Technology Shocks and Job Flows

CLAUDIO MICHELACCI
CEMFI

and

DAVID LOPEZ-SALIDO
Federal Reserve Board

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We consider a version of the Solow growth model where technological progress can be investment specific or investment neutral. The labour market is subject to search frictions, and the existing productive units may fail to adopt the most recent technological advances. Technological progress can lead to the destruction of technologically obsolete jobs and cause unemployment. We calibrate the model to replicate the high persistence that characterizes the dynamics of firms’ neutral technology and the frequency of firms’ capital adjustment. We find that neutral technological advances increase job destruction and job reallocation and reduce aggregate employment. Investment-specific technological advances reduce job destruction, have mild effects on job creation, and are expansionary. Hence, neutral technological progress prompts Schumpeterian creative destruction, while investment-specific technological progress operates essentially as in the standard neoclassical growth model. Using structural VAR models, we provide support to the key dynamic implications of the model.

1. INTRODUCTION

The adoption of new technologies may require the destruction of outdated relatively obsolete productive units. In the words of Schumpeter (1934), “firms must be driven into the bankruptcy court and people thrown out of employment, before the ground is clear and the way paved for new achievement of the kind which has created modern civilization”. Microeconomic evidence on productivity dynamics supports this view: the process of creative destruction, whereby newly created highly productive jobs displace old technologically obsolete jobs, greatly contributes to aggregate productivity growth, especially in industries and periods characterized by rapid technological change.1

Indeed, the Schumpeterian view has strongly influenced the literature on the linkages between growth and labour market outcomes; see Aghion and Howitt (1994), Mortensen and Pissarides (1998), Violante (2002), and Hornstein, Krusell and Violante (2002, 2005). Yet, the business cycle implications of technology adoption remain largely unexplored. Technology shocks are typically assumed to instantaneously affect every firm’s production technology. This contradicts the micro-evidence that firm-level technologies exhibit remarkable persistence and that the creation of new firms and jobs plays an important role in technology adoption.2 Building on this evidence, we argue that the waves of creative destruction prompted by some technology shocks can contribute to explaining business cycles.

We consider a version of the Solow (1960) growth model where technological progress can be investment specific or investment neutral. Investment-specific technological advances make

1. See Foster, Haltiwanger and Krizan (2001) for an exhaustive review of the literature on the relation between aggregate and firm productivity dynamics.
2. See Bartelsman and Doms (2000) for a review on technology dynamics at the micro-level.
new capital equipment less expensive, while the adoption of neutral technological advances yields productivity gains even in the absence of capital investment.\textsuperscript{3} We assume that the reallocation of workers is sluggish due to the existence of search frictions in the labour market and that job technologies persist over time. Specifically, as in Aghion and Howitt (1994) and Mortensen and Pissarides (1998), newly created jobs embody the most advanced technologies (both neutral and investment specific) available at the time of their creation. Existing jobs instead may fail to upgrade their previously installed capital equipment, their neutral technology, or both. The idea is that the adoption of new technologies requires the performance of some new worker-specific tasks, so workers initially hired to operate specific technologies may not be suitable for their upgrading.\textsuperscript{4}

In the long run, any technological advance (either neutral or investment specific) leads to greater labour productivity and output. But the short-run response of the economy to a technology shock may be expansionary or contractionary on employment due to two opposite forces affecting job destruction. On the one hand, old jobs which fail to upgrade their technology become relatively more obsolete, thereby raising the incentive to destroy in order to create new more technologically advanced jobs. On the other hand, the desire to smooth consumption makes the economy spread out over time the pruning of relatively outdated technologies. In the model, the adoption of the new technology requires time and investment in capital, so consumption falls below its long-run steady-state value, and the marginal utility of consumption correspondingly increases. But this makes leisure relatively less valuable; it increases the net value of a job with a given technology and thereby reduces the incentive to destroy jobs.

When old jobs cannot easily upgrade their technology, the first effect dominates and technological progress causes a wave of Schumpeterian creative destruction characterized by a simultaneous increase in the destruction of technologically obsolete productive units and in the creation of new technologically advanced ones. But since labour market frictions make reallocation sluggish, employment temporarily falls. Conversely, when the old jobs’ technologies can be readily upgraded, technological advances make all jobs relatively more profitable, so job destruction falls and the economy experiences an expansionary phase characterized by greater employment and output.

We calibrate the economy to replicate features of technology dynamics at the micro-level. In particular, we reproduce the remarkably high persistence that characterizes the dynamics of firms’ neutral technology, as evidenced by Baily, Hulten and Campbell (1992) and Bartelsman and Dhrymes (1998), and the frequency at which firms adjust their capital equipment, as reported by Cooper and Haltiwanger (2006). We find that a neutral technology shock prompts a wave of creative destruction, where job creation, job destruction, and unemployment simultaneously increase, while the adoption of investment-specific technologies operate essentially as in the standard neoclassical growth model, leading to an expansion in economic activity.

To test the key dynamic implications of the analysis, we notice that the model implies that investment-specific technological progress is the unique driving force of the secular trend in the relative price of equipment goods, while neutral technological progress explains any remaining

\textsuperscript{3} Examples of investment-specific technological advances include the introduction of more effective software, more powerful computers, or more efficient means of telecommunication and transportation. Conversely, innovations in products and services, improvements in managerial practices and in the organization of production are examples of neutral technological progress; see Bresnahan, Brynjolfsson and Hitt (2002) and Acemoglu, Aghion, Lelarge, Van Reenen and Zilibotti (2007) for a firm-level analysis of the effects of various forms of information technology and organizational change on skill demand.

\textsuperscript{4} Gordon (1990) provides examples from different industries where the adoption of new technologies requires the worker to perform a variety of new tasks. See also Brynjolfsson and Hitt (2000) for a review of the empirical evidence documenting the relation between adoption of information technologies and transformation of organizational structure and work practices.

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component in the trend of labour productivity. We impose these long-run restrictions in structural vector auto regression (VAR) models, and we find that a neutral technological advance causes a short-run increase in job destruction and job reallocation and a contraction in aggregate employment. In contrast, an unexpected reduction in the price of new capital equipment reduces job destruction, has mild effects on job creation, and it is expansionary on employment, output, and investment. In the long run, either technology shock makes output and labour productivity increase. This is also what our model predicts.

Our model falls into the labour market search tradition pioneered by Mortensen and Pissarides (1994). Several other papers have considered labour market search within general equilibrium models with capital accumulation. This paper is, however, the first in analysing the dynamic response to technology shocks in a model with vintage effects in the job technology. Thus, the paper provides a methodological contribution in showing how to compute the equilibrium of a model with a frictional labour market, microeconomic heterogeneity, and aggregate uncertainty. The claim that neutral technology shocks are “Schumpeterian” is also novel.

We are not the first to analyse the relevance of creative destruction for business cycle analysis. Caballero and Hammour (1996, 2005) consider a vintage model where ongoing technological progress makes all old jobs obsolete since their technology cannot be upgraded. They analyse the response of unemployment and job reallocation to aggregate shocks that equally affect the productivity of any job in the economy. None of these papers analyse whether technological advances are expansionary or lead to a temporary rise in job reallocation and technological unemployment.

Our empirical results are related to the recent findings by Galí (1999). Galí assumes that there exists only one technology shock that determines productivity in the long run. Using structural VAR models, he shows that this technology shock leads to a fall in the aggregate number of hours worked. These results have cast some doubts about the possibility that technology shocks drive business cycles. We notice instead that, under fairly general balanced growth conditions, neutral and investment-specific technological change independently determines the evolution of aggregate labour productivity in the long run. We find that investment-specific technology shocks cause an expansion in employment, output, and investment—which is the typical dynamics of an expansionary phase of the business cycle. We also find that neutral technology shocks explain a relevant proportion of the cyclical fluctuations of key cyclical variables such as output, job destruction, employment, and consumption. Intuitively, neutral technology shocks induce jobless recoveries, which appear to be a prominent feature of some business cycles: following the initial rise in job destruction, output builds up until it reaches its new higher long-run value, but during the whole transition path employment remains below trend—that is, the rise in output is jobless.

Finally, our results should be related to Fisher (2006) and Altig, Christiano, Eichenbaum and Linde (2005). These papers have also analysed the effects of neutral and investment-specific technology shocks using structural VAR models. Our sample period differs from theirs, and differently from them, we focus on job flows to better investigate the effects on reallocation which are key to identify creative destruction. Furthermore, we analyse labour market adjustment along the extensive margin (number of employees) separately from adjustment along the intensive margin (number of hours worked), which allows us to stress that the two margins can behave

6. See the computational appendix for details.
7. These results have been subject to subsequent investigation. See Galí and Rabanal (2004) for a review of this literature.
8. In our model, jobless recoveries are the result of technological change and the transitory need to reallocate factors of production. This is also one of the likely explanations for jobless recoveries put forward by Bernanke (2003).
differently. In particular, in response to a neutral technology shock, employment falls but, as some jobs adopt the more advanced technology and working hours adjust, the number of hours worked per employee increases. This composition effect makes aggregate hours worked respond little to neutral technology shocks, which can explain why their contribution to the volatility of hours worked appears to be small in the data.

The rest of the paper is structured as follows: The findings about the effects of technology shocks on job reallocation appear in Section 2. Section 3 describes the model. Section 4 characterizes the equilibrium. Section 5 discusses calibration. The results appear in Section 6, while Section 7 discusses some extensions and some robustness exercises. Section 8 concludes. The Appendix contains some technical derivations.

2. EMPIRICAL EVIDENCE

We first discuss how we identify the effects of neutral and investment-specific technology shocks in the data. Then, we discuss the data used and present the empirical results.

2.1. Identification strategy

Our identification scheme hinges on assuming that aggregate productivity is the sum of a stationary component and a technology component driven by neutral and investment-specific technology shocks. This decomposition holds in several version of the Solow (1960) growth model, including the version considered in Section 3. To illustrate the decomposition, consider a simple version of the Solow (1960) growth model where there are two inputs, capital, $\tilde{K}$, and labour, $N$, and the production function is Cobb–Douglas:

$$\tilde{Y} = Z\tilde{K}^\alpha N^{1-\alpha}, \quad 0 < \alpha < 1.$$  

Here, $\tilde{Y}$ is the final output and $Z$ is the investment-neutral technology. Final output can be used for either consumption $\tilde{C}$ or investment $\tilde{I}$, that is, $\tilde{Y} = \tilde{C} + \tilde{I}$. A stationary fraction of output $s$ is invested, $\tilde{I} = s\tilde{Y}$. Next, period capital stock, $\tilde{K}'$, is given by

$$\tilde{K}' = (1-\delta)\tilde{K} + Q\tilde{I},$$

where $0 < \delta < 1$ is the depreciation rate which is assumed to be stationary. The variable $Q$ formalizes the notion of investment-specific technological change. A higher $Q$ implies a fall in the cost of producing a new unit of capital in terms of consumption. If the sector producing new units of capital is competitive, the inverse of its relative price (i.e. relative to consumption) is an exact measure of $Q$.9

One can easily check that the economy evolves around the (possibly stochastic) trend given by

$$X \equiv Z^{1-\alpha} Q^{\alpha/(1-\alpha)}$$

and that the quantities $Y \equiv \tilde{Y}/(XN)$ and $K \equiv \tilde{K}/(XQN)$ tend to converge to $Y^\ast = (s/\delta)^{\alpha/(1-\alpha)}$ and $K^\ast = (s/\delta)^{1/(1-\alpha)}$, respectively. Thus, the model predicts that the logged level of aggregate productivity, $y_n \equiv \ln \tilde{Y}/N$, evolves as

$$y_n = y^\ast + \epsilon + x = y^\ast + \epsilon + \frac{1}{1-\alpha}z + \frac{\alpha}{1-\alpha}q,$$  \hspace{1cm} (1)

9. For simplicity, we do not distinguish between capital equipment and capital structure. Empirically, the price of structures has remained approximately constant, while that of equipment is downwards trended, so investment-specific technology progress mainly pertains to equipment goods.
where a quantity in small letters denotes the log of the corresponding quantity in capital letters, while $\varepsilon$ is a stationary term which accounts for transitional dynamics in the convergence to the steady state. Equation (1) decomposes aggregate productivity as the sum of a stationary term, which accounts for the steady state and any transitional dynamics, plus a trend induced by the evolution of the neutral and the investment-specific technology, which independently determines aggregate productivity in the long run. Equation (1) allows to identify technology shocks by using long-run restrictions in structural VAR models, as in Blanchard and Quah (1989), Galí (1999), and more recently Fisher (2006) and Altig et al. (2005). Specifically, we identify a neutral technology shock (a $z$-shock) as having zero long-run effects on the level of $q$ and non-nil long-run effects on labour productivity. Conversely, an investment-specific technology shock (a $q$-shock) can simultaneously affect the long-run level of labour productivity and $q$. Any other shock has no long-run effects on $q$ and labour productivity.

2.2. Data

We consider a VAR with a vector of variables $X = (\Delta q, \Delta y_n, jc, jd, iy, h, cy)'$, where $\Delta$ is the first difference operator. The variable $q$ is equal to minus the logged price, in terms of consumption units, of a quality-adjusted unit of new equipment, $y_n$ is logged labour productivity where output (for consistency with the Solow model) is measured in the same unit as $q$, while $jc$ and $jd$ denote the job creation rate and the job destruction rate, respectively. The variables $iy$, $h$, and $cy$ represent the (logged) investment expenditures over output ratio, (logged) aggregate hours worked per capita, and the (logged) consumption expenditures over output ratio, respectively. These additional variables are suggested by the balanced growth implications of the Solow model and are important to characterize the effects of technology shocks. Notice that this specification allows recovery of the effects of a shock on net employment growth (the difference between the job creation and the job destruction rate), the logged employment level, and the job reallocation rate (the sum of the job creation and job destruction rate).

We use quarterly U.S. data over the period 1972:I–1993:IV. The choice of the sample period is dictated by the availability of quarterly series for job flows, which are from Davis, Haltiwanger and Schuh (1997). The data for the job creation rate, $jc$, and the job destruction rate, $jd$, refer to manufacturing. The data on $q$ are taken from Cummins and Violante (2002), who extend Gordon’s (1990) measure of the quality of new equipment till 1999. The original series was annual, and it is converted into quarters as in Fisher (2006). The remaining series used in the VAR analysis are obtained from the USECON database commercialized by Estima and are all seasonally adjusted. Over the sample period, the rate of growth of labour productivity and the relative price of investment appear to be stationary. This is important since trend breaks in technology growth could bias the estimate of the effects of technology shocks; see, for example, Fernald (2004). Figure 1 characterizes how well manufacturing employment tracks the cyclical dynamics of aggregate employment. The first graph plots the difference between the job creation rate and the job destruction rate (which corresponds to the dashed line in the graph) together with the growth rate of manufacturing employment (the solid line), which is obtained from Federal Reserve Economic Data II (FREDII) (mnemonic MANEMP). The two series are very close, which just confirms that the data of Davis and Haltiwanger are representative of the whole manufacturing industry. More
In the first graph, the dashed line corresponds to the difference between the job creation rate and the job destruction rate and the solid line to the growth rate of manufacturing employment as obtained from FREDII. In the second graph, the solid line corresponds to manufacturing employment (as obtained from FREDII), the dashed line to minus civilian unemployment (as obtained from the Bureau of Labour Statistics), and the dotted line corresponds to the aggregate number of hours worked per capita (in logs). The areas in grey correspond to the NBER recessions.

Informative is the content of the second graph in the figure. It plots in the same graph the series for manufacturing employment (which corresponds to the solid line), for minus civilian unemployment (the dashed line), and for aggregate hours worked per capita (dotted line). The series for total civilian unemployment is obtained from the Bureau of Labour Statistics (mnemonic LR). The three series exhibit a very similar cyclical pattern. As first observed by Caballero and Hammour (2005), this implies that the cyclical properties of manufacturing employment over the period 1972:I–1993:IV represent quite accurately the cyclical properties of aggregate employment. Finally, notice that, over our sample period, hours worked per capita are stationary, which is in line with the favourite specification for hours worked proposed by Altig et al. (2005) as well as with the model in the next sections.

2.3. Evidence

Figure 2 displays the impulse response (together with the 90% confidence interval) of labour productivity, job creation, job destruction, job reallocation, employment, hours worked, output, investment, and consumption to a neutral technology shock. The shock induces a short-run increase in productivity that builds up till reaching its long-run value after around three years. On impact, job destruction increases while job creation slightly falls. As a result, employment decreases and job reallocation increases. Over the transition path, job creation increases, job destruction quickly returns to its average level, and employment recovers. The figure also evidences that a z-shock leads to a rise in consumption and a fall in investment. Output is sluggish to respond, but then gradually builds up until it reaches its new higher steady-state value after around three years. Hours worked slightly falls on impact and then recovers. Over the adjustment path, however, hours worked per employee tend to remain above normal levels.

Figure 3 displays the response of the economy to an investment-specific technology shock. The shock leads to a fall in the relative price of capital equipment that tends to reach its long-run value after around four quarters. On impact, job destruction falls while job creation hardly moves. As a result, job reallocation falls and employment rises. Over the transition path, job creation falls, job destruction quickly returns to its average level, and the initial increase in employment is...
gradually absorbed. Output, hours worked, consumption, and equipment investment also increase in response to a $q$-shock.

Canova, Lopez-Salido and Michelacci (2006) provide further complementary evidence by analysing the effects of technology shocks on the ins and outs of unemployment. They use the recently produced data by Shimer (2005) who draws on the Current Population Survey public micro-data to calculate monthly series for the rate at which employed workers become unemployed (i.e. the separation rate) and unemployed workers find a job (i.e. the finding rate). Their estimated responses of the finding and separation rate to a $z$-shock and a $q$-shock are reproduced in Figures 4 and 5, respectively. The figures again show that, on impact, a neutral technology shock makes the separation rate increase and employment fall. Over the adjustment path, the job-finding rate falls, and it takes time to recover. In response to an investment-specific technology shock, instead, the separation rate falls and employment rises. Over the adjustment path, the job-finding rate remains above normal levels. Canova et al. (2006) also analyse the contribution of the finding and the separation rate to fluctuations in the unemployment rate due to technology shocks. They show that the separation rate accounts for a major portion of the response of the unemployment rate in the first quarters after the shock. Three quarters after, however, unemployment is mainly explained by fluctuations in the job-finding rate.

As discussed in the introduction, Fisher (2006) and Altig et al. (2005) have also analysed the effects of neutral and investment-specific technology shocks using long-run restrictions in structural VAR models. Our sample period differs from theirs. Also differently from them, we focus on job flows and we simultaneously analyse labour market adjustment along both the extensive

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FIGURE 3
Response to an investment-specific technology shock, seven variables VAR, sample period 1972:I–1993:IV. Solid lines represent impulse responses; dashed lines represent the 5% and 95% quantiles of the distribution of the responses simulated by bootstrapping 1000 times the residuals of the VAR.

FIGURE 4
Response of the ins and outs of unemployment to a ρ-shock. The graphs are taken from Canova et al. (2006). Solid lines represent impulse responses; dashed lines represent the 5% and 95% quantiles of the distribution of the responses simulated by bootstrapping 1000 times the residuals of the VAR. The sample period is 1973:II–1997:II, which follows the considerations in Fernald (2004). The results remain unchanged when considering the 1972:I–1993:IV period analysed in the paper. The original VAR is ran with three lags and contains six variables which are the rate of growth of q and labour productivity, (logged) unemployment–employment transition rate (job-finding rate in the figure), (logged) employment–unemployment transition rate (separation rate in the figure), (logged) unemployment rate, and (logged) aggregate hours worked per capita. The rates are constructed by Shimer (2005; see his webpage http://home.uchicago.edu/~shimer/data/flows/ for further details)
Response of the ins and outs of unemployment to a $q$-shock. See Figure 4 for further details.

**TABLE 1**

Forecast error variance decomposition: percentage of variance explained by $z$-shocks and $q$-shocks at different time horizons for the selected variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>$z$-shock</th>
<th>$q$-shock</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Horizon (quarters)</td>
<td>Horizon (quarters)</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>8</td>
</tr>
<tr>
<td>Job destruction</td>
<td>36.3</td>
<td>33.1</td>
</tr>
<tr>
<td>Job creation</td>
<td>37.6</td>
<td>23.1</td>
</tr>
<tr>
<td>Job reallocation</td>
<td>9.8</td>
<td>14.8</td>
</tr>
<tr>
<td>Employment</td>
<td>51.6</td>
<td>39.9</td>
</tr>
<tr>
<td>Aggregate hours worked</td>
<td>43.9</td>
<td>20.2</td>
</tr>
<tr>
<td>Output</td>
<td>9.3</td>
<td>47.6</td>
</tr>
<tr>
<td>Investment</td>
<td>13.3</td>
<td>43.2</td>
</tr>
<tr>
<td>Consumption</td>
<td>5.7</td>
<td>17.5</td>
</tr>
</tbody>
</table>

Margin (number of employees) and the intensive margin (number of hours worked). Thus, the results are hard to compare. The short-run responses of output, hours worked, and investment to a $q$-shock are similar to those reported by Fisher (2006) and Altig et al. (2005). The responses of labour productivity, investment, output, and consumption to a $z$-shock in Fisher and Altig et al. are similar to ours, in that we both find that the variables gradually build up till they reach their new higher long-run value. Differently from them, however, we find a slight initial fall in output and hours worked. Such differences, however, are not very important since both Fisher and Altig et al. find that the response of output and hours worked is not statistically different from zero in the first quarters after the shock.

Table 1 reports the percentage of variance explained by each technology shock at different time horizons for some selected variables. We focus on time horizons between 1 and 32 quarters which are the frequencies typically associated with business cycles. $z$-shocks account for a substantial proportion of the volatility of key cyclical variables: they explain between 30% and 40% of the volatility of job destruction, around 30% of the volatility of output, and more than 30% of the volatility of employment. Their contribution to the volatility of hours worked is instead smaller. Fisher (2006) also finds that neutral technology shock explains little of the cyclical

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12. We present the results from a VAR with three lags. When considering a four-lag specification, the contribution of investment-specific technology shocks falls slightly.
volatility of hours worked. For frequencies in the range of 16–32 quarters, $q$-shocks instead explain almost 40% of the volatility of hours worked. The two technology shocks together are an important source of cyclical volatility: if we consider output and we focus on a time horizon between 16 and 32 quarters, we obtain that around 60% of the volatility of output is explained by technology shocks.

3. THE MODEL

To rationalize the previous findings, we consider an extension of the Solow (1960) growth model where the labour market is subject to search frictions and where technology differences across productive units persist over time.\(^{13}\) Exactly as in (1), labour productivity can be decomposed as the sum of a stationary component and a stochastic trend, driven just by neutral and investment-specific technology shocks. Time is discrete and there is just one consumption good, which is the numeraire.

3.1. Job output and technologies

Final output is produced in jobs which consist of firm–worker pairs. A worker can be employed in at most one job where he supplies one unit of labour at an effort cost (in utility terms) $c_{w}$. A job with neutral technology $z$ and capital stock $k$ produces an amount of output equal to $e^{z_k^\alpha}$, $0 < \alpha < 1$.

Newly created jobs always embody leading-edge technologies, while old jobs may be incapable of upgrading their previously installed technologies. The idea is that the adoption of new technologies requires the performance of new tasks. Hence, workers initially hired to operate specific technologies may not be suitable for their upgrading.

Specifically, a job which starts producing at time $t$ operates with a neutral technology $z_{it}$ equal to the economy leading technology $z_t$ of that time, while old jobs are capable of adopting the current leading technology only with probability $a_z \in [0, 1]$.\(^{14}\) Formally, with probability $1 - a_z$ the current-period job’s neutral technology, $z_{it}$, remains in expected value unchanged, so that

$$z_{it} = z_{it-1} + \epsilon_{it},$$

where $\epsilon_{it}$ is an idiosyncratic shock which is iid normal with zero mean and standard deviation $\sigma_\epsilon$, while, with probability $a_z$, a job catches up with the leading technology in the economy and

$$z_{it} = z_t + \epsilon_{it},$$

so that the job technology equals (in expected value) the leading technology of that time, $z_t$. Hereafter, we will refer to the difference between the leading technology $z_t$ and the job’s neutral technology $z_{it}$ as the job technological gap, $\tau_{it} = z_t - z_{it}$.

As in Solow (1960) and Greenwood, Hercowitz and Krusell (1997), the sector producing capital is perfectly competitive and at time $t$ can produce one unit of quality-adjusted capital at marginal cost $e^{-qt}$, which will also be the price of a capital unit at that time. A newly created

\(^{13}\) The modelling of search frictions and technology adoption borrow from Aghion and Howitt (1994) and Mortensen and Pissarides (1998). See also Jovanovic and Lach (1989), Caballero and Hammour (1996), and Postel-Vinay (2002) for examples of vintage models that bear similarities to the Aghion–Howitt–Mortensen–Pissarides approach.

\(^{14}\) Following Mortensen and Pissarides (1998) and Jovanovic and Nyarko (1996), we could endogenize the adoption probabilities $a_z$ and $a_q$ (see below) by assuming that firms face idiosyncratic time-varying adoption costs which may depend on workers’ versatility and the complexity of the new tasks to be learned. In equilibrium, only a fraction of old jobs will switch onto the technological frontier.
job installs its desired capital level acquired at the price of the time when it starts production. Conversely, an old job in operation at time $t$ can adjust its capital stock only with probability $a_q \in [0, 1]$. In that case, new capital can be installed at marginal cost $e^{-q_t}$. Otherwise, the job makes use of the capital stock inherited from the previous period. Capital (stochastically) depreciates by a factor $e^{-\delta}$, where $\delta$ is iid normal with mean $\mu_\delta$ and standard deviation $\sigma_\delta$.\footnote{The idiosyncratic shocks $\epsilon$ and $\delta$ guarantee that the cross-sectional distribution of job technology and capital has no mass points. In turn, this property ensures a smooth transitional dynamics by ruling out the possibility that persistent oscillations occur over the transition path—that is, the “echo effects” that typically arise in vintage models; see, for example, Benhabib and Rustichini (1991).}

If $a_z$ and $a_q$ are both equal to zero, the model corresponds to a standard vintage model where technological progress is entirely embodied into new jobs, while if $a_z$ and $a_q$ are equal to one, the model corresponds to a standard real-business-cycle model, where technological progress is new jobs disembodied.\footnote{Pissarides and Vallanti (2007) argue that, conditional on remaining in operation, old jobs experience a productivity growth similar to that of new jobs. This provides support to our modelling choice of quantifying the importance of technological disembodiment by focussing on the probability with which old jobs upgrade their technology: conditional on remaining in operation, any old job eventually adopts the state-of-the-art technologies so that its productivity growth coincides with that of the economy.} Generally, the parameters $a_z$ and $a_q$ quantify over the unit interval the extent to which firms can upgrade their neutral and investment-specific technology without replacing part of the current workforce.

Jobs are destroyed when their technology and/or capital stock become too obsolete relative to the current leading technology and the optimal capital level. In case of destruction, the capital stock of the job is recovered while the worker can be employed in another job.

3.2. Technology frontier

The leading technology, $z_t$, and (minus) the logged price of new capital, $q_t$, both exhibit a stochastic trend. Specifically, the stochastic process that governs the evolution of $z_t$ is given by

$$z_t = z_{t-1} + g_{zt},$$

where $g_{zt}$ is iid normal with mean $\mu_z$ and standard deviation $\sigma_z$, while $q_t$ evolves according to

$$q_t = q_{t-1} + g_{qt},$$

where $g_{qt}$ is iid normal with mean $\mu_q$ and standard deviation $\sigma_q$.

3.3. Search frictions

The labour market for workers is subject to search frictions. The matching process within a period takes place at the same time as production for that period. Workers and firms whose matches are severed can enter their respective matching pools and be rematched within the same period. All separated workers are assumed to re-enter the unemployment pool (i.e. we abstract from workers’ labour force participation decisions). Workers and firms that are matched in period $t$ begin active relationships at the start of period $t+1$, while unmatched workers remain in the unemployment pool.

Following Pissarides (2000), we model the flow of viable matches using a matching function $m(u, v)$ whose arguments denote the masses of unemployed workers and vacancies, respectively. This function is homogeneous of degree one, increasing in each of its arguments, concave, continuously differentiable, and satisfies $m(u, v) \leq \min(u, v)$. Its homogeneity implies that a vacancy gets filled with probability

$$q(\theta) = \frac{m(u, v)}{v} = m\left(1, \frac{1}{\theta}\right).$$
which is decreasing in the degree of labour market tightness $\theta \equiv v/u$. Analogously, an unemployed worker finds a job, with probability $p(\theta) \equiv \theta q(\theta)$, which is increasing in $\theta$.

Free entry by firms determines the size of the vacancy pools. Processing the applications for a vacancy requires the services of a recruiter which can be hired in a perfectly competitive labour market. We denote by $\tilde{r}$, the wage paid to a recruiter for processing the applications for a vacancy at time $t$.

3.4. Wages

If a firm and a worker who have met separated, both would lose the opportunity of producing and each would have to go through a time-consuming process of search before meeting a new suitable partner. Hence, there is a surplus from a job. We assume that at each point in time, the worker and the firm split such surplus by using a generalized Nash bargaining solution in which the bargaining powers of the worker and the firm are $\beta$ and $1 - \beta$, respectively. Division of the surplus is accomplished via wage payments. Nash bargaining also determines the conditions upon which a job is destroyed.

3.5. Representative household

The economy is populated by a continuum of identical infinitely lived households of measure one. Each household is thought of as a large extended family which contains a continuum of workers and one recruiter. For simplicity, the population of workers in the economy is assumed to be constant and normalized to one. We follow, among others, Andolfatto (1996) and den Haan et al. (2000) in assuming that workers and recruiters pool their income at the end of the period and choose consumption and effort costs to maximize the sum of the expected utility of the household’s members; thus, a representative household exists. The instantaneous utility obtained by the representative household in a given period is

$$\ln \tilde{C} - c_w N - \frac{\tilde{r} v^{1+v}}{1+v}, \quad \tilde{r} > 0, \quad v \geq 0,$$

where $N$ and $v$ denote the number of employed workers and the stock of vacancies, respectively. The first term implies that the utility of consumption is logarithmic, the second term accounts for the fact that every employed worker incurs an effort cost $c_w$, while the third term is the utility cost incurred by the representative recruiter to process the applications for $v$ vacancies. This formulation implies that the recruiter has decreasing marginal utility to leisure. The inverse of the parameter $v$ reflects the elasticity of the labour supply of recruiters with respect to wages, holding consumption constant (i.e. the Frisch elasticity). The representative household maximizes the expected present value of its instantaneous utility discounted with a factor $\rho$.

We assume that the claims on the profit streams of firms are traded. In equilibrium, the household owns a diversified portfolio of all such claims, implying that the discount factor used by firms to discount future profits from time $t + j$ to time $t$ is consistent with the household’s inter-temporal decisions and therefore equal to the expected discounted value of the ratio of the marginal utility of consumption at time $t + j$ to its value at time $t$.

4. EQUILIBRIUM CONDITIONS

We first review the timing of events within a period. Then, we characterize the balanced growth path of the economy and derive the equilibrium conditions of the model. In doing so we first characterize firms’ decisions in terms of capital choice, job destruction, and vacancy creation and
Then we turn to the determination of market-clearing conditions. We conclude by defining the equilibrium for the economy.

4.1. Timing

We adopt the following convention about the timing of events within a given period $t$:

i. Aggregate technology shocks $g_{zt}$ and $g_{qt}$ are realized;

ii. Upgrade possibilities materialize for the neutral technology of old jobs;

iii. Old jobs realize their idiosyncratic shocks $\epsilon_{it}$ and $\delta_{it}$ to the neutral technology and capital depreciation, respectively. New jobs (resulting from matches at time $t-1$) start with neutral technology $z_t$;

iv. Upgrade possibilities for capital are realized;

v. Decisions about job destruction, investment, and posting of vacancies are taken;

vi. Output is produced, $m_t$ new jobs (that start producing next period) are created, wage income of recruiters and workers is earned;

vii. Income of all household members is pooled and consumed. Next period begins.

4.2. Stochastic trend

Our economy fluctuates around the stochastic trend given by $X_t \equiv e^{xt}$, where

$$x_t = \frac{1}{1-\alpha} z_t + \frac{\alpha}{1-\alpha} q_t$$

is a composite index of the neutral and investment-specific technology. To make the environment stationary, we hereafter scale all quantities, unless otherwise specified, by $X_t \equiv e^{xt}$—that is, we explicitly refer to a non-stationary variable as unscaled if we refer to its level. Notice that, given (2) and (3), $x_t$ evolves as

$$x_t = x_{t-1} + g_{xt},$$

where $g_{xt}$ is iid normal with mean $\mu_x = \frac{\mu_z}{1-\alpha} + \frac{a \mu_q}{1-\alpha}$ and variance $\sigma_x^2 = \frac{\sigma_z^2 + a^2 \sigma_q^2}{(1-\alpha)^2}$.

4.3. Job net surplus

Hereafter, we keep the convention that a suffix $t$ added to a given quantity implies that this is a function of the aggregate state variables of that time. Let $k_t \equiv \tilde{k} e^{-(q_t+x_t)}$ denote the time $t$ capital value of a job whose unscaled capital stock is $\tilde{k}$. Then, the time $t$ net surplus of a job with capital value $k$ and technological gap $\tau$, $S_t(k, \tau)$, solves the following asset equation:

$$S_t(k, \tau) e^{x_t} = e^{\tilde{c}_t} - e^{-(q_t+x_t)} \alpha \tilde{C}_t$$

$$+ J_t(k, \tau) e^{x_t} + E_t \left[ \frac{\tilde{C}_t}{C_{t+1}} \left[ H_{t+1} e^{x_{t+1}} + \int_R e^{-i-q_{t+1}+q_{t+1} + x_t} kdG_\delta(i) \right] \right]$$

$$- H_t e^{x_t} - k e^{x_t},$$

where $G_\delta$ denotes the distribution function of the random variable $\kappa$, while $H_t$ denotes the value to the worker of staying at home at time $t$. To understand the expression, notice that the terms in the first row of the R.H.S. computes the instantaneous net return of the job as the difference between job output and the effort cost of working, measured in consumption units by dividing

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by the marginal utility of consumption. The terms in the second row represent instead the
discounted future value of the job. This is equal to the sum of \( J_t(k, \tau) \), which denotes the expected
present value of the job future net surplus, and the future outside options of the worker and the
firm, equal to the future value to the worker of staying at home and the future value of capital,
respectively. To obtain an expression for the job net surplus, the last row subtracts from the value
of a job the current outside options of the worker and the firm, respectively.

After dividing the L.H.S. and R.H.S. of the previous equation by \( e^{\alpha t} \), and after rearranging,
it follows that

\[
St(k, \tau) = e^{-\tau} k^\alpha - k - c_{it} C_t - H_t + E_t \left( \frac{\rho C_t}{C_{t+1}} \left[ H_{t+1} + \int_R \Delta_{t+1}(i) kdG(\delta) \right] \right) + J_t(k, \tau),
\]

where \( C_t \equiv \frac{\hat{C}_t}{X_t} \) represents aggregate consumption, while
\[
\Delta_{t+1}(\delta) = e^{-\delta - g_{qt+1} - g_{xt+1}}
\]
is the (actual) depreciation factor of the value of capital between time \( t \) and time \( t + 1 \).

4.4. Optimal capital choice

Given (6), the net surplus of a job with technological gap \( \tau \) that can upgrade its capital level is

\[
S_t(\tau) = \max_k S_t(k, \tau),
\]

while its optimal capital choice \( k^*_t(\tau) \) solves

\[
e^{-\tau} \alpha [k^*_t(\tau)]^{\alpha-1} + \frac{\partial J_t(k^*_t(\tau), \tau)}{\partial k} = 1 - E_t \left( \frac{\rho C_t}{C_{t+1}} \int_R \Delta_{t+1}(i) dG(\delta) \right),
\]

which says that the optimal capital level is obtained by equating the sum of its current marginal
productivity and its future marginal value to the user cost of capital.

4.5. Job destruction

A job is kept in operation only if it yields a positive net surplus. Thus, there exists a critical
technological gap \( \bar{\tau}_t \) which solves

\[
S_t(\bar{\tau}_t) = 0,
\]
such that a job which can deploy its optimal capital level remains in operation only if its techno-
logical gap is smaller than \( \bar{\tau}_t \). Similarly, a job with a given capital value \( k \), whose level cannot
be upgraded, is destroyed whenever its technological gap is greater than the threshold \( \tau^*_t(k) \) that solves

\[
S_t(k, \tau^*_t(k)) = 0.
\]

Given (7) and the fact that \( S_t(k, \tau) \) is decreasing in \( \tau \), these expressions immediately imply
that jobs whose capital can be upgraded remain in operation for greater technological gaps,
\( \tau^*_t(k) \leq \bar{\tau}_t, \forall k \).
4.6. Future job net surplus

The present value of the future job net surplus $J_t(k, \tau)$ solves the asset equation

$$J_t(k, \tau) = E_t \left\{ \frac{\rho C_t}{C_{t+1}} (1 - a_q) a_z \int_{R^2} \max(0, S_{t+1}(\Delta_{t+1}(i)k, j)) dG_{\delta}(i) dG_{\epsilon}(j) \right\}$$

$$+ E_t \left\{ \frac{\rho C_t}{C_{t+1}} (1 - a_q) (1 - a_z) \int_{R^2} \max(0, S_{t+1}(\Delta_{t+1}(i)k, \tau + g_{z,t+1} + j)) dG_{\delta}(i) dG_{\epsilon}(j) \right\}$$

$$+ E_t \left\{ \frac{\rho C_t}{C_{t+1}} a_q \int_{R} [\max(0, S_{t+1}(j)) + (1 - a_z) \max(0, S_{t+1}(\tau + g_{z,t+1} + j))] dG_{\epsilon}(j) \right\},$$

where, in writing the expression, we made use of the fact that the idiosyncratic shock $\epsilon$ is symmetric around zero. To understand the expression, notice that jobs are destroyed whenever they yield a negative surplus. Thus, the first term in the R.H.S. accounts for the net surplus generated by a job which tomorrow (in expected value) will use today depreciated capital and the next-period leading technology, the second for the net surplus of a job which will use the today depreciated capital and the today technology, while the third (which is independent of the current value of $k$) accounts for the net surplus generated by a job which will update its capital level and will use either the leading technology of the next period or the same technology as the current one.

4.7. Free entry

Once bargaining with a firm, the worker always receives his outside option (the value of staying at home) plus a fraction $\beta$ of the job net surplus. As newly created jobs install their optimal capital level and operate the leading technology of the time when they start producing, $\tau = 0$, the worker’s value of staying at home, $H_t$, solves the asset-type equation

$$H_t = E_t \left\{ \rho \frac{C_t}{C_{t+1}} \left[ H_{t+1} + p(\theta_t)\beta S_{t+1}(0) \right] \right\},$$

where $H_{t+1}$ is next-period worker’s outside option, while $\beta S_{t+1}(0)$ is the amount of net surplus appropriated by the worker in case he finds a job, which occurs with probability $p(\theta_t)$.

Analogously, a firm which bargains with a worker receives his outside option (the value of a vacancy) plus a fraction $1 - \beta$ of the job net surplus. Thus, the value of a vacancy at time $t$, $V_t$, satisfies the asset equation

$$V_t = E_t \left\{ \rho \frac{C_t}{C_{t+1}} [V_{t+1} + q(\theta_t)(1 - \beta) S_{t+1}(0)] \right\} - r_t,$$

where the first term in the R.H.S. represents the expected future present value of searching for a worker today, while $r_t \equiv \bar{r}(\tau)$ is the wage paid to a recruiter for his services. In equilibrium, this wage is equal to the ratio of the marginal disutility of working for recruiters to the marginal utility of consumption. Thus,

$$r_t = \bar{r} [\theta_t(1 - N_t)]^\gamma C_t,$$

where $\theta_t(1 - N_t)$ is the aggregate stock of vacancies, which is equal to the product of labour market tightness and the unemployment rate. Since vacancies are posted till the exhaustion of
any rents, in equilibrium $V_t = V_{t+1} = 0$, so the free-entry condition

$$
\frac{r_t}{q(\theta_t)} = E_t \left\{ \rho \frac{C_t}{C_{t+1}} (1 - \beta) S_{t+1}(0) \right\}
$$

holds at any point in time.

### 4.8. Employment and job creation

Let $f_t(k, \tau)$ denote the time $t$ measure of old jobs which inherits a depreciated level of capital of value $k$ from the previous period and that, in case they are kept in operation, would produce with technological gap $\tau$. In other words, $f_t$ describes the beginning-of-period distribution of old jobs previous to any investment and destruction decision at time $t$. In the sequence of events described in Section 4.1, this is the distribution resulting after the events in (iii). It then follows from the definition of the two critical technological gaps $\bar{\tau}_t$ and $\tau^*_t(k)$ that time $t$ employment is equal to

$$
N_t = a_q \int_{R} \left[ \int_{-\infty}^{\bar{\tau}_t} f_t(k, \tau) d\tau \right] dk + (1 - a_q) \int_{R} \left[ \int_{-\infty}^{\tau^*_t(k)} f_t(k, \tau) d\tau \right] dk + m_{t-1}
$$

since any job which can (not) upgrade its capital stock $k$ is kept in operation only if its technological gap is no greater than $\bar{\tau}_t$ ($\tau^*_t(k)$) while all newly created jobs, $m_{t-1}$, are productive. Notice that, given aggregate employment and the degree of labour market tightness, $m_{t-1}$ can be expressed as

$$
m_{t-1} = p(\theta_{t-1})(1 - N_{t-1}).
$$

### 4.9. Aggregate feasibility constraint

The time $t$ (scaled) value of aggregate output is equal to

$$
Y_t = a_q \int_{R} \left[ \int_{-\infty}^{\bar{\tau}_t} e^{-\tau} [k^*_t(\tau)]^\alpha f_t(k, \tau) d\tau \right] dk + (1 - a_q) \int_{R} \left[ \int_{-\infty}^{\tau^*_t(k)} e^{-\tau} k^\alpha f_t(k, \tau) d\tau \right] dk + m_{t-1}[k^*_t(0)]^\alpha,
$$

where the first integral accounts for the output produced by the old jobs which adjust their capital stock, the second for those which produce with the capital level they inherit from the previous period, while the term in the second row is the output produced by new jobs. Then, the aggregate feasibility constraint can be conveniently expressed as

$$
Y_t = C_t + I_t,
$$

where $I_t$ denotes aggregate investment expenditures (in consumption units). By definition, $I_t$ is equal to

$$
I_t \equiv I^u_t - D^d_t,
$$

where $I^u_t$ denotes the investment expenditures of those firms which are kept in operation and upgrade the capital stock, while $D^d_t$ is the value of the disinvestment triggered by job destruction. Formally, the component of investment due to capital upgrading is given by

$$
I^u_t = a_q \int_{R \times [-\infty, \bar{\tau}_t]} [k^*_t(\tau) - k] f_t(k, \tau) dk d\tau + m_{t-1}k^*_t(0)
$$

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since, provided they are not destroyed, a fraction $a_q$ of old jobs upgrade their capital while all new jobs acquire a capital stock of value $k_1^*(0)$. By similar logic, the disinvestment due to job destruction is equal to

$$D_t^d = \int_R \left[ a_q \int_{\tau_t}^{\infty} k f_t(k, \tau) d\tau + (1-a_q) \int_{\tau_t^*(k)}^{\infty} k f_t(k, \tau) d\tau \right] dk$$

since jobs are destroyed whenever the technological gap is too large, given the capital stock that could be used in case of production.

4.10. Dynamics of the beginning-of-period distribution

Consider the sequence of events that characterize the evolution of the beginning-of-period distribution between time $t-1$ and time $t$. At time $t-1$, and depending on whether capital can be upgraded, some old jobs are destroyed while some others that remain in operation upgrade their capital level. The result of these decisions is the “end-of-period” distribution of old jobs at time $t-1$ which determines employment and aggregate output at that time. Then, to obtain the beginning-of-period distribution of old jobs at time $t$, one has to take account (i) of the (aggregate and idiosyncratic) shocks to the job’s neutral technology that determine the job technological gap, (ii) of the shocks to capital depreciation that affect the value of job capital at the beginning of time $t$ and, finally, (iii) of the inflow of newly created jobs at time $t-1$, $m_{t-2}$, that will belong to the pool of old jobs at time $t$.

Thus, the law of motion of $f_t$ can be described through an operator $\Phi$ that maps $f_{t-1}$, the capital-adjustment and job destruction decisions, the aggregate shocks, and $m_{t-2}$ into $f_t$ so that

$$f_t = \Phi(f_{t-1}, k_{t-1}^*, \tilde{\tau}_{t-1}, \bar{\tau}_{t-1}, g_{zt}, g_{qt}, m_{t-2}), \quad (19)$$

where $f_{t-1}$, $k_{t-1}^*$, and $\bar{\tau}_{t-1}$ are functions while the remaining quantities are scalars. The exact form of the relation between these quantities is described by (22) in the Appendix.

4.11. Equilibrium

An equilibrium consists of a stationary tuple

$$(k_1^*(\tau), \bar{\tau}_t, \bar{\tau}_t^*(k), \theta_t, N_t, m_t, C_t, f_t(k, \tau))$$

which satisfies the condition for the optimal capital choice (8), the two job destruction conditions (9) and (10), the free-entry condition for vacancy creation (13), the constraint on the number of employees (14), the constraint on job creation (15), the aggregate feasibility constraint (17), and the law of motion of the beginning-of-period distribution (19). We solve the model by log-linearizing the first-order conditions around the steady state of the model without aggregate shocks, $g_{zt} = \mu_z$ and $g_{qt} = \mu_q$. This yields a system of linear stochastic difference equation that can be solved, for example, with the method proposed by Sims (2002). To characterize the beginning-of-period distribution, $f_t$, we follow Campbell (1998) in considering its values at a fixed grid of technological gaps and capital values. A computational appendix describes in more details the procedure used.

Before proceeding, notice that the logged level of unscaled aggregate productivity, $y_{nt} \equiv \ln(Y_t/N_t) + x_t$, evolves as in (1). Specifically, let $Y$ and $N$ denote the constant level of output and employment around which the economy fluctuates. Then, one can easily check that (1) holds.
where \( y^* = \ln Y - \ln N \) and \( \varepsilon \) accounts for the stationary fluctuations of \( Y_t \) and \( N_t \) around their mean. This makes the previous empirical analysis fully consistent with the following analysis of the effects of neutral and investment-specific technology shocks in the model.

5. CALIBRATION

We start defining some useful statistics. We then discuss the parameters values used in our baseline specification.

5.1. Some definitions

Job destruction at time \( t \) is equal to

\[
JD_t = \int R \left[ a_q \int_{\tau_t}^{\infty} f_t(k, \tau) d\tau + (1 - a_q) \int_{\tau_t}^{\infty} f_t(k, \tau) d\tau \right] dk
\]

since jobs are destroyed whenever their technological gap is too large given the capital that can be used. The law of motion of employment satisfies

\[
N_t = N_{t-1} + JC_t - JD_t,
\]

where \( JC_t = m_{t-1} \) denotes job creation at time \( t \).\(^{17}\) Finally, and given Davis et al. (1997), we define the time \( t \) job destruction and job creation rate as equal to

\[
jd_t = \frac{2JD_t}{N_{t-1} + N_t} \quad \text{and} \quad jc_t = \frac{2m_{t-1}}{N_{t-1} + N_t},
\]

respectively. We follow den Haan et al. (2000) in positing the following matching function:

\[
m(u_t, v_t) = \frac{u_tv_t}{[(u_t)^\eta + (v_t)^\eta]^{\frac{1}{\eta}}},
\]

where \( u_t \) and \( v_t \) denote the pool of searching workers and firms, respectively.

5.2. Parameters choice

We calibrate the model using information available at the plant level. This is coherent with the model structure where a productive unit (a “plant”) consists of a single job. More importantly, this is arguably the right level at which the model should be calibrated. As reviewed by Brynjolfsson and Hitt (2000), technology adoption in a plant (or a firm) alters its entire jobs structure, which makes it generally hard to separately adopt new technologies in just some jobs within the same plant. Since the original series on job flows are created from plant-level information available at the quarterly frequency, we also follow the bulk of the business cycle literature and we calibrate the model at this frequency.\(^{18}\) The values of the parameters used in our baseline specification are summarized in Table 2.

\(^{17}\) We define time \( t \) employment as given by all workers producing at that time. Alternatively, one could also include in the pool of employed workers those who find a job at time \( t \) and will start producing at time \( t+1 \). In this case, the definition of job creation and job destruction should be modified accordingly so as to satisfy a law of motion for employment analogous to (21).

\(^{18}\) The choice of the length of the model period can affect the extent of search frictions. For example, our choice implies that the minimum unemployment spell duration in the model is one quarter. Yet, given that the VAR is ran with quarterly data, calibrating the model at a higher frequency (say at the monthly level) would force us into specifying when the shock has occurred within a given quarter (say in which month within the quarter), which is an issue that we preferred to sidestep.
The choice for the discount factor $\rho$ and the workers’ bargaining power $\beta$ is standard. The probabilities of technology upgrading, $a_z$ and $a_q$, play a key role in determining whether technology shocks cause Schumpeterian creative destruction or they operate as in the neoclassical growth model. We choose their value to match feature of technology dynamics at the plant level. The value for the jobs’ probability of capital upgrading is set to $a_q = 0.45$. This yields a 91% probability of capital adjustment at the yearly frequency, which corresponds to the fraction of plants adjusting capital equipment in a year, as reported by Cooper and Haltiwanger (2006) (see their Table 1). To calibrate $a_z$, notice that the first-order correlation of the relative neutral technology of a continuing “plant” is simply $(1 - a_z)$. Baily et al. (1992) report that the analogous correlation at the five-year level is around 30% (see their Table 8). In their regression, Baily et al. also include size of the plant and its age, although their effects are not very significant. They also focus on continuing plant that might introduce some selection biases in the estimation. Thus, we calibrate $a_z$ (together with all the other parameters of the model), so that the same regression as in Baily et al. (1992) estimated on simulated data (from the steady-state version of the model without aggregate shocks) matches a coefficient on past total factor productivity (TFP) of 30%. We measure size in terms of capital and age in number of years since creation.

The remaining 10 parameters of the model ($\mu_q$, $\mu_z$, $\mu_\delta$, $\alpha$, $\sigma_\delta$, $\sigma_\epsilon$, $r$, $\eta$, $c_w$, $v$) are set to match the following 10 moment conditions in the steady-state version of the model without aggregate shocks: i) a yearly growth rate of $q$ of 3.21%, ii) a yearly growth rate of $z$ of 0.39%, iii) a yearly average depreciation rate of capital of 12.4%, iv) a labour share of 64%, v) a ratio of plants with positive investment to the total number of plants adjusting capital of 89%, vi) a fraction of existing jobs with neutral technology greater than the neutral technology of a newly created job of 40%, vii) a job destruction rate of 3.2%, viii) a firm’s hiring probability, $q(\theta)$, of 0.71, ix) a worker’s employment probability, $p(\theta)$, of 0.45, and x) a Frisch elasticity of the recruiters’ labour supply of 0.5. The moment conditions (i) and (ii) correspond to the historical trend of the corresponding variables in the U.S. as calculated by Greenwood et al. (1997). Together with

<table>
<thead>
<tr>
<th>Parameter values used in the baseline specification</th>
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</thead>
<tbody>
<tr>
<td>$\rho : 0.99$</td>
</tr>
<tr>
<td>$\mu_q : 0.8025%$</td>
</tr>
<tr>
<td>$\sigma_\delta : 3.31%$</td>
</tr>
<tr>
<td>$c_w : 0.8378$</td>
</tr>
</tbody>
</table>

19. To see this, notice that the neutral technology of a continuing job evolves as

$z_{it} = a_z z_t + (1 - a_z)z_{it-1} + \bar{\epsilon}_{it}$

where $\bar{\epsilon}_{it}$ is a zero-mean idiosyncratic expectation error. After taking expectation in the previous equation, one obtains an expression for the law of motion of the average neutral technology of continuing jobs, $\bar{z}_t$. After subtracting the resulting expression from the previous one, it immediately follows that the first-order correlation of the relative neutral technology, $z_{it} - \bar{z}_t$, is $(1 - a_z)$.

20. It turns out that controlling for the capital size and age of the plant affects little the estimated coefficient of TFP five years earlier. As correctly pointed out by a referee, it is also unclear whether Baily et al. (1992) measure plant-level capital stock in consumption units or in efficiency units, as the model would require to correctly estimate $z$. To check this concern, we constructed an alternative TFP measure in the model, using output and capital measured in consumption units. When we reran the regression of Baily et al. with this alternative TFP measure, we find that the coefficient on past TFP drops. For example, it becomes equal to 0.248 in the baseline specification. Matching a coefficient of 0.3 requires lowering $a_z$ by around 0.02 points. Our results are roughly unchanged under this alternative lower value of $a_z$.

21. Although the 10 parameters and $a_z$ have to be set simultaneously to match the 10 moment conditions and the regression coefficient, the order of presentation is such that a given moment condition allows to (intuitively) identify the corresponding parameter in the list.
the calibrated value of \( \alpha \), they imply a long-run yearly growth rate of labour productivity of about 2.4%, which is reasonably in line with its historical trend in the U.S. Conditions (iii) and (iv) are the same as in Greenwood et al. (1997) and Prescott (1986), respectively. The Appendix shows how to calculate the labour share in the model. Condition (v) comes from Cooper and Haltiwanger (2006) who study the pattern of capital adjustment at the plant level and report the fraction of plants with zero, positive, and negative investment in capital equipment (see their Table 1).\(^{22}\) Condition (vi) comes from Baily et al. (1992), and it corresponds to the fraction of existing plants that have neutral technology higher than the average neutral technology of a newly created plant, see their Table 4.\(^{23}\) Conditions (vii)–(ix) are taken from den Haan et al. (2000).\(^{24}\) Notice that the job destruction rate differs from the average destruction rate in the sample because job destruction may arise for other causes than technology shocks. Finally, the choice for the Frisch elasticity of the recruiters’ labour supply is in line with standard microeconomic estimates; see, for example, Blundell, Meghir and Neves (1993) and Lee (2001). In Section 7, we further discuss the implications of alternative choices for the labour supply elasticity of recruiters.\(^{25}\)

6. RESULTS

We next analyse the response of the economy to a neutral technology shock, \( g_{zt} \), and to an investment-specific technology shock, \( g_{qt} \). Then, we evaluate how well the model matches the observed fluctuations in employment, output, and job flows over the 1972–1993 period. In the model, a technology shock can be either expansionary or contractionary on employment due to two opposite forces affecting job destruction. On the one hand, old jobs that fail to upgrade their technology become more obsolete relatively to a newly created job. This effect raises the incentive to destroy a job with a given technology. On the other hand, job destruction and the subsequent job creation are costly in terms of forgone output and investment. Thus, the desire to smooth consumption makes the pruning of relatively obsolete technologies spread out over time, which implies that the critical technological gaps \( \tau_t(k) \)’s that lead to job destruction increase. The former effect dominates when the probability of technology upgrading is low and the latter when this probability is high.\(^{26}\)

6.1. A neutral technology shock

Figures 6 and 7 characterize the response of the economy to a 1% increase in the leading technology, \( z_t \). As \( z_t \) increases, old jobs tend to become more obsolete relative to the technological frontier so the marginal distribution of the beginning-of-period technological gaps, \( \int f_t(k, \tau)dk \), shifts to the right on impact—see the dotted line in Figure 6. The horizontal shift tends to make job destruction increase, while the demand for consumption smoothing tends to make

\(^{22}\) Specifically, the value of 89% is the ratio of the fraction of plants with positive investment, equal to 81.5%, to the fraction of plants adjusting capital, which equals 91.9%.

\(^{23}\) In the model simulated data, this fraction changes little when we consider the approximated TFP measure (using output and capital measured in consumption units) rather than the exact \( z \).

\(^{24}\) Notice that the job-finding probability computed by den Haan et al. (2000) is obtained by considering a group of workers that includes both unemployed workers and workers from out of the labour force. Since both types of workers matter for the job flows data, this approach is coherent with the main focus of the paper.

\(^{25}\) As a result of the calibration, we obtain an investment expenditures’ GDP ratio of 0.252 that is exactly the same as in Cooley (1995).

\(^{26}\) Consumption smoothing is necessary to obtain a fall in job destruction. When we consider a version of the model where agents are risk neutral and all quantities are (exogenously) scaled by the economy’s technology level, \( X_t \), as in the original vintage model by Aghion and Howitt (1994) and Mortensen and Pissarides (1998), we always obtain that any technology shock leads to a rise in job destruction.
job destruction fall. To see more clearly the effects of consumption smoothing in the model, notice that consumption, $C_t$, falls below its long-run steady-state value since the adoption of the new technology requires time and investment in capital. This reduces the value of the effort cost of working, $c_w C_t$, which makes the net surplus of a job with a given $k$ and $\tau$ increase, thereby reducing the incentive to destroy jobs. Given the high persistence that characterizes the dynamics of the neutral technology of old jobs, the first effect dominates and job destruction increases. To see why, notice that the initial horizontal shift of the marginal distribution of $\tau$ is inversely related to the old jobs’ probability of upgrading their neutral technology, $a_z$, since only jobs which fail to upgrade their neutral technology tend to experience an increase in their technological gap. Thus, when $a_z$ is low enough (as it turns out to be the case in our parametrization), a sufficiently large number of jobs becomes technologically obsolete and the economy experiences a surge in job destruction, see Figure 7. Quantitatively, a $z$-shock that leads to a 1% long-run increase in unscaled productivity causes an increase in job destruction of slightly less than a percentage point which is in line with the empirical findings in Figure 2.

The initial cleansing of technologically outdated jobs prompts a reduction in employment as well as in unscaled output, while unscaled consumption slightly increases on impact. The impact effect on unscaled labour productivity is positive due to both the destruction of relatively unproductive jobs and the productivity gains of those which successfully upgrade their technology. The component of investment due to capital upgrading increases on impact since jobs that remain in operation and adopt the new technology increase their investment. But disinvestment, due to the increase in job destruction, increases more so that aggregate investment falls on impact.

In the quarter immediately after the shock, the job creation rate rises sharply because the pool of searching workers has increased. Thus, the initial upsurge in unemployment is gradually absorbed and, as new and old jobs adopt the more advanced technology, unscaled output, unscaled investment, and unscaled labour productivity reach their permanently increased new long-run value. Interestingly, employment in the first quarters after the shock falls by almost a percentage point, and it takes around 20 quarters to go back to normal levels. The dynamics of the job-finding rate, that remains below steady-state level over the whole adjustment path, explains these persistent effects. The increase in reallocation pushes up the wage of recruiters which directly increases the cost of posting vacancies. This reduces labour market tightness and consequently the job-finding rate. Quantitatively, a long-run increase in unscaled labour productivity of 1% leads to a fall in the job-finding rate of around four percentage points, which is similar to the quantitative effects implied by Figure 4.
6.2. An investment-specific technology shock

Figures 8 and 9 describe the response of the economy to a 1% fall in the price of capital. As $q_t$ rises, the value of the previously installed capital gets reduced. Thus, the marginal distribution of the beginning-of-period capital values, $\int f_t(k, \tau) d\tau$, shifts to the left on impact—see the dotted line in Figure 8. The leftwards shift of the distribution would make job destruction increase, but overall job destruction falls since the effects of consumption smoothing dominate. The costly (in terms of time and resources) adoption of the new capital quality prompts a fall in consumption, $C_t$, which reduces the value of the effort cost of working, $c_w C_t$, so that the critical technological gaps $\tau_t(k)$’s that lead to job destruction increase. Since the old jobs’ probability of upgrading their capital is high enough, this last effect dominates and job destruction falls. Quantitatively, the fall in job destruction in response to a 1% increase in $q$ is around 0.2 percentage points, which is close to the analogous value implied by Figure 3.

The fall in job destruction makes employment increase. Unscaled output and unscaled investment also increase sharply; the latter even overshoots its new steady-state value. The impact
effect on unscaled labour productivity is instead quite small since the fall in job destruction implies that relatively unproductive jobs temporarily remain in operation.

In the quarters following the shock, the job creation rate falls due to the reduction in the pool of searching workers. Thus, the initial increase in employment and investment is gradually absorbed and, after around six years, employment has returned to its pre-shock level while unscaled output and unscaled investment have reached their new long-run value. The persistent effects on employment are again due to the response of the job-finding rate that remains above its steady-state level over the whole adjustment path. This is due both to the fall in the wage of recruiters, which encourages firms to post more vacancies given the current unemployment level, and to the increase in the value of new jobs, due to the improvement in the available technologies.

6.3. Historical decomposition

The previous analysis shows that the model replicates quite accurately the sign and shape of the response of key cyclical variables to technology shocks. We now evaluate more accurately the model’s ability to match the size of the effects and to reproduce the contribution of technology shocks to fluctuations in the U.S. economy between 1972 and 1993. We first analyse the historical contribution of technology shocks to fluctuations in logged employment, job destruction, job creation, and logged output. The graphs in the left column of Figure 10 represent as a solid line the original series and as a dotted line its component due just to technology shocks (either neutral or investment specific), as recovered from the VAR of Section 2 with four lags. All series are detrended with a Hodrick Prescott filter with smoothing parameter equal to 1600. It is apparent that, aside from the recession of the early 1980’s, technology shocks account for a relevant fraction of the cyclical fluctuations of the selected variables.27 The graphs in the right column permit to evaluate how accurately the model replicates the fluctuations due to technology of the corresponding variable. Each graph contains the previously calculated technology component of the relevant series (again represented as a dotted line) together with the model-generated series obtained by feeding the $z$-shocks and the $q$-shocks recovered by the VAR into the model. Notice that the two series share only the value of shocks, while the mechanics of the transmission of these shocks to the economy is obtained completely independently.

The model appears to be quite successful in reproducing the technology component of employment and job destruction. It also reproduces reasonably well the dynamics of job creation,

---

27. Interestingly, several recent papers have emphasized the important role of monetary policy in explaining the recession of the early 1980’s; see, for example, Goodfriend and King (2005).
although job creation fluctuates slightly more in the model than in the data. The peaks and troughs of the model-generated series for job creation tend to anticipate one or two quarters of the corresponding actual series. This may be (at least partly) due to the model convention that job creation cannot respond on impact to a shock. The model’s ability to reproduce the technology component of output is also remarkable. The model just fails to correctly date the peak of the expansion of the late 1980’s and the subsequent trough in the early 1990’s, that the model identifies with a delay of about one quarter.

Table 3 separately reports the standard deviation of the technology component due to either z-shocks or q-shocks of the selected variables. Neutral technology shocks tend to contribute more to the volatility of the selected variables than investment-specific technology shocks. This is in line with the results of the variance–covariance decomposition exercise performed in Section 2. The model generates approximately the right degree of volatility in output for both shocks. The volatility of job creation and job destruction due to z-shocks is instead slightly higher in the model than in the data, while the converse is true when considering the effects of q-shocks.

28. Hagedorn and Manovskii (2006) have recently shown that the standard model of Mortensen and Pissarides (1994) can reproduce the right volatility of key labour market variables only if the difference between job output and the income forgone by employed workers is low enough. In our baseline calibration, the difference between new jobs’ output, payments to capital, and the value of the effort cost of working is around 0.144, which is close to the favourite value by Hagedorn and Manovskii of 0.057.
Effects of technology shocks in data and model. Left column: solid line refers to raw data and the dotted line refers to the component due to technology shock (either neutral or investment specific) as recovered from the VAR with job flows of Section 2. Right column: the dotted line is again the component due to technology shocks in the data and the solid line is the series obtained after feeding the shocks obtained from the VAR into the model. All series are detrended with a Hodrick Prescott filter with smoothing parameter equal to 1600

### TABLE 3

*Standard deviation of selected variables in model and data. The shocks are obtained from the seven variable VAR using job flows described in Section 2. Employment refers to logged employment, output to logged output. All series are detrended with a Hodrick Prescott filter with smoothing parameter equal to 1600.*

<table>
<thead>
<tr>
<th></th>
<th>Employment</th>
<th>Job destruction</th>
<th>Job creation</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Raw data</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>3.48</td>
<td>1.15</td>
<td>0.61</td>
<td>2.23</td>
</tr>
<tr>
<td>Due to technology</td>
<td>2.48</td>
<td>0.81</td>
<td>0.41</td>
<td>1.36</td>
</tr>
<tr>
<td><strong>Technology shocks</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Data</td>
<td>2.48</td>
<td>0.81</td>
<td>0.41</td>
<td>1.36</td>
</tr>
<tr>
<td>Model</td>
<td>1.89</td>
<td>1.02</td>
<td>0.66</td>
<td>1.32</td>
</tr>
<tr>
<td><strong>z-shocks only</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Data</td>
<td>2.51</td>
<td>0.82</td>
<td>0.38</td>
<td>1.30</td>
</tr>
<tr>
<td>Model</td>
<td>1.83</td>
<td>1.00</td>
<td>0.64</td>
<td>1.26</td>
</tr>
<tr>
<td><strong>q-shocks only</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Data</td>
<td>0.58</td>
<td>0.20</td>
<td>0.16</td>
<td>0.41</td>
</tr>
<tr>
<td>Model</td>
<td>0.29</td>
<td>0.17</td>
<td>0.07</td>
<td>0.37</td>
</tr>
</tbody>
</table>
7. ROBUSTNESS AND EXTENSIONS

In our baseline calibration, neutral technological progress is Schumpeterian, while investment-specific technological progress roughly operates as in the neoclassical growth model. We now evaluate the robustness of this conclusion when (i) we choose alternative values for the labour supply elasticity of recruiters, (ii) we increase the average job destruction rate of the economy, and (iii) we modify the bargaining power of workers. In all cases, the parameters of the model are calibrated in equilibrium to match the statistics discussed in Section 5. We also briefly discuss an extension of the model where employed workers can choose the number of hours worked in the job. An interesting implication of the extension is that labour market adjustment along the extensive margin (number of employees) and the intensive margin (number of hours worked per employee) can respond in opposite directions to a $z$-shock. The empirical evidence in Section 2 provides some evidence supporting this implication of the model.

7.1. Costs in vacancy posting

In our baseline specification, we have set the value of the parameter $\nu$ in equation (4) so as to match a Frisch elasticity of the recruiters’ labour supply equal to one half. This is in line with some microeconometric estimates of the Frisch elasticity of labour supply. In standard versions of the search model (see, for example, Mortensen and Pissarides 1994, 1998), $\nu$ is set equal to zero, which implies that the cost of posting a vacancy is constant and independent of the amount of reallocation. We now show that a sufficiently high value of $\nu$ is needed to match the behaviour of the job-finding rate in the data. Figure 11 compares the responses in the baseline specification to the responses that arise when $\nu$ is set equal to zero. We focus on the response of the job-finding rate and employment to a $z$-shock and a $q$-shock. The baseline specification corresponds to the solid line and the specification with $\nu$ equal to zero corresponds to the dotted line. With $\nu$ equal to zero, the job-finding rate increases rather than falls in response to a $z$-shock and a $q$-shock. The baseline specification corresponds to the solid line and the specification with $\nu$ equal to zero corresponds to the dotted line. With $\nu$ equal to zero, the job-finding rate increases rather than falls in response to a $z$-shock and a $q$-shock. As a result, the initial fall in the employment is absorbed much faster than in the baseline specification. Moreover, since reducing $\nu$ also reduces the costs of reallocating a large amount of workers, we also have that the

![Figure 11](image-url)

Response of the finding rate and employment for different values of $\nu$. The solid line corresponds to baseline specification and the dotted line to $\nu = 0$. Upper panel deals with a $z$-shock. Lower panel with a $q$-shock.
lower is $\nu$, the greater is the initial fall in employment. The effects of changing $\nu$ on the responses of the economy to a $q$-shock are instead less remarkable.\footnote{To match the response of the job-finding rate, posting a vacancy must become more costly when worker reallocation increases. In the model, this is achieved by making the cost increasing in the stock of vacancies. Of course, the same effect can be obtained in other ways, for example, by assuming directly that the cost increases with job creation. An implication of our specification is that the correlation between vacancies and unemployment is positive.}

7.2. Exogenous job destruction

In the model, we only allowed for endogenous job destruction. This, however, represents only a fraction of actual job destruction in the data. But having a higher job destruction rate also implies a higher level of unemployment that may affect the quantitative results of the paper. To evaluate the robustness of results to this criticism, we allowed for the possibility that in every period a fraction $\lambda$ of the jobs in the economy is destroyed exogenously. We set $\lambda$ equal to 6.8\% to match an average separation rate of 10\% as in den Haan \textit{et al.} (2000). Figure 12 compares the response of employment to technology shocks in the baseline specification and in the specification with $\lambda = 0.068$. The solid line corresponds to the baseline specification and the dotted line to the specification with positive $\lambda$. Overall, increasing the average job destruction rate in the model has little effect on the response of employment, possibly because, with a constant return to scale matching technology, the stock of unemployed workers has minor effects on firms’ decisions.\footnote{The impulse responses partly differ also because, with the higher average destruction rate, $\alpha_t$ has to increase slightly from 0.06327 to 0.0689 to match the calibration targets.}

7.3. Bargaining power

Hagedorn and Manovskii (2006) have recently emphasized the issue of the choice of the worker’s bargaining power parameter $\beta$ in the standard model of Mortensen and Pissarides. They argue that lowering $\beta$ may help to increase the volatility of vacancies and employment in response to technology shocks that raise the productivity of all jobs in the economy. We now analyse the effects of changing workers’ bargaining power in our model. Figure 13 plots the response of employment to a $z$-shock and a $q$-shock for different values of $\beta$. The solid line corresponds to the baseline
Effects of changing bargaining power on the response of employment to a $z$-shock and a $q$-shock. Solid line corresponds to baseline specification. Dotted line corresponds to a workers’ bargaining power parameter equal to $\beta = 0.3$ and dashed line corresponds to $\beta = 0.7$. The qualitative effects of technology shocks remain unchanged. But with a lower $\beta$, employment increases more in response to a $q$-shock while it falls less in response to a $z$-shock. This confirms the result by Hagedorn and Manovskii (2006) that reducing workers’ bargaining power amplifies the effects of aggregate shocks that increase the productivity of most jobs in the economy, such as $q$-shocks in our model. The figure, however, also suggests that lowering the workers’ bargaining power dampens the aggregate effects of shocks that lead to an increase in reallocation of workers, such as $z$-shocks in the model. This is because, with a low bargaining power, the outside options of employed workers change little in response to changes in aggregate conditions, which dampens the response of job destruction. In the data, $z$-shocks appear to contribute substantially to the volatility of employment. Davis and Haltiwanger (1999) also find that shocks leading to an increase in job reallocation are important in explaining business cycles. This may provide a warning to the claim that lowering the workers’ bargaining power increases the aggregate volatility of employment.

7.4. Hours worked

An important property of the model is that labour market adjustment along the extensive margin (number of employees) and the intensive margin (number of hours worked per employee) can respond in opposite directions to a $z$-shock. To analyse the response of hours worked in the model, assume that a job with neutral technology $z$ and unscaled capital stock $\tilde{k}$ produces an amount of output equal to $e^{\tilde{k}\alpha}e$, where $e$ denotes the number of hours worked in the job. Assume also that the utility cost of working $e$ hours is given by $c_{w} = \tilde{c} + c_{e}e^{1+\phi}1+\phi^{-1}$, where $\phi$ is the elasticity of the disutility of working with respect to the number of hours worked. The baseline model

31. In this case, the instantaneous utility of the representative household becomes

$$\ln\tilde{C} = \int_{0}^{N} \left( \tilde{c} + c_{e}\frac{e^{1+\phi}}{1+\phi^{-1}} \right) di - \bar{r}^{1+\nu}1+\nu,$$

where $e_{i}$ denotes the number of hours worked by worker $i$ when employed.

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corresponds to the case $\phi = 0$ and $c_e = 0$. Since wages are set so as to split the net surplus of a job with the firm, the number of hours worked in a job is determined so as to maximize the job’s net surplus. This implies that at any point in time, $e$ is chosen so that

$$e^z k^\alpha = c_e e^\frac{1}{\phi} C_t,$$

which simply equates the marginal productivity of labour in the job to the disutility of working, measured in consumption units. One can solve for the equilibrium number of hours worked, so as to obtain $e = (\frac{e^z k^\alpha}{c_e C_t})^\phi$, and then substitute the resulting expression (which is function of $\tau$ and $k$) into the various equilibrium conditions of the model; see the computational appendix for details.

In response to either technology shock, $C_t$ falls below its long-run value, so the marginal disutility of working falls, and a worker in a job with a given technological gap and capital value works longer hours. As a result, the average number of hours worked per employee increases in response to either technology shock, see Figure 14. Thus, in response to a $z$-shock, the number of employed workers falls, but the number of hours worked per employee increases. This composition effect can explain why in Table 1 neutral technology shocks contribute little to the cyclical volatility aggregate hours worked.

8. CONCLUSIONS

The microeconomic literature on technology dynamics has evidenced that technology differences are large, very persistent, and that the creation of new firms and jobs plays an important role in technology adoption. In this paper, we considered a general equilibrium business cycle model, where these features are explicitly embedded into the analysis. The model is just a version of the Solow (1960) growth model where the labour market is subject to search frictions and technology adoption is sluggish, so that existing productive units may fail to adopt the most recent technological advances. After matching some features of technology dynamics at the micro-level, we found that advancements in the neutral technology lead to an increase in job destruction, job reallocation, and unemployment; while output, consumption, and investment gradually increase till they reach their new higher long-run value. Conversely, reductions in the price of new capital equipment are expansionary on employment, output, and investment. Using structural VAR
models, we provided support to these key implications of the model. Our analysis supports the view that neutral technological progress prompts waves of Schumpeterian creative destruction, where outdated, technologically obsolete productive units are pruned out of the productive system. Investment-specific technology shocks instead lead to an expansion in economic activity as in the standard neoclassical growth model since a substantial proportion of old jobs upgrade their capital equipment and reap the benefits of the most recent advancements in capital equipment.

APPENDIX

The operator $\Phi$ The operator $\Phi$ in (19) is implicitly defined by the following equation that relates $f_t(k, \tau)$ to $f_{t-1}$ and the jobs’ destruction and investment decisions at time $t-1$:

$$f_t(k, \tau) = (1-a_q)az \left[ \int_{-\infty}^{\tau_{t-1}} g_\delta(\ln j - \ln k - g_{qt} - g_{st})g_\epsilon(\tau)f_{t-1}(j, i) dj \right]$$

$$+ (1-a_q)(1-az) \left[ \int_{-\infty}^{\tau_{t-1}} g_\delta(\ln j - \ln k - g_{qt} - g_{st})g_\epsilon(i + g_{st} - \tau)f_{t-1}(j, i) dj \right]$$

$$+ a_qaz \left[ \int_{-\infty}^{\tau_{t-1}} g_\delta(ln k_{t-1}^*(i) - \ln k - g_{qt} - g_{st})g_\epsilon(\tau)f_{t-1}(j, i) dj \right]$$

$$+ a_q(1-az) \left[ \int_{-\infty}^{\tau_{t-1}} g_\delta(ln k_{t-1}^*(i) - \ln k - g_{qt} - g_{st})g_\epsilon(i + g_{st} - \tau)f_{t-1}(j, i) dj \right]$$

$$+ g_\delta(ln k_{t-1}^*(0) - \ln k - g_{qt} - g_{st})[azg_\epsilon(\tau) + (1-az)g_\epsilon(g_{st} - \tau)]m_{t-2},$$

(22)

where in writing the expression we made use of the fact that the distribution of $\epsilon$ is symmetric around zero. To get familiarized with the expression, consider the sequence of events that characterize the evolution of $f_t$ between time $t-1$ and time $t$ and focus on the first term in the R.H.S. which deals with old jobs that fail to upgrade their capital level at time $t-1$ and that, at time $t$, catch up with the leading technology. This occurs with probability $1-a_q$ and $az$, respectively. These units are kept in operation at time $t$ and to catch up with the leading technology at time $t$. Then, this job will end up with capital stock $j$ and technological gap $\tau$ at the beginning of time $t$ only if the following two events occur. First, it must be that the realization of the idiosyncratic shock $\epsilon$ is equal to $-\tau$, which has probability $g_\epsilon(\tau)$. Second, the capital stock must depreciate at a rate such that the beginning of period capital stock at time $t$ is exactly equal to $k$, which occurs with probability $g_\delta(ln j - \ln k - g_{qt} - g_{st})$. The term in the first row then integrates over all possible values of the capital stock $j$ and technological gap $i$, which do not lead to job destruction at time $t-1$.

The terms in the remaining rows are obtained analogously. The second row deals with old jobs that fail to upgrade their capital level at time $t-1$ and to catch up with the leading technology at time $t$. The third row corresponds to old jobs that upgrade their capital level at time $t-1$ and their neutral technology at time $t$. The fourth row deals with old jobs that upgrade their capital level at time $t-1$ but fail to catch up with the leading technology at time $t$. Finally, the last row accounts for the inflow of newly created jobs at time $t-1$, $m_{t-2}$, that enter at the leading technology of that time and with an optimal capital level.

Calculating workers’ wage and labour share To calculate the labour share, notice that the net value to the firm of a job with technological gap $\tau$ and capital $k$ is given by

$$W_t(k, \tau) = e^{-\tau}k^a - k - w_t(k, \tau) + Et \left[ \frac{\rho C_t}{C_{t+1}} \int_R \Delta_{t+1}(i)kG_\delta(i) \right] + (1-\beta)J_t(k, \tau),$$

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where \( w_t(k, \tau) \) denotes the wage received by the worker in the job. Nash bargaining implies that

\[
W_t(k, \tau) = (1 - \beta) S_t(k, \tau);
\]

thus,

\[
w_t(k, \tau) = e^{-\tau} k^a - k + E_t \left[ \frac{\rho C_t}{C_{t+1}} \int R \Delta_t(i) k G_\delta(i) \right] - (1 - \beta)[S_t(k, \tau) - J_t(k, \tau)].
\]

By using the expression for \( S_t(k, \tau) \) in (6), we obtain that

\[
S_t(k, \tau) - J_t(k, \tau) = e^{-\tau} k^a - k - c_w C_t - H_t + E_t \left[ \frac{\rho C_t}{C_{t+1}} \left[ H_{t+1} + \int R \Delta_t(i) k d G_\delta(i) \right] \right]
\]

which substituted in the expression above allows to express wages as equal to

\[
w_t(k, \tau) = \beta \left[ e^{-\tau} k^a - k + E_t \left[ \frac{\rho C_t}{C_{t+1}} \int R \Delta_t(i) k G_\delta(i) \right] \right] + (1 - \beta) \left[ c_w C_t + H_t - E_t \left( \frac{\rho C_t}{C_{t+1}} H_{t+1} \right) \right].
\]

From here, we can calculate the labour share as equal to

\[
\int R \left[ \int -\infty \int w_t(k^*_t(\tau), \tau) f_t(k, \tau) d\tau + (1 - a_q) \int -\infty \int w_t(k, \tau) f_t(k, \tau) d\tau \right] dk
\]

\[
+ m_{t-1} w_t(k^*_t(0), 0) + r_t \theta_t (1 - N_t) \cdot \frac{1}{Y_t},
\]

where \( r_t \theta_t (1 - N_t) \) represents the wage income of recruiters.

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