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Research, innovation and economic growth

Technology diffusion

Research and Innovation

Research, innovation and economic growth: Technology diffusion

European Commission
Directorate-General for Research and Innovation
Directorate A– Policy Development and Coordination
Unit A.4 Analysis and monitoring of national research and innovation policies
Contact: Roberto MARTINO
E-mail: Roberto.MARTINO@ec.europa.eu

RTD-PUBLICATIONS@ec.europa.eu
European Commission
B-1049 Brussels

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Research innovation and economic growth

Technology diffusion

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EXECUTIVE SUMMARY

QUEST III is a macro-economic model developed by the Directorate General for Economic and Financial Affairs (DG ECFIN) to support its macroeconomic policy and research. The model is primarily designed to evaluate fiscal and monetary policies, however, some structural reforms and policies associated with research and innovation can also be analysed.

A key aspect of the research and innovation sector within QUEST III is that once technologies are invented they can immediately be used in production. This feature is inconsistent with the empirical evidence that suggests that technologies diffuse slowly or are adopted with a time lag.

The objective of this report is to develop a methodology to incorporate technology diffusion within QUEST III. Incorporating this feature is important as it could improve the model's forecasting power but also facilitate policy-making by allowing the evaluation of specific reforms that aim to increase the speed of diffusion.

The model presented in this report builds upon the work of Comin and Gertler (2006), and Anzoategui et al. (2015). The model differentiates between the stock of developed technologies and the stock of adopted technologies. The latter is modelled as a function of high skilled labour and the stock of invented technologies.

Apart from the diffusion model, the report provides a number of recommendations around integrating the model into QUEST III and calibrating its parameters. A model simulation is also carried out that illustrates the benefits of incorporating technology diffusion into QUEST III.

1 Introduction

Technology and innovation are critical drivers of living standards. Understanding the drivers of innovation has been the core issue studied by the endogenous growth literature (for instance, see Romer, 1990; Aghion and Howitt, 1992; Grossman and Helpman, 1991). However, innovation captures just one aspect of productivity dynamics. New technologies are not used immediately in production. There is time lapse between the time of invention and the time of adoption which is known as the adoption lag.

Researchers have documented long adoption lags across a wide range of technologies and countries (see Rogers, 2003; Griliches, 1957; Cox and Alm, 1996). Comin and Hobijn (2010), for instance, found that the average adoption lag in a large sample of countries and a long sample period (1820-2003) was 45 years. They also document that adoption lags vary considerably across both technologies and countries whereas newer technologies have diffused faster than older technologies.

The QUEST III model assumes that once technologies are invented they can be immediately used in production. This feature is inconsistent with the empirical evidence that suggests that technologies diffuse slowly. Incorporating technology diffusion in QUEST III is important for three reasons.

- A number of studies have shown that technology diffusion is a significant driver of Total Factor Productivity (TFP) and long-run economic growth and can account for a large proportion of the variation in income between poor and rich countries. Comin and Hobijn (2010) show that variations in technology diffusion account for at least a quarter of per capita income differences.[1] Comin and Mestieri (2013)

[1] They also showed that a portion of the growth in Japan and the East Asian Tigers in the 1980s and 1990s could be explained by the decline in the adoption lag.

find that 82% of the income gap between Western and non-Western countries could be explained by differences in the evolution of technology diffusion. Therefore, a model that incorporates technology diffusion could in principle provide a more realistic framework to analyse and predict differences in productivity and long-term economic growth across countries.

- The speed of technology diffusion is pro-cyclical (Comin, 2009; Anzoategui et al., 2015).[2] During periods of economic growth companies invest more resources adopting new technologies than during recessions. This feature suggests that the response of the speed of technology diffusion to business cycle conditions and policies contributes to the propagation (persistence and amplitude) of business cycle shocks. A model that incorporates technology diffusion could therefore better explain short- to medium-term fluctuations in economic variables.

- Finally, incorporating technology diffusion in QUEST III could support policy-making through the evaluation of the impact of innovation policies that aim to enhance the speed of technology diffusion such as programmes that accelerate the commercialisation of research outputs or enhance knowledge circulation between public and private sectors on economic growth and job creation.

The objective of this report is to develop an approach to integrate technology diffusion in QUEST III. More specifically, the goals are to:

1. Develop a model of technology diffusion;

2. Define a strategy to integrate technology diffusion into QUEST III;

3. Develop a strategy to calibrate the key new parameters; and

4. Show the relevance of endogenous diffusion for TFP dynamics.

This remainder of this report is structured as follows:

- Section 3 develops a model of endogenous technology diffusion based on Comin and Gertler (2006), and Anzoategui et al. (2015);

- Section 4 discusses how the model can be integrated into QUEST III;

- Section 5 discusses how to calibrate the key parameter values; and

- Section 6 shows the relevance of endogenising the diffusion of technologies for the dynamics of models of endogenous technological change such as QUEST III.

[2] That is, it tends to increase in expansion and tends to decrease in recession.

2 Model of Technology Diffusion

This section describes a model of technology diffusion, primarily drawn upon Comin and Gertler (2006), and Anzoategui et al. (2015).[3]

To introduce the concept of diffusion, it is necessary to differentiate between the stock of developed technologies and the stock of adopted technologies. Secondly, a model of endogenous technology needs to specify the determinants of the speed of technological diffusion. Finally, if adoption activities are intensive in some scarce resource such as skilled labour, the model needs to specify a resource constraint or market clearing condition.

The model is comprised of four key elements, which are described in the remainder of this section:

1. Law of motion for the technology frontier, which describes the process by which technology or new ideas are created;

2. Law of motion for adopted technologies, which defines the process by which invented technologies are adopted in production;

3. Optimal adoption of new technologies; and

4. Market clearing for skilled workers.

2.1 Law of motion for the technology frontier

The diffusion model assumes that new technologies are created by hiring skilled labour. Total skilled labour employed in research and development (R&D) activities is denoted by S_t. Each unit of research labour can develop φ_t new technologies. It is assumed that φ_t takes the following functional form:

$$\varphi_t = \varkappa_t Z_t S_t^{\rho-1} \qquad (1)$$

where $\varkappa_t$ is the stochastic productivity of R&D activities, the term Z_t captures a positive spillover effect from the stock of already developed technologies[4] and the term $S_t^{\rho-1}$ captures the possibility that innovation becomes less productive as the number of researchers increases.[5] This formulation closely follows the one adopted in Romer (1990) and in Anzoategui et al. (2015).

As shown by Anzoategui et al. (2015), aggregating over all the innovators, the resulting aggregate law of motion for the stock of developed technologies, Z_t, is:

$$Z_{t+1} = \left(\varkappa_t S_t^{\rho} + 1\right)\phi Z_t \qquad (2)$$

Intuitively, the stock of developed technologies at *t+1* is given by the technologies available in *t* that do not become obsolete (ϕZ_t) plus the flow of newly developed technologies ($\phi \varkappa_t S_t^{\rho} Z_t$). It is standard in this class of models to assume that technologies become obsolete exogenously at rate 1-ϕ.

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[3] The literature on technology diffusion in DSGE models is quite limited. These papers reflect the key contributions of the literature on this subject.
[4] This spillover effect captures the advantage from having an expertise in developing new technologies for the subsequent engagement in R&D activities.
[5] That is, ρ<1. Griliches (1990) summarizes the evidence on the estimates of ρ which range from 0.6 to 1.

2.2 *Law of motion for adopted technologies*

The process by which invented technologies are being adopted in production is central in the diffusion model. In the model presented in this document, the stock of adopted technologies (A_{t+1}) is modelled as a function of the flow of new technologies($Z_t - A_t$), which are being adopted at a rate λ_t, and past adopted technologies (A_t) which have not become obsolete. [6]

$$A_{t+1} = \phi\lambda_t(Z_t - A_t) + \phi A_t \qquad (3)$$

The following parsimonious functional form is assumed for the adoption rate:

$$\lambda_t = \lambda_0(Z_t h_t)^\gamma \qquad (4)$$

The adoption rate is effectively a function of the amount of skilled labour devoted to the adoption of technologies (h_t) and the stock of invented technologies(Z_t). The latter captures a learning-by-doing externality whereby countries that are on the technology frontier are more effective at adopting new inventions.[7] In this formulation, the adoption rate is assumed to be subject to diminishing returns to the number of skilled workers. Familiarity with some predecessor technology is often an essential input in adopting a new technology. For instance, familiarity with personal computers is likely to be conducive to the adoption of the internet.[8]

2.3 *Optimal adoption of new technologies*

To pin down the optimal adoption rate of technologies, it is necessary to derive expressions for the value of adopted and un-adopted intermediate goods. The value of an adopted intermediate good (v_x) is given by the expected present discounted value of future profits. This can be expressed using the following Bellman equation, where π_t represents profits accrued to an adopted intermediate good producer, and R_{t+1} is the relevant discount rate faced by intermediate goods producers.

$$v_t = \pi_t + E_t[\phi v_{t+1}/R_{t+1}] \qquad (5)$$

The value of un-adopted intermediate goods (j_t) is the option value to adopt them. Formally:

$$j_t = max_{h_t} - w_t^s h_t + E_t\left[\phi\left(\lambda(h_t)v_{t+1} + \left(1 - \lambda(h_t)\right)j_{t+1}\right)/R_{t+1}\right] \qquad (6)$$

The first term in the right-hand side represents the cost of adoption ($w_t^s h_t$). Adopting companies invest in adoption services h_t and this gives them an option to convert the intermediate good from un-adopted to adopted. The likelihood of being successful in adopting the intermediate good is $\lambda(h_t)$, and the associated capital gains are (v_{t+1}-j_{t+1}).

Optimal adoption is the solution to Bellman equation (6) and is given by:[9]

[6] ϕ is the survival rate of new technologies which drives both previous period's stock of adopted technologies (A_t) and the flow of new technologies ($Z_t - A_t$). With regards to the latter, technologies that have been invented could become obsolete before they are considered for adoption.

[7] Familiarity with some predecessor technology is often an essential input to adopt a new technology. For instance, familiarity with personal computers is likely to be conducive to the adoption of the internet. More importantly, the presence of this term ensures the existence of a balanced growth path with a constant adoption rate.

[8] Furthermore, the presence of diminishing returns ensures the existence of a balanced growth path with a constant adoption rate.

[9] This expression follows from solving the maximization problem in (6). Intuitively, the option value of adopting a technology is evaluated at the adoption level (h_t) that maximizes its value. Hence, the max operator in equation (6).

$$w_t^s = E_t[\phi Z_t \lambda'(Z_t h_t) * (v_{t+1} - j_{t+1})/R_{t+1}] \quad (7)$$

Intuitively, at the margin, adoption companies equalise the cost of hiring one skilled worker (w_t^s) with the expected capital gains from the services provided by the skilled worker. These are equal to the discounted capital gain from successful adoption,$(v_{t+1} - j_{t+1})/R_{t+1}$, times the marginal impact that this worker has on the probability of succeeding in adopting the intermediate good, $\phi Z_t \lambda'(Z_t h_t)$.

2.4 Market clearing for skilled workers

Finally, the last equation that needs to be modified in QUEST III is the labour market clearing condition for skilled workers. In particular, the demand for skilled labour services now includes not only R&D workers but also adoption services labour. This implies that the labour market clearing condition is:[10]

$$L_t^s = S_t + (Z_t - A_t) * h_t \quad (8)$$

2.5 Discussion

This section discusses some additional key features and implications of the diffusion model.

- First, both the stock of developed technologies and the stock of adopted technologies are state variables. While the former is the result of R&D activity, the former results from engaging in adopting activities on the stock of un-adopted technologies (Z-A).

- Second, this formulation has a balanced growth path with no population growth. If population growth is incorporated in the model, balanced growth can be achieved by re-scaling the cost of R&D and the probability of adoption by the population level. In this case, S and h can be interpreted as the shares of population devoted to R&D and adoption activities.

- Another issue that is relevant is the cyclicality of R&D and the speed of technology diffusion. In this model, there are two endogenous forces that affect the cyclicality of these investment decisions. One is the pro-cyclicality of wages for skilled workers. The second is the cyclicality of the value of un-adopted technologies (for R&D) or the capital gain from adoption (for adoption investments). To the extent that wages are less volatile than the capital gains from R&D and adoption, these investments will be pro-cyclical in the model (as they are in the data). One way to make sure this condition holds is by introducing wage rigidities.[11]

- Finally, the model assumes that once a technology is adopted, all companies can use it. Therefore, there is no heterogeneity in the use of a given technology across companies.[12] However, there is heterogeneity across the technologies of a given vintage. In this way, the model can capture heterogeneity in technology diffusion despite being a representative agent model.

[10] In QUEST III, skilled labour is used in R&D and to produce final output.
[11] This is the approach followed by Anzoategui et al. (2015)
[12] This simplification is necessary to make the model tractable.

3 QUEST III Integration

The diffusion model set out above could be directly integrated into QUEST III as both models rely on similar assumptions. In particular, the model assumes that:

- Non-liquidity constrained households own all intermediate goods, both adopted and un-adopted;
- Households buy newly developed intermediate goods (at price P_A). They rent them to adoption companies which transform them into adopted, and experience a capital gain of v_{t+1} - j_{t+1};
- Adopted intermediate goods are purchased back from adoption companies by households and held in their portfolio;
- Households rent adopted intermediate goods to companies that commercialise them to final good producers; and
- Rental rates for adopted and un-adopted intermediate goods given by (equation 35c in Varga et al., 2013) with the difference that the growth rate of the price of the asset, $\pi_{A,t+1}$, needs to be adjusted accordingly.

One aspect that requires further consideration is the innovation process in a multi-country environment. In the current formulation of QUEST III, each intermediate good needs to be developed in each country before it is used in production. This assumption is made in QUEST III to allow for the slow diffusion of technologies.[13] However, the speed of diffusion is exogenous and constant. Furthermore, it has two additional undesirable features. First, it does not allow innovators to extract rents from selling their goods in other countries. Second, it is difficult to evaluate the effect of innovation policies that aim to affect the speed of diffusion.

The model could be modified to take into account a multi-country context by formulating the law of motion of developed technologies as follows:

$$Z_{t+1} = \left(\sum_c \varkappa_{ct} S_{ct}^{\rho} + 1\right)\phi Z_t \qquad (9)$$

where the sub-index c denotes the country. In this formulation, all countries engage in R&D and produce innovations that add to the common technology frontier. The productivity of R&D and $\lambda_0$may be allowed to vary across countries, capturing cross-country differences in adoption lags.[14,15]

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[13] That is the case because the stock of foreign technologies increases the productivity of domestic R&D causing an effect from the stock of foreign technologies on domestic ones which could be interpreted as exogenous diffusion.

[14] See Comin and Hobijn (2010).

[15] One final issue that may require further consideration is how much of the revenues obtained by patent owners from selling intermediate goods in other countries can be preserved. If patents are perfectly enforceable across countries, then the principles of the model presented above would be consistent with the innovation dynamics predicted by theory in the multi-country context.

4 Calibration

Accommodating endogenous technology diffusion into QUEST III, along the lines described in section 3, requires calibrating three parameters:

1. The adoption effectiveness, λ_0;

2. The curvature in the adoption function, γ; and

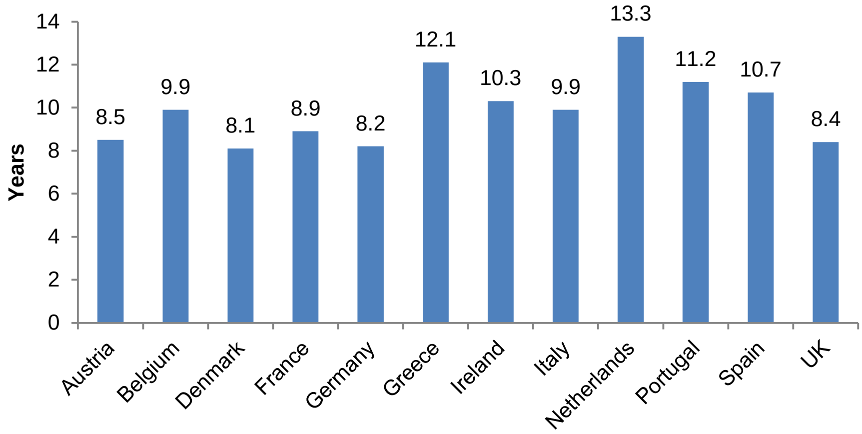
3. The obsolescence rate, 1-ϕ.

This section describes alternative approaches that could be used to calibrate these values.

Adoption effectiveness

The adoption effectiveness, λ_0, can be calibrated to match the average adoption lag observed across countries. There are various studies that have estimated adoption lags for a number of technologies.[16] For instance, Comin and Metieri (2013) provide average adoption lags for a number of technologies[17] and European countries (see Figure 1) which can be used to calibrate the adoption effectiveness in QUEST III.

Figure 1: Average adoption lags



Source: Comin and Metieri (2013)

Curvature in the adoption function (γ)

The curvature of the adoption rate captures the responsiveness of the adoption rate to the amount of skilled labour. As discussed earlier, this is assumed to be a positive function of and concave to skilled labour, capturing diminishing returns to scale.

The optimal adoption and free entry conditions imply that the R&D to GDP ratio is a decreasing function of γ. This relationship can be used to calibrate the value of γ. Anzoategui et al. (2016), for instance, follow this approach and set γ to 0.95.[18]

[16] See for example, Comin and Hobijn (2010), Comin and Mestieri (2013), Cox and Arm (1996).
[17] These technologies include: personal computers, cellphones, and internet.
[18] They validate this ex-post calibration by comparing the volatility of the speed of technology diffusion with two data counterparts. One is the volatility of the speed of adoption of 26 technologies in the UK and the U.S relative to the volatility of GDP. The speed of diffusion is approximately four times more volatile than GDP. The second exercise Anzoategui et al. (2016) conduct is to compare the series of the adoption rate produced by a

Obsolescence rate

There are three main approaches that could be used to calibrate the obsolescence rate.

1. A first approach consists of using information on the rate of decline of patent citations as in Caballero and Jaffe (1992) who estimate the obsolescence rate of new technologies to be 4% per year (or 1% quarterly).

2. A second approach could use obsolescence rate estimates based on the rate at which new technologies have historically replaced old technologies. Taking as a benchmark the technologies in Comin and Hobijn's CHAT dataset (Comin and Hobijn, 2009) this approach yields obsolescence rates of less than 1% per year. For example, it took more than 100 years for trains to be taken over by cars, the telegraph to be taken over by phones, and those to be replaced by cell-phones.[19]

3. A third approach could be based on the rate of depreciation of patents inferred from patent renewal data. Using this strategy Bosworth (1978) estimates an annual obsolescence rate of 12%.

The range of estimates from these approaches suggests the value of the obsolescence rate could be determined within the range of 4% to 8% per year, which lies approximately in the centre of the estimates discussed above.[20]

model with a value of 0.95 for γ , with the actual speed of diffusion of three technologies related to the use of internet to procure and sale goods and services in the U.K. Again, the series simulated by the model produce a decline in the speed of diffusion around the Great Recession very similar to that observed in the UK data.

[19] One way to measure this is by exploring the year in which, say, the number of telegrams sent scaled by some measure of economic activity (e.g., GDP) or population started to decline.

[20] If newer technologies are being adopted faster, then the obsolescence rate could be higher than the values reported in the literature which are based on older technologies.

5 Diffusion & TFP

This section focuses on evaluating the role of technology diffusion on TFP and growth by (1) studying the role of the adoption lag on TFP and (2) exploring the impact of endogenous technology diffusion on the amplification and propagation of business cycle shocks. These exercises aim to illustrate the importance of incorporating technology diffusion into QUEST III.

To conduct these exercises, the model developed by Anzoategui et al. (2016) is adopted and simulated. This model is appropriate because (other than for the treatment of technology diffusion) it is similar to QUEST III. In particular, this model features price and wage rigidities *a la Calvo*, endogenous development of new technologies through R&D that is intensive in skilled labour, habit formation, endogenous accumulation of capital with flow adjustment costs to investment, and a Taylor rule determining monetary policy. Additionally, this model includes shocks to the exogenous preference for liquid assets, i.e. riskless bonds that propagates like a financial shock.

5.1 The role of adoption lags

To explore the role of adoption lags on TFP dynamics, the impulse response function to a shock to the number of developed technologies in the economy is computed. It is assumed that the law of motion for developed intermediate goods is defined as in (2):

$$Z_{t+1} = \phi Z_t \varkappa_t S_t^{\rho} + \phi_t Z_t$$

where the survival rate is stochastic and follows the AR(1) process:

$$\phi_{t+1} = (1-\rho_\phi)\phi + \rho_\phi \phi_t + \epsilon_t \qquad (10)$$

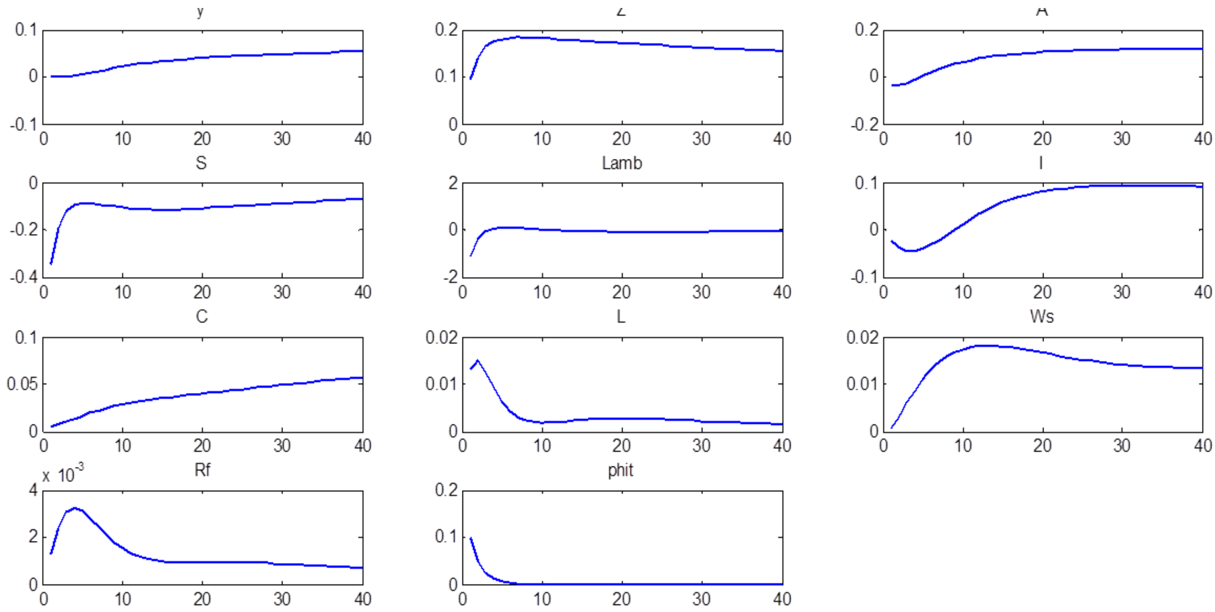
In particular, a positive innovation, ϵ_t, leads to a lower obsolescence of the stock of technologies, and hence to a higher stock of developed technologies next period. This shock is isomorphic to an exogenous increase in the number of technologies in QUEST III.

Figure 2 plots the impulse response functions associated with a 10% increase in ϕ_t.[21] The main focus is the evolution of output and stock of developed and adopted technologies. However, other model variables and parameters are also displayed for completeness. The main insight is that in response to an exogenous increase in ϕ_t, the stock of developed technologies (Z) jumps, but there is no immediate effect on the stock of adopted technologies (A) and in output (Y). This is the case because technologies need to be adopted before they are useable for production. Indeed, the shock causes an initial decline in the rate of adoption (λ), and in R&D labour (S). This is the case because the increase in the stock of developed technologies reduces the return to both developing and adopting new technologies.[22]

[21] ρ_ϕ is calibrated to 0.5, quarterly.

[22] This is a consequence of the increase in the wage for skilled labour (panel 9) due to the higher demand for adoption services in the aggregate.

Figure 2: Impulse response function to a shock to ϕ_t



Notes: Impulse response functions computed using the Anzoategui et al. (2016) model and assuming a 10% increase in ϕ_t; y: output, Z: stock of developed technologies; A: stock of adopted technologies; S: R&D labour; Lamb: adoption rate; I: investment; C: consumption; Ws: wages; Rf: risk free rate; phit: survival rate of technologies.

The increase in the stock of developed technologies only impacts productivity slowly as the new technologies are adopted. This is manifested in the slow increase in the stock of adopted technologies and output. This evolution is very different from the impulse response functions that a model without slow diffusion such as QUEST III would produce. In this type of models, the productivity of the economy is given by the stock of developed technologies, and therefore an immediate jump in output and TFP would be observed.

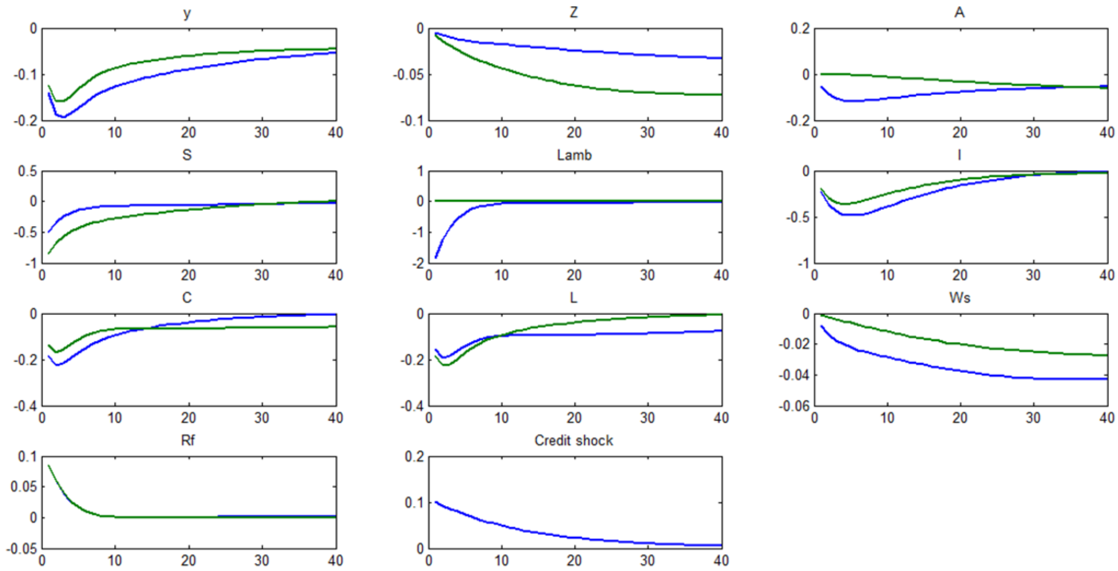
5.2 The role of an endogenous diffusion process

The endogenous nature of technology diffusion may be a powerful source of amplification and propagation of business cycle fluctuations and economic policies. Recent work by Comin (2009) and Anzoategui et al. (2016) has shown that the speed of technology diffusion is pro-cyclical.

To explore the implications of the cyclicality of the speed of diffusion of technologies for business cycle fluctuations, Figures 2 and 3 plot the impulse response functions to two standard shocks in the model developed in section 3 (in blue) and in a version of that model with a fixed speed of technology diffusion (in green).

In particular, Figure 2 considers a shock to liquidity demand that transmits like a shock to financial frictions. This can be thought of as the shock observed in financial markets in the fall of 2008. Figure 3 considers an exogenous TFP shock. This shock can be interpreted as a general increase in the efficiency of the production factors (Kydland and Prescott, 1982).

Figure 2: Impulse response functions to a 10% increase in liquidity demand



Notes: Impulse response functions computed using the Anzoategui et al. (2016) model and assuming a 10% shock to liquidity demand; y: output, Z: stock of developed technologies; A: stock of adopted technologies; S: R&D labour; Lamb: adoption rate; I: investment; C: consumption; Ws: wages; Rf: risk free rate; blue line assumes endogenous diffusion and green line a model with fixed diffusion.

The liquidity demand shock leads agents to save in the form of the liquid asset. This lowers consumption and investment in physical capital (C and I) as well as output (Y). The flip side of this effect is that, in equilibrium, agents need to be compensated with a higher return to hold the risky assets. The higher discount rate applied to R&D and adoption activities leads to a significant reduction in the amount of skilled labour devoted to these technology upgrading activities (S and λ).

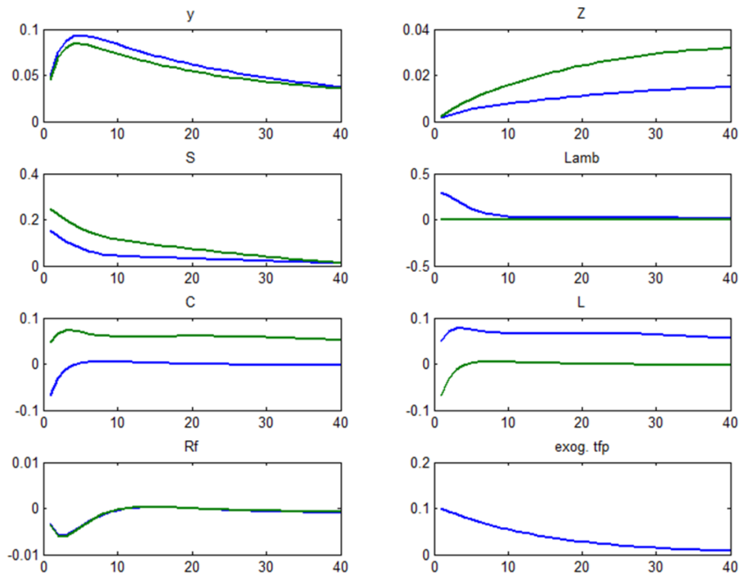
Comparing the blue and the green lines sheds light on the effect of endogenous diffusion. In the model with endogenous diffusion (blue), the response of output is larger and more protracted. The greater amplification and propagation produced by endogenous adoption comes from the pro-cyclical response of adoption. The reduction in the stock of adopted technologies (A) and TFP[23] is faster in the model with endogenous adoption. As a result, the drop in permanent income is also greater and consumption falls by more when adoption is endogenous.

The evolution of the stock of adopted technologies in the model with endogenous adoption reaches the minimum after approximately five quarters. From there it levels off but it takes 30 quarters for the level of adopted technologies to converge in the two models. In contrast, the stock of un-adopted technologies declines faster in the model with a fixed adoption rate. This follows from the fact that, in this model, all skilled labour is employed in R&D activities. As a result, the reduction in skilled labour supply is fully transmitted into a lower flow of R&D.

Figure 3 shows the impulse response functions to an exogenous TFP shock and shows that the key findings from Figure 2 are robust to the exogenous TFP shock. In particular, the endogenous adoption mechanism increases both the amplification and propagation of the shock because of the faster impact of the shock on the stock of adopted technologies and endogenous TFP.

[23] In this model, TFP has an endogenous component that is proportional to A.

Figure 3: Impulse response function to a 10% increase in exogenous TFP



Notes: Impulse response functions computed using the Anzoategui et al. (2016) model and assuming a 10% shock to total factor productivity; y: output, Z: stock of developed technologies; A: stock of adopted technologies; S: R&D labour; Lamb: adoption rate; I: investment; C: consumption; Ws: wages; Rf: risk free rate; exog tfp: total factor productivity; blue line assumes endogenous diffusion and green line a model with fixed diffusion.

6 Appendix

This section provides estimates of the speed of diffusion across a number of countries. The approach builds the estimates of Comin and Mestieri (2013), where the adoption lags for the adoption of various technologies for a number of countries have been estimated. For each technology and country, the speed of technology diffusion is computed as:

$$\lambda_{c\tau} = Min\left(\frac{1}{Max(Lag_{c\tau},0)}, 1\right). \qquad (11)$$

In turn, adoption lags are regressed on a full set of country and technology dummies. The focus is on technologies invented since 1950 since there has been a secular acceleration in the speed of diffusion of technologies (Comin and Hobijn, 2010).[24][25] This allow computation of the average speed of diffusion of technology for each country. The speed of diffusion estimates are reported in the following table.

Country	Speed of Diffusion[26]
USA	0.229
UK	0.102
Ukraine	0.009
Turkey	0.066
Switzerland	0.159
Sweden	0.332
Spain	0.086
Slovenia	0.016
Slovakia	0.007
Romania	0.006
Portugal	0.080
Poland	0.023
Norway	0.112
New Zealand	0.071
Netherlands	0.121
Japan	0.080
Italy	0.073
Ireland	0.054
Hungary	0.036
Greece	0.057
Germany	0.095
France	0.115
Finland	0.235

[24] These include PCs, internet, cellphones, Blast oxygen steel, heart, kidney and liver transplants.
[25] The historical adoption lags may differ from those of existing or future technologies.
[26] The estimates of adoption lags for some countries are very long, in the ballpark of 100 years. This implies that the speed of diffusion is very low (around 1%). However, this is the case in just a few of the countries in the sample. The method used to estimate adoption lags is such that those are identified from the curvature of the diffusion curves. Because diffusion curves are typically very non-linear, the estimates of adoption lags are very precise. In all cases they are significant and the confidence interval is smaller than 1 year.

Denmark	0.376
Czech Republic	0.215
Croatia	0.013
Canada	0.254
Bulgaria	0.006
Belgium	0.093
Austria	0.106
Australia	0.220

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The Directorate General for Research and Innovation of the European Commission commissioned Deloitte and RAND Europe to undertake a study with the aim to better understand the impact of public policy on innovation. In particular, the objective of the study is twofold: enhance the evidence base around the impact of public policy on research and innovation; explore possible modifications in QUEST III to evaluate a number of innovation policies and reforms.

This report focuses on the update of the parameters of the knowledge production function in QUEST III using more up-to-date data and a broader set of countries. Furthermore, the current specification of the knowledge production function is extended by differentiating between public and private R&D.

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