The drivers of productivity dynamics over the last 15 years[1]

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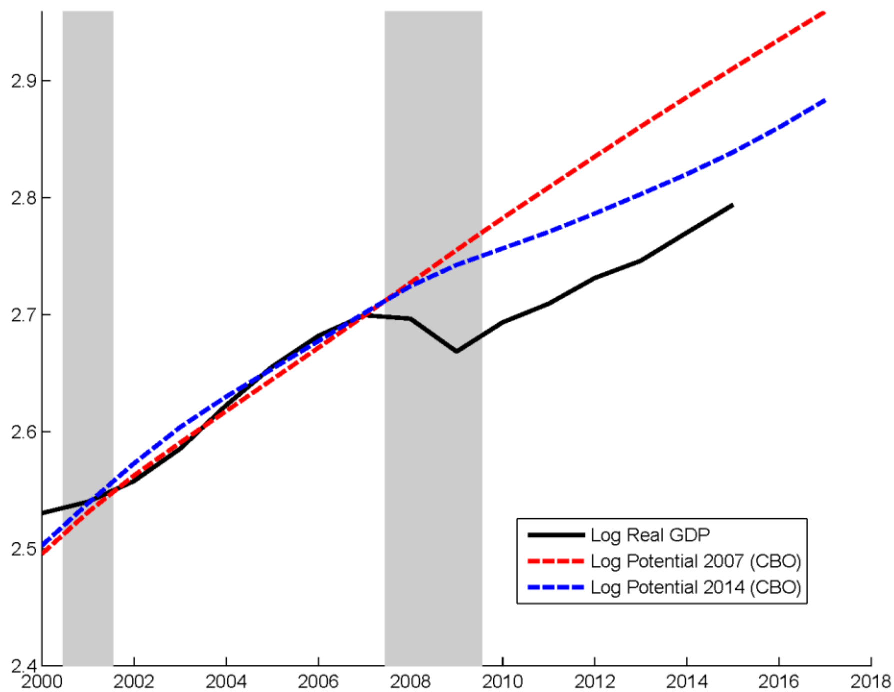
Motivation

The labor markets have recovered to the level of activity before the Great Recession. In May 2016, the unemployment rate was 4.7%, the same rate as in November 2007, the last month before the official start date of the Recession. In contrast, output has not converged to the pre-recession trend. Figure 1 plots the evolution of the log-level of output (in black) together with the level of potential output as projected by the Congressional Budget Office (CBO) in 2007. Note that subsequently the CBO revised the potential output estimates to reflect the effect that the Great Recession has had on potential output.

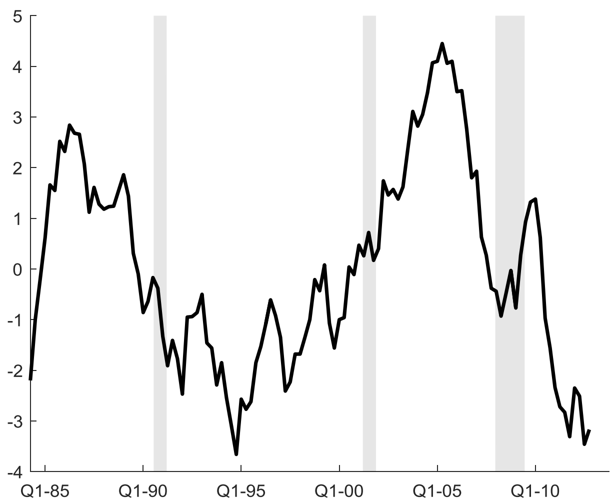
Figure 1: Evolution of Real and Potential Output



[1] Much of what is described in this article builds on Anzoategui, Comin, Gertler and Martinez (2016).

The fact that employment has recovered but output has not suggests that there has been a significant slowdown in productivity growth. Figure 2 documents this fact. The goal of this article is to study what has driven the slowdown of productivity.

Figure 2: Evolution of (linearly detrended) capacity adjusted Total Factor Productivity, from Fernald (2014)



The two hypotheses

To rationalize the behavior of productivity I am going to consider two hypotheses. The first, put forth by Fernald (2014), is that for exogenous reasons TFP growth slowdown around 2004/5. Under this bad luck hypothesis, the decline in TFP growth during the recession was not caused by cyclical factors but by a secular trend or by the exhaustion of the growth possibilities offered by information and communication technologies (ICTs). This hypothesis is related to Gordon (2014) who argues that the US economy has suffered a secular stagnation in its innovation capacity and hence in TFP. In support for this theory, Fernald argues that the slowdown in productivity preceded the Great Recession. Hence, he concludes, it could not be caused by the Great Recession.

The second hypothesis presented by Anzoategui et al. (2016) argues that the decline in TFP growth during and after the Great Recession was a consequence of firms' responses to the downturn. In particular, they cut their investments in the development and, especially, adoption of new technologies. The 2004-08 slowdown in productivity can similarly be rationalized by the sharp decline in R&D activity during the 2001 recession. Because it takes time for new technologies to diffuse, the drop in innovation activity may have impacted TFP growth only after 2004.

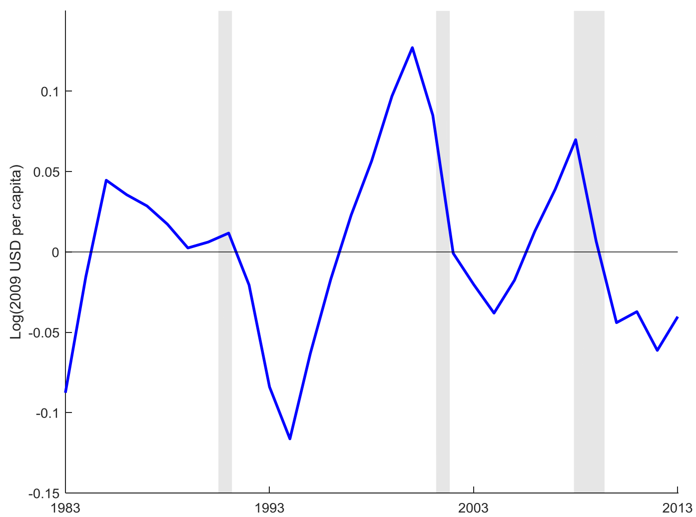
Prima Facie Evidence

Before showing the results from a formal analysis, it is helpful to present some a priori evidence that may help us assess the potential for the endogenous response theory. In particular, I'll explore the evolution of both measures of innovation as well as technology diffusion.

R&D cyclicality —

Figure 3 plots the detrended level of expenses on R&D conducted by US corporations.[2] During the Great Recession, there was a significant decline in R&D potentially consistent with endogenous growth factors contributing to the productivity slowdown.

Figure 3: Private US expenditure in Research and Development (linearly detrended)



There was also a large decline in R&D expenditures following the 2001-2002 recession, which is consistent with the possibility that the productivity slowdown prior to the Great Recession was also in part a response to cyclical factors.

Cyclicality of the speed of technology diffusion —

Most companies do not directly engage in R&D activities but need to adopt the technologies they use in production. This reality suggests that the processes of diffusion and adoption may be more important to understand the drivers of productivity growth at short and medium term frequencies.

Anzoategui et al. (2016) and Comin (2009) estimate the cyclicality of the speed of diffusion of new technologies. They use a panel that contains information on the diffusion of 26 specific technologies in the US and UK.[3] Many of the technologies consist in manufacturing processes invented between 1945 and 1990. The measure of diffusion is the fraction of potential adopters

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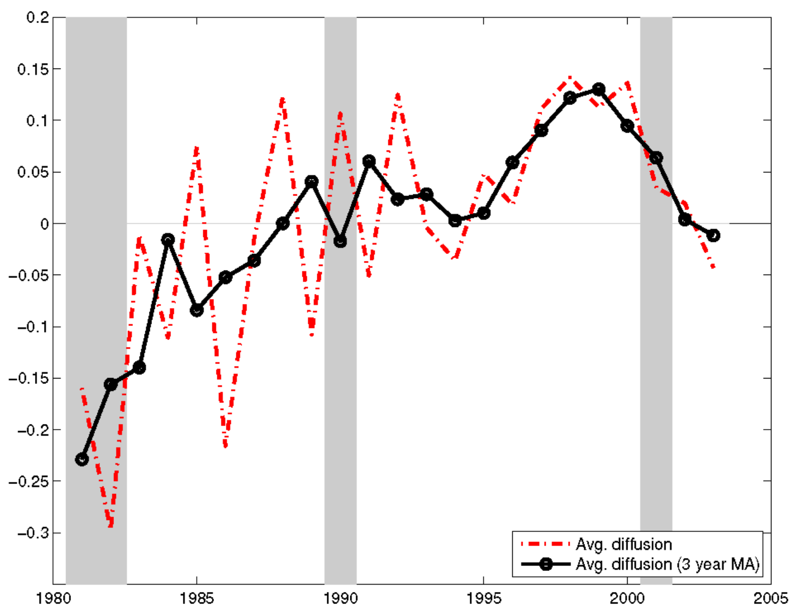
[2] All expenditure measures reported in what follows are deflated by the GDP deflator, scaled by population over 16 years and expressed in logarithms. This variable is then linearly detrended to obtain the series plotted.

[3] The data on UK technologies comes from Davies (1979) and covers special presses, foils, wet suction boxes, gibberellic acid, automatic size boxes, accelerated drying hoods, basic oxygen process, vacuum degassing, vacuum melting, continuous casting, tunnel kilns, process control by computer, tufted carpets, computer typesetting, photo-electrically controlled cutting, shuttleless looms, numerical control printing presses, numerical control turning machines and numerical control turbines. The data for the five technologies in the US comes from Trajtenberg (1990), and Bartel et al. (2009) and covers the diffusion of CT scanners, computerized numerical controlled machines, automated inspection sensors, 3-D CAD, and flexible manufacturing systems.

that have adopted a specific technology.[4] The speed of diffusion is the first difference in the ratio of adopters to non-adopters. Anzoategui et al. (2016) find that the speed of diffusion of technologies is both pro-cyclical and very volatile. In particular, the elasticity of the speed of diffusion with respect to measures of detrended output is approximately 4. That means that in booms companies greatly accelerate the rate of adoption of new technologies while in recessions they slowdown the process and as a result, their productive capacities fall relative to the state of the art.

Figures 4 and 5 plot the evolution of the average speed of diffusion for two subsamples of technologies. The first is a group of four information technologies in the US during the 1980s and 90s. The second is a group of three internet related technologies in the UK during the 2000s.[5]

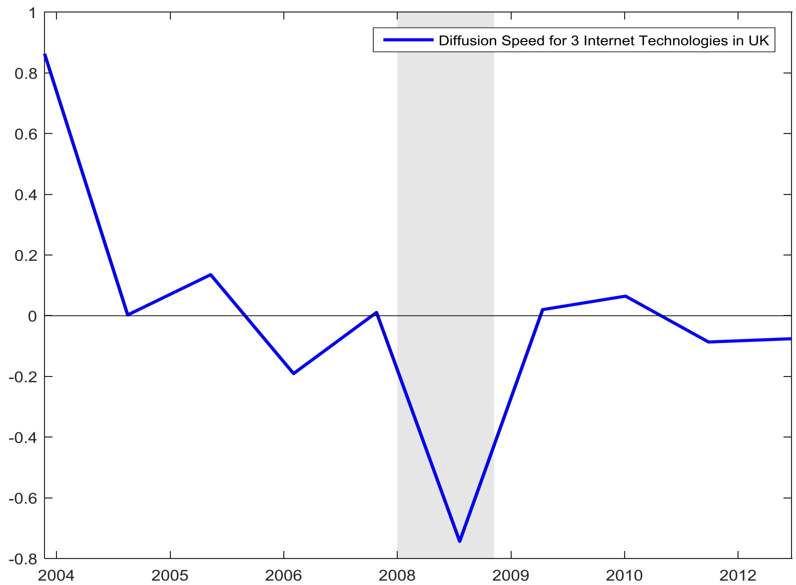
Figure 4: Speed of diffusion of 4 ICT manufacturing technologies in the US



Consistent with the patterns and magnitudes estimated by Anzoategui et al. (2016), both during the 1982 recession and the Great Recession we see very large declines in the speed of diffusion of new technologies.

[4] In particular, they are computerized numerical controlled machines, automated inspection sensors, 3-D CAD, and flexible manufacturing systems.
[5] In particular, they are the fraction of firms that (i) have access to broadband internet, that (ii) actively purchase online products and services and that (iii) actively sell online products and services (actively is defined as constituting at least 1% of sales/purchases).

Figure 5: Speed of diffusion of three internet technologies in the UK

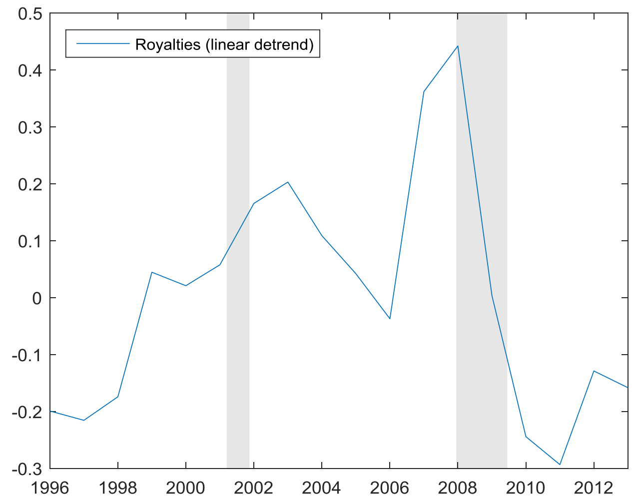


Decline in adoption expenditures —

An alternative way to study the variation in the diffusion of technologies is by looking at the expenditures incurred by companies to bring in new technologies. Unfortunately it does not exist an aggregate time series that covers all the investments in technology adoption by companies. However, we can cleanly study one component of this measure. Namely, the expenditures by companies in licensing technologies developed by universities. This variable is measured by a survey conducted by the association of university technology managers (AUTM). Figure 6 plots the evolution of university revenues from technology licensing (and linearly-detrended).[6] The plot documents a very large drop in university revenues from technology licensing in the survey. In particular, in 2009, this series declined 60% relative to trend. It is significant to note that the decline seems to have been quite persistent. And by the end of the sample, we still have not recovered to the pre-recession level.

[6] As with all series, the nominal series is deflated by the GDP deflator, scaled by population over 16 years old, and logged.

Figure 6: Evolution of university revenues from the licensing of technologies



Dispersion in productivity —

A final, albeit more indirect, way to measure the diffusion of new technologies consists in measuring the dispersion of productivity across companies. Andrews et al. (2015) study the evolution of distribution of productivity across companies in a given sector. To this end, they divide an OECD sample of companies between the most productive in a sector vs. the rest. The most productive firms in the sample have much greater stocks of patents which suggest that they are closer to the frontier than those that are less productive.

The main finding of Andrews et al. (2015) is that the productivity gap between the most productive and the rest has increased significantly during the Great Recession. They interpret the increase in the productivity gap as evidence that followers have slowed down the rate at which they incorporate frontier technologies developed by the leaders.

Structural analysis

These co-movement patterns between the business cycle and measures of investments in technology development as well as measures of the rate of technology adoption are suggestive evidence of the potential role of an endogenous technology response to business cycle conditions. To evaluate quantitatively the relevance of this endogenous evolution of technology for the evolution of TFP, we need to conduct a more structured analysis based on an economic model.

In what follows, I report the results from the analysis conducted by Anzoategui et al. (2016). Their workhorse model is a standard Neo-Keynesian dynamic stochastic general equilibrium (DSGE) model[7] augmented to allow for the possibilities of endogenous development and adoption of technologies. The model permits to decompose TFP into two components. One

[7] Their model includes the standard features in Neo-Keynesian models. These are habit formation in consumption, flow investment adjustment costs, variable capital utilization and "Calvo" price and wage rigidities. In addition, monetary policy obeys a Taylor rule with a binding zero lower bound constraint.

component is the standard exogenous TFP shock. The second component which I refer to as endogenous reflects the factors that drive the stock of technologies used in production.

The model recognizes that, on average, it takes a while for new technologies to be adopted in production. This key feature of the data invites us to differentiate between the stock of technologies developed in the economy and the stock of technologies used in production. The difference between these two is the fact that the latter have been already adopted while the former may have not. This structure allows the authors to study the drivers and evolution of innovation as well as the adoption rate or the speed of diffusion which in this setting are the same.

The model includes a number of shocks that can produce business cycle fluctuations. Two are particularly relevant for this article. The authors allow for an exogenous evolution of the productivity of research and development that may capture Gordon (2014)'s hypothesis that the innovation capacity of the US economy has deteriorated. The model also includes a shock to liquidity demand that captures disruptions in credit markets such as those that cause the Great Recession.

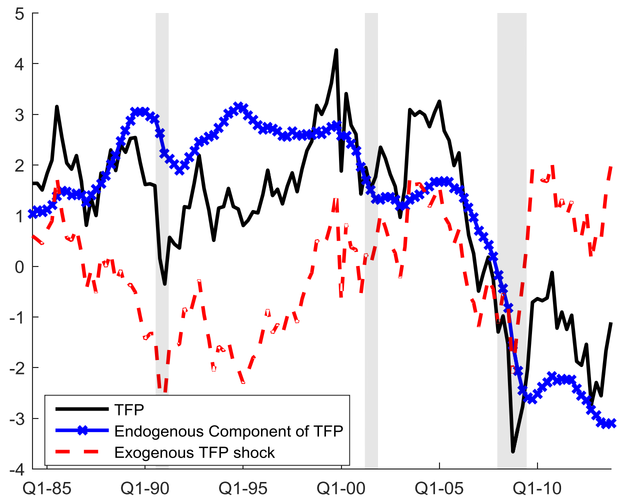
The model is estimated to match the behavior of eight observable series which include the growth in output, consumption, investment, private R&D investments, real wages, hours worked, the feds fund rate, and inflation. The estimation delivers the series for the shocks that are necessary to produce the evolution of the observed variables. The analysis of the estimates is very helpful to answer three questions:

- What is the contribution of the endogenous and exogenous components of TFP to productivity dynamics?
- What shocks have been responsible for the evolution of the endogenous component of TFP?
- What mechanisms have been responsible for the evolution of the endogenous component of TFP?

TFP decomposition —

Figure 7 plots the evolution of (detrended) TFP as well as the endogenous component of TFP. Except for the middle to late 1990s, the endogenous component of TFP accounts for much of the cyclical variation in TFP. The model attributes the rise in TFP during the late 90s mainly to its exogenous component.

Figure 7: Evolution of TFP, and its endogenous and exogenous component[8]



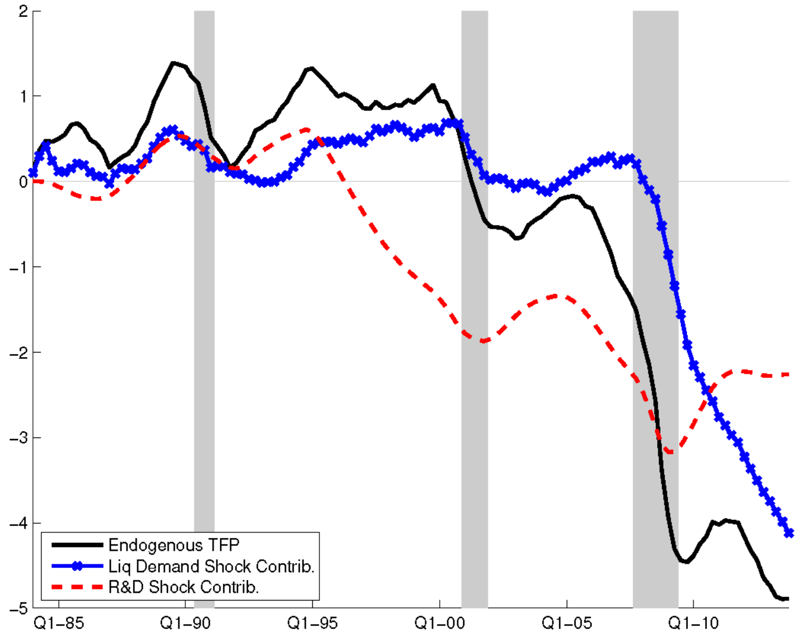
After 2000, however, the endogenous component drives the overall behavior of TFP. Importantly, the endogenous component explains virtually all of the decline in TFP immediately before the Great Recession, as well as the decline during and after that episode. In particular, between the starting point of the recent productivity slowdown, 2005, and the end of our sample, 2013, total TFP declined by approximately 5 percentage points (relative to trend). The endogenous component accounts for 4.75 percentage points of decline.

Role of key shocks —

While endogenous TFP declines steadily after 2005, the main sources forces of the drop vary over time. Figure 8 presents a historical decomposition of endogenous TFP (black) that isolates the effects of the two shocks that were the main causes of the decline: (i) shocks to the productivity of R&D (dashed-red) and (ii) the liquidity demand shock (crosses-blue). We note first that the liquidity demand shock accounts for nearly all of the decline in endogenous TFP after the start of the recession at the end of 2007. This result is consistent with the notion that liquidity demand shocks were the main disturbance driving the recession.

[8] See text for definitions and details about how they are computed.

Figure 8: Decomposition of endogenous TFP by source of fluctuations



In the period just prior to the Great Recession, 2005-2007, however, the liquidity demand shock is unimportant. Instead the decline in endogenous TFP is mainly the result of negative shocks to the productivity of R&D.[9]

The downward trend in R&D productivity actually begins in the mid-1990s, which is consistent with Gordon (2014)'s hypothesis of a secular decline in the contribution of technological innovations to productivity. After a brief upturn following the 2000-01 recession, shocks to R&D productivity induce a sharp downturn in TFP from 2005 until the height of the crisis.

Intuitively, the exogenous decline in R&D productivity generated fewer technologies for a given level of R&D spending, which ultimately slowed the pace of new technology adoption. Our finding that shocks to R&D productivity mainly account for the pre-recession slowdown in TFP is consistent with Fernald (2014)'s hypothesis that exogenous medium-term factors, as opposed to cyclical factors were at work. At the same time, our endogenous productivity mechanism allows cyclical shocks as well shocks to R&D productivity to drive TFP. In this regard, our accounting suggests that once the recession began, it was cyclical shocks in the form of liquidity demand shocks that largely drove the subsequent decline in endogenous TFP.

Role of key propagation mechanisms —

We next explore the relative importance of the specific mechanisms that drive endogenous TFP. There are two mechanisms that drive fluctuations in the stock of available technologies for production: movements in the adoption rate and movements in the stock of un-adopted technologies.

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[9] Shocks to the productivity of R&D are identified by comparing the model implications for the cyclicality of R&D with the data.

Figure 9: Decomposition of endogenous TFP between adoption and innovation margins

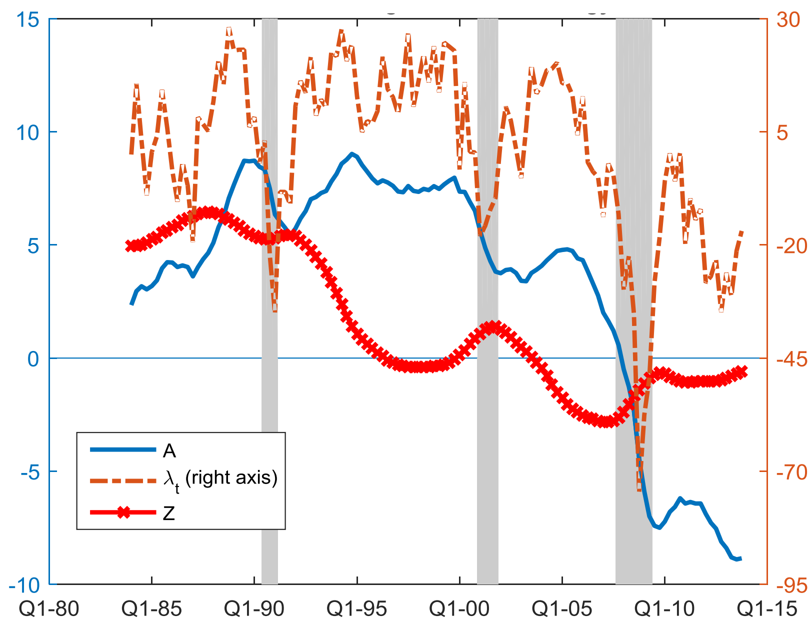

Figure 9 explores the drivers of the evolution of the stock of technologies used in production by plotting it together with the evolution of the speed of diffusion of new technologies (denoted by λ) and the stock of developed technologies (denoted by Z).

We find that cyclicality in the adoption rate, λ, is the main driver of cyclical fluctuations in endogenous productivity: λ co-moves closely with the stock of adopted technologies, while the stock of all technologies, both adopted and un-adopted, does not. During each of the recessions, λ declines implying that the slowdown in adoption drives the cyclical contraction in endogenous TFP.

Further, the magnitude of fluctuations in λ implied by the model is consistent with the estimates in Anzoategui et al. (2016). The standard deviation of λ is 4.45 times that of output, a similar magnitude to our estimate of the elasticity of the speed of diffusion with respect to output (of around 4). Additionally, the fall in λ during the Great Recession implied by the model is plausible in light of the observed fall in adoption speeds for the sample of UK technologies (Figure 5).

Fluctuations in the stock of developed technologies, Z, do play a role in the evolution of endogenous productivity. Following the 2000-01 recession there is a steady decline in Z, consistent with the negative shocks to R&D productivity which contributed to the decline in R&D investments illustrated in Figure 3. Because of the presence of adoption lags, this decline in the stock of developed technologies did not show up in lower TFP growth until the mid-2000s. Hence, the drop in Z helps account for the pre-Great Recession drop in productivity that Fernald (2014) emphasizes.

After the start of the Great Recession, however, the fall in the adoption rate becomes the main driver of the productivity decline. The failure of the adoption rate to return to normal levels, after a brief recovery in 2010, is the reason endogenous TFP continues to decline.

Interestingly, while λ remains low following the Great Recession, the stock of unadopted technologies reaches a peak over the sample. The latter occurs mostly because the stock of adopted technologies declines, but also because there is a modest increase in Z. This finding is consistent with the evidence presented by Andrews et al. (2015) that suggests that innovation by leading edge firms continued after the Great Recession but adoption by followers slowed. An important implication is that the economy may not be doomed to low productivity growth for the foreseeable future. Given the high stock of unadopted technologies, to the extent that increasing aggregate demand pushes up the adoption rate, productivity growth should increase. Conversely, if the economy continues to stagnate, adoption rates will remain low, keeping productivity growth low.

Conclusions

This analysis provides two key insights into the productivity dynamics over the last 15 years.

First, the slowdown in TFP during and after the great recession is due to the decline in the speed of adoption of new technologies in response to the credit disruptions that shocked the US economy since the end of 2007 and that have affected the cost and availability of funds for companies until the end of 2013.

Second, the pre-recession slowdown in productivity was mainly a consequence of the decline in the productivity of R&D activities between 2001 and 2004.

References

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