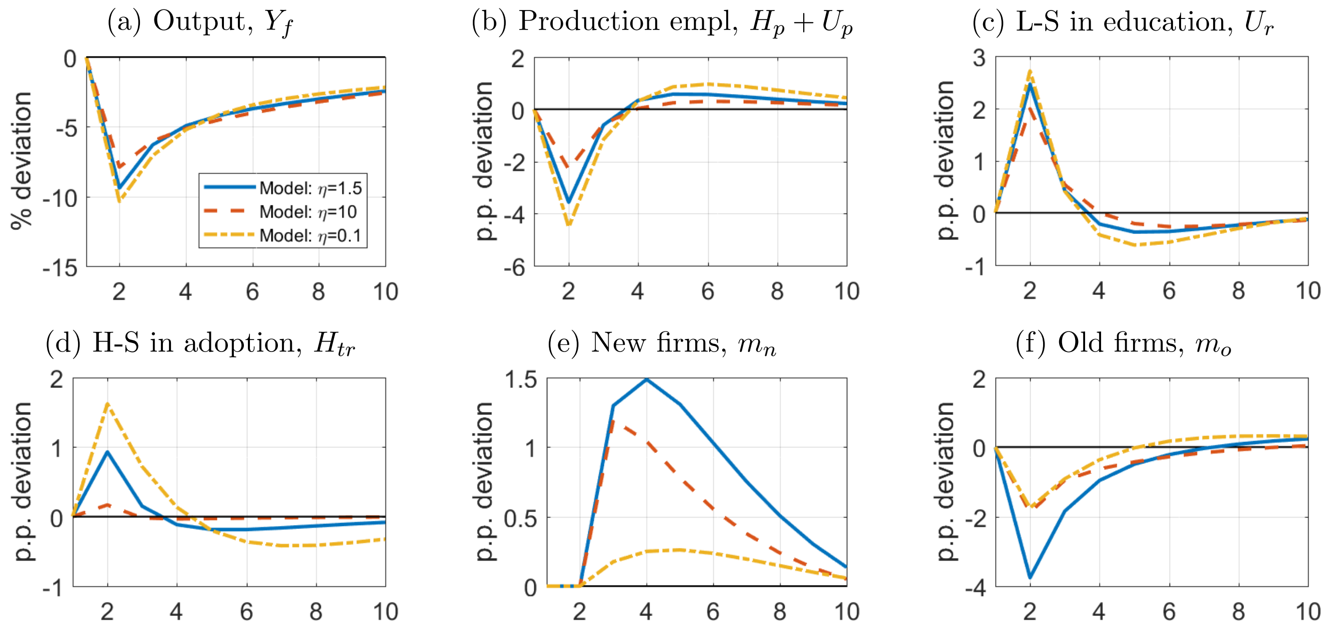

Figure A6: IRFs after a negative z shock: role of η

and business cycles remains the same both qualitatively and quantitatively.

C Diffusion externality

In our benchmark analysis, we assume that the technology adoption requires both time and resources (capital and high-skill labor). One potentially important aspect of the adoption process, left aside in the main text, is diffusion externality (Andolfatto and MacDonald, 1998). The idea is that the ease of technology learning is positively related to the mass of its users. In our model, a negative TFP shock leads to enhanced restructuring and an increase in m_n. Interaction between the diffusion externality and business cycles therefore is nontrivial. An increase in m_n after a negative TFP surprise incentivizes remaining old firms to adopt the technology. Given that the adoption process is costly, the impact of the shock is more prolonged.

We reparametrize the adoption probability function in order to capture the aforementioned externality:

$$\xi(m_n, k, h) = (p_0 + p_1 m_n) \times \left(1 - \exp\left(-\eta k^{\beta_{tr}} h^{1-\beta_{tr}}\right)\right),$$

so the law of motion of the mass of new firms becomes

$$m_n' = m_n + \xi(m_n, k, h)(\bar{m} - m_n - m_o).$$

The parameter $p_1 \geq 0$ captures the strength of externality. If p_1 is high then increase in the probability due to increase in m_n is large. $p_0 > 0$ guarantees that the probability is positive in the initial steady state, where $m_n = 0$. Our default analysis implies $p_0 = 1$, $p_1 = 0$. In the new steady state $m_n = 0.675$. We consider two alternative values of p_1: $p_1 = 0.5$ and $p_1 = 1$. We set p_0 in order to have the same mass of new firms in the new steady state as in the benchmark model.

Figure A7 illustrates the impact of the diffusion externality on the dynamics of the employment shares. Higher values of p_1 correspond to slower adoption. This is due to our recalibration strategy. Our target is to have the same steady states, meaning that $p_0 + p_1\bar{m}$ is the same for any (p_0, p_1) pair. As a result, probability of successful adoption is low along the transition path when p_1 is high.

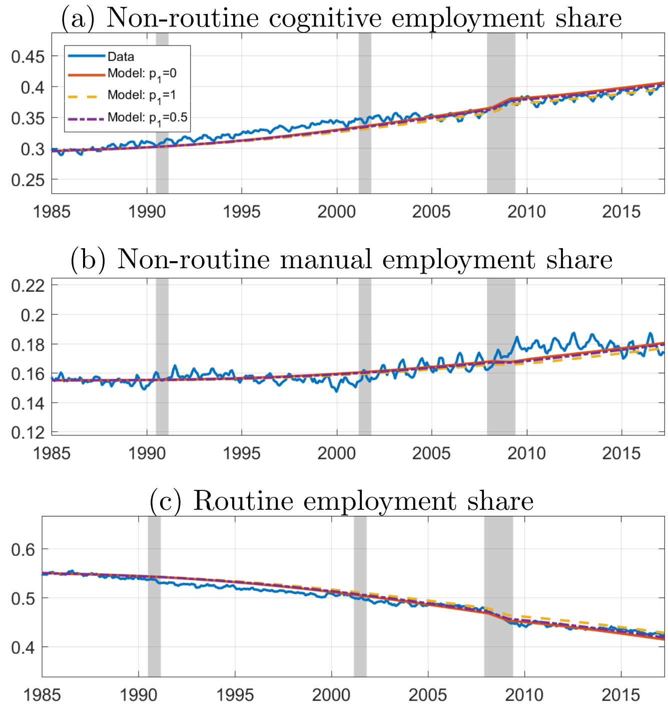

Figure A7: Employment shares by type of jobs: role of p_1

For the same reason, amplification of a negative TFP shock is weaker for high p_1 (Figure A8 illustrates the interaction between the diffusion externality and business cycles). Since the adoption probability is low, the value of switching option is also low, and fewer old firms choose to postpone their production for the same z shock. At the same time, the impact is more prolonged: the half life of the shock for $p_1 = 1$ is 1 year longer than for $p_1 = 0$. If the externality is strong, an increase in m_n right after the shock translates into enhanced adoption probability later on. This is in contrast to the benchmark case, where probability stays constant.

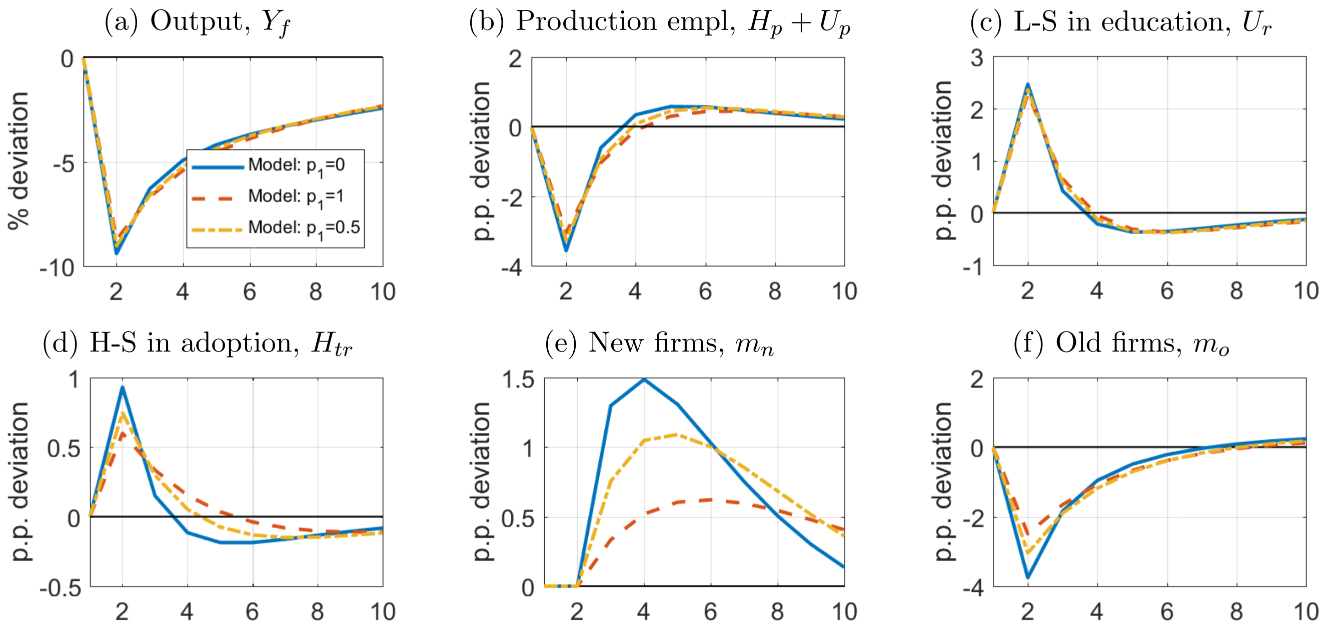

Figure A8: IRFs after a negative z shock: role of p_1

D Business cycles in the new steady state

In the model, the new technology arrival is associated with a change in production function. This can affect the economy's responses to business cycle shocks by itself. In order to verify that the results in the main text are driven by the interaction between the adoption and business cycle, rather than by a new structure of the production function, we compare the impulse responses to the same 2.5 standard deviation negative z shock in three scenarios. In the first case, the economy is the initial steady state; in the second case, the economy is in transition; in the third case, the economy is in the new steady state.[3] The results are given in Figure A9. When the economy is in the steady state (either new or old), the only amplification mechanism is reallocation of labor from the production to schooling. It turns out that this channel is weaker in the new steady state. The economy in transition is marked by a specific reallocation dimension (towards the adoption process), which generates an additional drop in the final good production.

E Different output measures

In the main text our main measure of output is the production of the final good Y_f. We adjust our output measure by taking into account elevated learning costs due to reallocation of high-skill

[3]For the latter case, we assume that the technology is fully absorbed, so the masses of new and old firms are constant along business cycles.

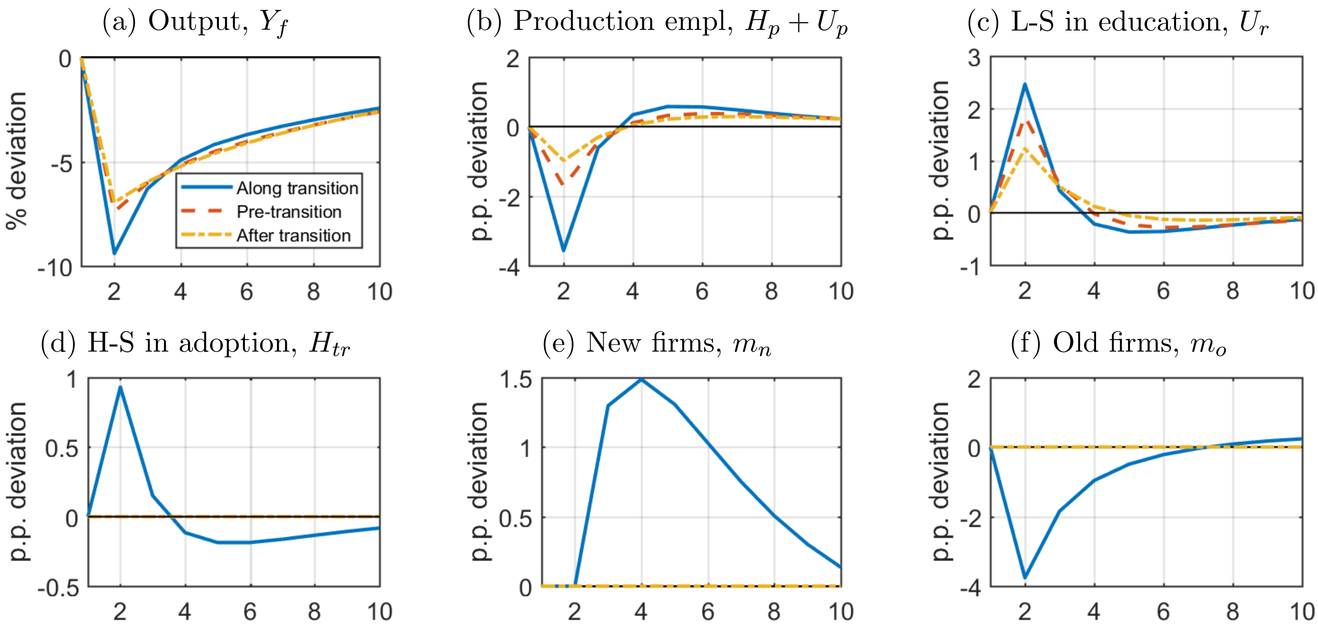

Figure A9: IRFs after a negative z shock

labor and capital towards the education and adoption sectors,

$$Y_{adj,1} = Y_f + w_h H_s + r K_s,$$

$$Y_{adj,2} = Y_f + w_h(H_{tr} + H_s) + r(K_{tr} + K_s),$$

and repeat the exercise from Section 5.1.2.[4] The results are given in Figure A10. Right panel of this figure demonstrates that the same z shock leads to a larger drop in aggregate product for the economy in transition, even if the output measure is adjusted for adoption and learning. The remaining difference is due two channels. First, the adoption sector uses not only high-skill labor and capital but also mass of firms as production factors, so ideally output measures should be adjusted for that as well. Similarly, the education sector's output should be adjusted by added value of low-skill labor.

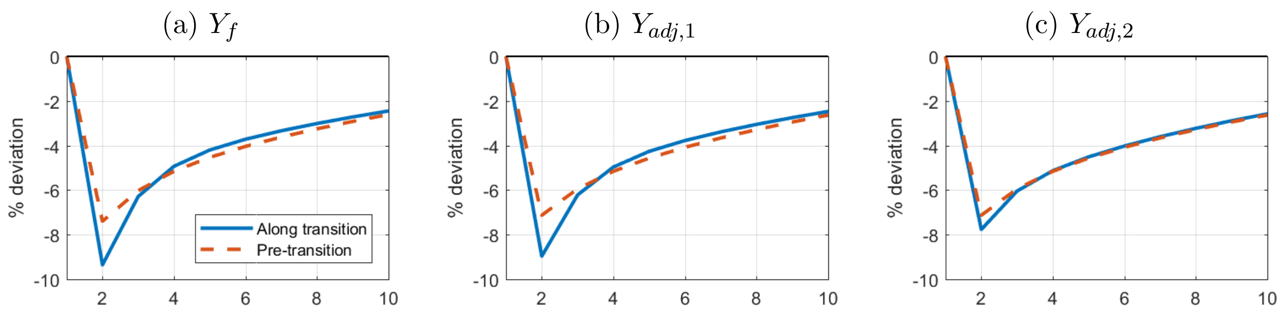

Figure A10: Impact of a negative z shock on two measures of output

[4]It is not clear whether output adjusted in this way makes the model closer to reality. In the data investment in human and organizational capital might be largely mismeasured, as pointed out by, for example, Brynjolfsson and McAfee (2014).

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