Estimating Total Factor Productivity during the Great Recession (2007-2009) in the U.S. Manufacturing Industries using the Levinsohn and Petrin (2003) approach over the period (1998-2019)

Dr. Salem Gheit
Faculty of Economics, Bani Waleed University, Libya
salemghait@bwu.edu.ly

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Abstract:

This paper aims to explore the patterns and causes of change in total factor productivity TFP in the U.S. manufacturing industries during the Great Recession period (2007-2009). Using STATA statistical software this study fits a conventional Cobb-Douglas production function, and a Levinsohn and Petrin (2003) production function to estimate TFP using labour hours as a free variable, capital services as a state variable and intermediate inputs as a proxy for unobservable productivity shocks. The LP and OLS TFP estimates at the industry level reveal an interesting story where the growth in productivity in each industry slowed down during and after the years of the (2007-2009) economic turbulence in the U.S. economy. This post-recession slowdown has been widespread and occurred in 70% of the world's advanced, emerging and developing economies, as well as 80% of the world's poorly developed economies. There can be all manner of reason as to what stands behinds this slowdown in TFP, as it is fairly difficult to pinpoint the exact factors that contributed to it, but it can be partly put down to the slowdown in the share of start-ups, deceleration in capital intensity and capital deepening, and a decrease in investment in the aftermath of the recession.

Keywords: Total Factor Productivity TFP, Great Recession, Production Function, Intermediate Inputs, Levinsohn and Petrin (2003) Approach.

تقدير إنتاجية العوامل الكلية أثناء الركود العظيم (2007-2009) في القطاع الصناعي الأمريكي خلال الفترة (1998-2019) باستخدام منهجية ليفِنسون – بِيترين (2003)

د. سالم غيث ماضي
كليـة الاقتصاد - جامعة بني وليد

الملخص:

تهدف هذه الورقة من خلال الاستقصاء العلمي إلى البحث في أنماط وأسباب التغيّرات التي طرأت على إنتاجية العوامل الكلية TFP في القطاع الصناعي الأمريكي خلال فترة الركود العظيم 2007–2009. قدمت هذه الورقة تقديرًا لدالة الإنتاج باستخدام منهجية ليفِنسون وبِيترين (2003) أو ما يُطلق عليها اختصارًا LP 2003 والمُصمّمة لتقدير الإنتاجية بالاستعانة بالمُدخلات الوسيطة كمؤشر على الصدمات التي تحدث في الإنتاجية على المستويين الجزئي والكلي في الاقتصاد. كما قدمت الورقة تقديرًا للإنتاجية بطريقة المربعات الصغرى الاعتيادية OLS وذلك بغرض مقارنتها بالتقديرات المُتحصّل عليها من منهجية LP 2003. إذ تُظهر التقديرات أن نمو الإنتاجية في أغلب الصناعات التي تضمنتها هذه الدراسة قد تباطأ بشكل ملحوظ خلال سنوات الركود الاقتصادي 2007–2009 وخلال السنوات اللاحقة لذلك. وبشكل عام فقد شهدت الاقتصادات المتقدمة والناشئة والنامية تباطؤات دراماتيكية في الإنتاجية بلغت 70% مقارنة بما كان عليه الحال قبل الركود، وبلغت هذه التباطؤات أشُدها في الاقتصادات الأقل نموًا إذ بلغت وتيرة التباطؤ مستويات قياسية وصلت إلى 80% خلال الفترة التي أعقبت الركود العظيم. ولعلّه من الصعوبة بمكان تحديد الأسباب الجوهرية وراء هذا الانحدار والتباطؤ الكبير في الإنتاجية، ولكن يُمكن إرجاعه إلى عدّة عوامل يمكن اعتبارها محدداتٍ أساسيةٍ لنمو الإنتاجية في الاقتصاد الأمريكي منها: الانخفاض في معدل نمو الشركات الجديدة والصغرى كنسبة من إجمالي الشركات في الولايات المتحدة، وانحسار كثافة رأس المال، وهبوط معدل تعمّق رأس المال، وانخفاض معدل الاستثمار بشكل عام في السنوات التي تلت الركود العظيم. بناءً على ذلك فإن هذه الورقة تبحث في محددات وأسباب وأبعاد هذا التباطؤ في إنتاجية العوامل الكلية وتحليل سلوك الإنتاجية قبل وأثناء وبعد تلك الأزمة المالية.

الكلمات المفتاحية: إنتاجية العوامل الكلية، الركود العظيم، دالة الإنتاج، المُدخلات الوسيطة، منهجية ليفِنسون وبيترين (2003).

1. Introduction:

Total Factor Productivity TFP has been given considerable attention in the theoretical analysis and the empirical research. Solow (1957), Jorgensen (1963), Hayashi (1991), Griliches (1996), and Hulten (2000) and others in the literature tend to favour productivity as the centrepiece in explaining the output growth and was regarded as a core factor in driving the economic growth, knowing that the U.S. Bureau of Labour Statistics supported this view and put it into use in their regular releases of data and analyses on productivity, but the argument here is that the impact of the errors associated with the measurement of total factor productivity are causing TFP estimates to be biased and prejudiced when applying data on real output growth, and the growth of real inputs according to the economic theory of production with the assumption of constant returns to scale CRS coupled with the necessary conditions to reach the producer's equilibrium. Thus, it is suggested that the allocation of both changes in output and inputs between their movements along the frontier of production function and its shifts needs to be corrected for this bias that is attributed to conceptual and measurement errors.

The influential contribution of Marschak and Andrews (1944) had referred to the problematic issues which constantly emerge in terms of the econometric identification for parameters, such as mark-ups, returns to scale, and productivity because of a potential correlation between inputs and productivity, which can directly lead to biased OLS estimates. In other words, the correlation between unobservable productivity shocks and inputs levels is the core matter of concern when estimating the production function, (Marschak and Andrews, 1944).

On the one hand, profit-maximising firms are expected to respond to the positive productivity shocks by utilising more inputs in order to expand their output, (Levinsohn and Petrin, 2003). On the other hand, the negative productivity shocks will urge these firms to reduce the use of inputs to pare back their output. Levinsohn and Petrin (2003) (LP 2003 henceforth) suggested an alternative approach to the one presented by Olley and Pakes (1996) (OP 1996 henceforth). This is where they pointed out that investment can be very lumpy based on evidence coming from the firm-level data, because of substantial costs' adjustments, (DeSouza 2006).

In the case of firms that make intermittent investments the zero-investment observations will be obvious, and they will be truncated from the estimation routine, which dismisses, in effect, the condition of monotonicity for these observations. This will lead to the fact that investment may not respond smoothly to the productivity shocks, which at the same time will violate the condition of consistency and unbiasedness that is required in the OLS estimates, (Levinsohn and Petrin 2003). Therefore, applying the OLS will yield biased and inconsistent estimates. The commonly used solutions to this endogeneity problem are the fixed effects technique and the instrumental variables estimation, but both did not work properly in practice.

The FE estimation has yielded unrealistic low estimates of the capital parameter, while using input prices as an IV has proved that these prices are not often observed and they do not vary enough across the firms that work in competitive input markets, (Ackerberg et al. 2007). Thereby, Levinsohn and Petrin proposed intermediate inputs to be the candidate as a proxy for productivity shocks, (Petrin et al. 2004). A greater attention will be paid to this approach in the methodology section. The overriding aim of this study is to examine the behaviour of TFP and the way it changes before, throughout and after the financial crisis that hit the U.S. economy between 2007 and 2009. For estimating production functions using panel data, (OP 1996) showed how, under certain assumptions, investment can be used as a proxy variable for unobserved, time-varying productivity. Specifically, they demonstrate how to invert an investment rule to express productivity as an unknown function of capital and investment (when investment is strictly positive). (OP 1996) present a two-step estimation method where, in the first stage, semiparametric methods are used to estimate the coefficients on the variable inputs. In the second stage, the parameters on capital inputs can be identified under assumptions on the dynamics of the productivity process. (LP 2003) propose a modification of the (OP 1996) approach to address the problem of lumpy investment. (LP 2003) suggest using intermediate inputs to proxy for unobserved productivity. Their work contains assumptions under which productivity can be written as a function of capital inputs and intermediate inputs (such as materials and electricity). As with (OP 1996) and (LP 2003) propose a two-step estimation method to consistently estimate the coefficients on the variable inputs and the capital inputs, (Wooldridge 2009).

2. Research Problem:

When tracking down the progress of total factor productivity in the United States over decades, it is noticed that during most of the recession waves in the U.S. economy, TFP was negatively affected, mainly during the recessions in

1973-1975, 1981-1982, the early 1990s, and recently the Great Recession 2007-2009. At all events, productivity growth shows signs of obscurity and ambiguity at the same time as it gives the impression of not being an easy phenomenon to understand fully because it is shrouded in multiple levels of enigma and because it is in fact a combination of different things. The important thing is that productivity grew by just 0.7% at an annual average rate during the aftermath of the Great Recession between 2010 and 2014. At industry level, and during the growth surge in the U.S. economy 1995-2004 the largest contribution to TFP growth came from the service sector by 0.44%, and then came the manufacturing sector with 0.39% and the wholesale trade by 0.15%. The manufacturing sector contribution was mainly driven by the semiconductors and information technology manufacturing boosted up by the decline in ICT prices in product markets which increased the growth in aggregate demand for this kind of products which in turn led to higher investments and increased productivity.

3. Research Questions:

- What are the main factors that could have possibly played significant roles in the TFP slowdown during and post the recession period?

4. Research Hypotheses:

- There are various factors that caused TFP growth to be weakened perior, during and post the Great Recession years (2007-2009).

5. Research Objectives:

- Investigating the main factors that affected the TFP growth prior, duirng and post the Great Recession years (2007-2009).

6. Research Importance:

This research derives its importance for the importance of total productivity growth itself. As it is regarded by notable economists including: P. Krugman – who is a Nobel prize laureate in Economics in 2008 – as the main source of economic growth in the long run.

7. Literature Review:

Krugman (1994) defines productivity as, “productivity isn’t everything, but in the long run it is almost everything. A country’s ability to improve its standards of living over time depends almost entirely on its ability to raise its output per worker”, (Krugman 1994). There is a proliferation of research dedicated to the growth of total factor productivity (TFP) and its drivers across countries. In the most recent research, Haider et al. (2021), examined the impact of R&D, trade, and ICT on TFP growth in 25 countries in Europe along with Japan and the U.S. over the period from 1990 to 2006. This is where they decomposed the growth in TFP into two components; 1) innovation and 2) catching up with the technological frontier. Kéïta and Hannu (2021), looked at to what extent corruption and taxation impeding TFP growth using a panel data spanning 90 nations over the period 1996 – 2014. The results of the study suggest that both corruption and taxes played significant role in disrupting and distorting growth in TFP.

Pegkas et al. (2020), investigated the effects of foreign and domestic research and development capital on total factor productivity in Europe during the period from 1995 to 2016, and found out that there is significant role played by R&D capital in promoting TFP. However, the role of the foreign R&D capital appeared to be more significant than the domestic one. Ngo et al. (2020), applied the generalised method of moments technique (GMM) to examine the different factors that impacted the growth in TFP in a panel data for 21 manufacturing industries – formed of firms with different sizes – in Vietnam over the period from 2010 to 2015. The findings suggest that TFP levels in larger enterprises seemed to be higher than that of smaller firms in this set of manufacturing industries.

Rfoa and Bakeer (2020), estimated both Cobb-Douglas and translog production function for 6 sectors in private sector in the Jordanian economy during the period (2000-2015). The results of the estimation showed that the Cobb- Douglas functional form is more appropriate for this set of data, and that theses sector are likely to be more labour-intensive than capital-intensive, given that the production elasticity of labour (0.58) was found to be higher than the production elasticity of capital which was equal to 0.49. Saleem et al. (2019). Examined the impact of innovation – as one of TFP determinants – on economic growth in Pakistan applying the Cobb-Douglas production function to a time series data covering the period from 1972 to 2016. The results of the estimation suggested that innovation has significant effects on growth and output level. Giang et al. (2019), suggests that the macroeconomic growth is largely dependent of the growth in productivity at the micro-level, and the vast majority of studies refer to TFP when discussing and estimating productivity Blazkova et al., (2020); Cieslik et al., (2018); Botric et al., (2017); Doumi (2017).

Apparently, there is a great number of studies which had estimated and assessed TFP with a variety of techniques, (Jung et al. 2008), (Van Biesebroeck 2007; 2008) observed and reviewed these methods and categorised them based on the more commonly-used approaches. These are (1) the index number by Tinbergen (1941), Kendrick (1955), Solow (1957), Diewert (1976), Caves et al

(1982), and lastly, Good et al (1999). (2) Data Envelopment Analysis or the so-called non-parametric frontier estimation DEA by Farwell (1957), and Charnes et al (1978). (3) Parametric estimation or instrumental variables estimation GMM by Blundell and Bond (1998, 2000). (4) Stochastic Frontier Analysis SFA by Farwell (1957), Aigner and Chu (1968), Aigner et al (1977), Meeusen and van den Broeck (1977), Cornwell et al (1990). (5) Semi-parametric estimation by (Olley and Pakes 1996; Levinsohn and Petrin 2003; Jung et al. 2008; , and Wooldridge 2009).

Estimating growth in total factor productivity tends to be a difficult business in some cases, but it is fundamental to assess any economy's performance. To estimate TFP, the start needs to be with a conventional Cobb-Douglas production function where the inputs are combined and mixed together to produce output.

GDP which is denoted by Y, is assumed to be produced by making use of two factors, human-capital-adjusted labour H, and physical capital K. Building on that, the Cobb-Douglas production function would be written as this:

$$Y = A\,K^{\alpha}H^{1-\alpha} \quad \text{.........} \; 1$$

Where A is TFP, and $\alpha, 1-\alpha$ measure the importance of physical capital and human capital in output, respectively. To estimate productivity growth, it is necessary to collect not only data on $Y, K, H,$ but it is also required to gather data on the production function parameters, because these are not directly observable. If we re-arrange the variables in equation (1) and re-write it in the growth rate form, TFP can be written as growth in output less a weighted average of growth in inputs.

$$g_A = g_Y - [\,\alpha g_K + (1-\alpha) g_H] \quad \text{............} \; 2$$

Where $g_A, g_Y, g_K,$ and g_H denote the growth rates of the variables $A, Y, K,$ and H

After obtaining the data on the growth rates of Y, K, and H, coupled with the information on the parameters of the production function, it is possible now to estimate the productivity growth as the difference between output growth and a weighted average of growth in inputs. With the observed growth rates of physical capital and human capital in mind, the chosen value can matter a lot for estimating TFP growth.

By increasing (α), the weight on the fastest growing factor of production will increase in equation (2), leading to lower estimated TFP growth. GDP Growth rates are easy to attain but measuring the growth rate of K and H is more complicated and difficult. In most cases the perpetual inventory method is used to measure physical capital, where an estimate of the capital stock is used in a base year, with assumptions on depreciation, and the flow of new investment. It is also worth mentioning that the production function depends on human-capital-adjusted labour input H. this summarises the contribution of “brains” (education) and “brawn” (the size of the labour force).

In their approach, (OP 1996) included in their estimates proxy controls for the correlation between the error term and inputs by bringing out any possible variation which could be related to the productivity term, (Olley and Pakes 1996).Based on their model, the production function will be written in the logs form as follows:

$$y_t = \beta_0 + \beta_l l_t + \beta_k k_t + \beta_m m_t + w_t + \eta_t \ldots\ldots 3$$

Where y_t is the log form of the firm’s production, (It is measured as gross revenue or value added) l_t and m_t are the freely variable production factors for labour and intermediate input. k_t is the log of the state variable capital, (Yasar et al. 2008). The key difference is that the Et (the error term) is divided into w_t andη_t, where the former is assumed to affect the firm’s decisions, whilst the latter does not affect the firm’s decisions. Thereby, η_t is not observed by the econometricians, even though it could affect the inputs choice, and ignoring it would lead to inconsistent estimates (especially with using OLS for the estimation). According to Olley and Pakes, the investment would be a function of the two state variables which are k_t and w_t.

$$i_t = i_t\,(w_t\,, k_t) \qquad \ldots\ldots 4$$

Pakes (1996) proved that optimising firms tend to invest more when w_t increases in a random way, so their investment functions are increasing in the unobserved productivity shocks. This means that better productivity shocks today will result in a better shock in the future, and hence it will generate the capital accumulation. That can lead us to say that w_t can be a function of investment and capital. Mathematically, $w_t\,(i_t, k_t)$. Based on this, the above equation can be rewritten as this:

$$y_t = \beta_t l_t + \Phi_t(i_t, k_t) + \eta_t \ldots\ldots 5$$

Where: $\Phi_t(i_t, k_t) = \beta_0 + \beta_k k_t + i_t\,(w_t\,, k_t)$

8. Productivity and Economic Recession:

The impact of financial crises can vary in degree from one country to another, and from one industry to another, likewise. One of these repercussions is to increase the level of productivity dispersion between firms, and therefore, the variation of productivity between industries.

Several studies including; Mulligan, (2011). Schaal, (2012). Escribano & Stucchi (2014). Fernald, (2015). Corrado, Haskel, Jona-Lasinio, & Iommi, (2016). Oulton, (2018). Tzeremes, (2021) were dedicated to investigating the effects of the economic downswings on the growth of productivity, but less attention has been paid to the impact of financial crises on the disparity of productivity within and between industries, because the focus was by and large on the patterns of change in productivity growth during the crisis, and not the differences in productivity before and after the crises periods.

This is where, according to Kim (2013) the accumulated inefficiencies in production will be cleansed out via the so-called “Cleansing Effect”, (Caballero and Hammour 1991), which will contribute to the growth in productivity in the long run in the light of what is known as the “Creative Destruction” by (Schumpeter 1942) or the concept of “Natural Selection” as formulated by (Nishimura et al. 2005).

The key argument is that the low and depressed aggregate demand, which prevails when an economic slack occurs, will cause firms to shift their interests to the low opportunity cost of productivity-ameliorating activities against production activities. Hence, they will centre their efforts to increase the future productivity, (Aghion and Saint-Paul 1991). As a result of this decision, firms are likely to hoard their labour in anticipation that the demand will recover in the future, where the labour productivity is also expected to recover and thrive owing to the increasing demand, (Kruppe and Scholz 2014). The reason why labour hoarding is an attractive tactic, from the firms’ point of view, is to avoid the costs of layoffs and dismissals during the downturns, and then the search as well as employment costs during the upturns. Some point out that human and physical capital per worker have both grown during the recession, and subsequently, labour productivity is likely to rise not to fall, and since the least skilled employees are highly likely to lose their jobs (or be involved in short-time work) human capital per worker is supposed to increase, (Kruppe and Scholz 2014).

To conclude this section, the (LP 2003) approach was mainly designed to extrapolate the behaviour of firm-level productivity taking into account both the unobservable productivity shocks and the shortcomings of (OP 1996) approach. The (LP 2003) methodology was rarely used to estimate TFP at the industry-level in the manufacturing sector, which is the main idea of this paper, and the main goal is to investigate and analyse the behviour of industry-level TFP and the factors that may play a role in the slowdown in its growth after the (2007-2009) recession period.

9. Methodology: The (LP 2003) Approach:

9.1. Intermediate inputs as a proxy:

The correlation between unobservable productivity shocks and input levels is the core matter of concern when estimating production function. On one hand, profit-maximizing firms are expected to respond to the positive productivity shocks by utilizing more inputs in order to expand their output. On the other hand, the negative productivity shocks will urge these firms to reduce the use of inputs to pare back their output.

(LP 2003) suggested an alternative approach to the one presented by (OP 1996) – as mentioned in the introduction – this is where they pointed out that investment can be very lumpy based on evidence coming from firm-level data, because of substantial costs adjustments. However, the firm's production function with β parameters is expected to be in this form:

$$y_{it} = f(x_{it}, E_{it}; \beta) \ldots\ldots\ldots 6$$

Where:

y_{it} is the firm's output.

x_{it} includes inputs that can be adjusted easily and those that develop gradually over time as a response to beliefs.

E_{it} are the errors of which often thought of as Hicks neutral productivity shocks.

The important point here is that when there is a contemporaneous correlation between x_{it} and E_{it}, a problem of simultaneity immediately arises. This simultaneity violates the unbiasedness and consistency conditions that are expected to be the prevailing attributes of the OLS estimates. What causes this simultaneity problem (on the firm-level data) is the firms' response in terms of inputs choice to the shocks in productivity.

9.2. The Econometric Models used in the TFP Estimation:

For a start, the conventional form of Cobb − Douglas production function is used as follows:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_{it} + \eta_{it} \ldots\ldots\ldots 7$$

Where:

y_{it} is the log of the output level in year t.

k_{it} represents the log of capital stock.

l_{it} expresses the log of labour input.

m_{it} denotes for the log-levels of intermediate inputs used in the production process.

$\omega_{it} + \eta_{it}$ are the two components which represent the error term, where ω_{it} is regarded as a state or quasi-fixed variable and it affects the firm's inputs rules which subsequently causes a simultaneity problem which in turn results in biased and inconsistent estimates. Therefore, this term represents the shocks that are certainly and potentially observed by firms when they opt for the optimal levels of labour and intermediate inputs. On the other hand, η_{it} is the identically, independently distributed random shock, it is intended to represent shocks to production that are not observable or predictable by firms before making their input decisions. In other words, it has no effect on the decision of a firm. However, the demand for intermediates is presumed to be a function of the two state variables (quasi-fixed inputs) $(k\,,\omega_{it})$as follows:

$$m_{it} = m_{it}(k_{it}, \omega_{it}) \ldots\ldots 8$$

It is worth noting that this function needs to monotonic in $\omega_{it}$for all k_{it} to be valid as proxy. Under the assumption of monotonicity, the demand function of input can be inverted to obtain the following:

$$\omega_{it} = \omega_{it}(m_{it}, k_{it}) \ldots\ldots 9$$

To proceed with intermediate inputs regarded as proxy:

$$y_{it} = \beta_l l_{it} + \Phi_{it}(m_{it}, k_{it}) + \eta_{it} \ldots\ldots 10$$

Where:

$$\Phi_{it}(m_{it}, k_{it}) = \beta_0 + \beta_m m_{it} + \beta_k k_{it} + \omega_{it}(m_{it}, k_{it}) \ldots\ldots 11$$

According to the OP 1996 approach productivity can be estimated using OLS procedures, but as mentioned above, this routine yields biased estimates. In the case of value-added gross output net of intermediate inputs, the production function can be written as follows:

$$y_t = b_0 + b_l l_t + b_k k_t + \omega_t + \eta_t$$
$$= b_0 + \Phi_t(k_t, m_t) + \eta_t$$

Where:

$$\Phi_t(k_t, m_t) = b_0 + b_k k_t + \omega_t(k_t, m_t)$$

And the above equation in the second stage changes would appear to take the form of:

$$y_{it}^* = \beta_0 + \beta_k k_{it} + \beta_m m_{it} + E[\omega_{it}|\omega_{it-1}] + \eta_{it}^* \ldots\ldots 12$$

Noting that, for any value of (β_k, β_m), $E[\omega_{it}|\omega_{it-1}]$ can be estimated. Taking into account that $E[k_t \eta_{it}^*] = 0$ is assumed to hold in the above equation, but the assumption of $E[m_{it}\eta_{it}^*] = 0$ does not hold due to the fact that intermediate inputs are somehow linked with η_{it}^* and it responds to the productivity innovations ξ_{it} over the last period’s expectations, which is given in this formula:

$$\xi_{it} = \omega_{it} - E[\omega_{it}|\omega_{it-1}] \ldots\ldots 13$$

Unlike in (OP 1996) methodology, firms report their positive use of materials and energy per annum, therefore (LP 2003) opted to use intermediate inputs rather than investment to retain most observations, so the monotonicity condition is valid. Whilst in (OP 1996) firms might report zero investments, which causes some truncation in some observations which gives rise to the validity of the monotonicity condition to be questionable.

9.3. Data Sources and Discussion:

A 22–year panel data for a 13–industry cluster was extracted from the database of the Bureau of Economic Analysis (BEA) on Value-added output; Capital services inputs, Labour Inputs, and Materials inputs. The data spans the period (from 1998 to 2019) based on the latest BEA-BLS-industry-level-production-accounts published by the U.S. BEA and which has been released on the 5th of March 2021. It is noteworthy to state that the gross output concept differs from the sectoral output concept used by the Bureau of Labor Statistics (BLS) in its industry-level TFP statistics. The sectoral output methodology elides intermediate production and purchases which come from within the industry (intra-industry transactions) from either outputs or inputs (Schreyer, 2001).

*The 3-digit 13 industries along with their **NAICS** codes are as follows:*

(1) Machinery (333), (2) Computer and Electronic Products (334), (3) Food and Beverage and Tobacco Products (311, 312), (4) Textile Mills and Textile Product Mills (313, 314), (5) Apparel and Leather and Applied Products (315, 316), (6) Paper Products (322), (7) Chemical Products (325), (8) Wood Products (321), (9) Primary Metals (331), (10) Electrical Equipment, Appliances, and Components (335), (11) Fabricated metal products (332), (12) Petroleum and coal products (324), (13) Plastics and rubber products (326).

The data is observed annually and measured as indexes of each of the real value-added output – as a dependent variable – and capital inputs, labour inputs and a measure of intermediate inputs including materials and purchased services as independent variables, knowing that all variables are converted into logarithm values. The data is available here: https://www.bls.gov/productivity/articles-and-research/bea-bls-integrated-production-accounts.htm

knowing that the latest year that had been added to the dataset is the year 2020, based on the last check on June the 5th 2023.

The rationale for choosing the period (1998-2019) can be justified as follows:

- The period from the 1st quarter of 1998 to the 3rd quarter of 2007 (9 years and 9 months) total factor productivity was booming and growing steadily in several industries in the manufacturing sector, so it is worth examining the factors that play significant roles in this growth.
- The period from the 4th quarter of 2007 to the 4th quarter of 2009 (2 years), the U.S. economy had been hit by the financial crisis which had been later

named as the “Great Recession”, this recession affeced productivity in the majority of industries in the manufacturing sector. This is where total factor productivity fell sharply during the two-year period.

- The period from the 1st quarter of 2010 to the 4th quarter of 2019 (10 years), the period which had been named as “the post-recession period”, where total factor productivity slowed down and decelerated markedly in the manufacturing sector and did not bounce back to the growth levels prior to the recession years. The researcher believes that this period is worthy of investigating, and more light should be shed on the number of factors that contributed the slowdown in TFP growth.

Table (1) Descriptive statistics about the variables used in the estimation processes

Names	Years	Average Value-added output	Average Intermediate inputs	Average Labour hours	Average Capital services
Apparel and leather and allied products	1998-2019	125.78	290.11	140.27	97.24
Chemical products	1998-2019	103.84	97.03	107.86	91.83
Computer and electronic products	1998-2019	76.81	161.03	112.56	100.80
Electrical equipment, appliances, and components	1998-2019	105.87	112.60	112.01	96.42
Fabricated metal products	1998-2019	101.90	98.77	102.80	99.45
Food and beverage and tobacco products	1998-2019	105.69	96.45	101.58	104.59
Machinery	1998-2019	87.24	86.31	101.42	97.45
Paper products	1998-2019	113.13	100.78	118.48	103.03
Petroleum and coal products	1998-2019	137.37	92.87	96.34	108.98
Plastics and rubber products	1998-2019	106.24	106.67	114.33	96.94
Primary metals	1998-2019	95.18	95.88	108.09	96.72
Textile mills and textile product mills	1998-2019	133.20	142.03	140.35	95.36
Wood Products	1998-2019	100.11	128.54	129.08	96.14
Number of observations	1998-2019	286	286	286	286
Grand Total	**1998-2019**	**1392.35**	**1609.08**	**1485.18**	**1284.95**

9.4. Variables for the production functions:

The variables included in the production function in shorthand are as follows:

Ln VA = Value-Added output. It is the aggregate value-added growth which is the sum of share-weighted value-added growth by industry. Value- added output represents compensations of employees, taxes on production and imports, fewer subsidies, and gross operating surplus. It does not include intermediate inputs.

Ln K = Capital services: are the services derived from the physical assets stock and intellectual property assets. In other words, capital services reflect the flow of productive services provided by an asset that is employed in production.

Ln L = Labour inputs which are denoted by hours at work by age, education, and gender group are weighted by each group's share of the total wage bill. Labour hours represent the annual hours worked by all persons employed in an industry. Labour inputs by industry in the industry-level production accounts published jointly by the Bureau of Economic Analysis BEA and Bureau of Labor Statistics BLS are measured as Tornqvist quantity indexes of hours worked classified by gender, age group, and education group. The education group includes grade school, less than high school degree, high school degree, some college, college degree, and more than a college degree.

Ln M = Intermediate inputs: the number of commodities, in the form of intermediate materials used to produce output, also known as materials inputs which are used in the production process to produce other goods or services rather than for final consumption. They represent a large share of production costs, and it is found that the substitution among inputs has its impact on the changes in productivity.

10. Econometric Results and Economic Analysis:

The estimated production function using the LP productivity estimator for the manufacturing industries presented in table (2) shows that the elasticity of the output with respect to labour and capital is significantly different from zero. It also indicates that the elasticity of output to labour is relatively higher than that of capital, implying that labour plays more important role in the production process. It is also found that the contributions of both capital and labour to be significant with some advantage to labour on capital. This could lead to say that firms in these industries tend to be heading towards a more labour-intensive production process. Overall, for the two main variable inputs included in the estimation routine (labour and capital) it seems that the coefficients obtained from OLS are on average larger than those obtained from the LP intermediate input proxy estimator.

The first thing that can be noticed in table (2) is that the materials inputs estimates are not shown in Levinsohn and Petrin productivity estimator's results, because it has been used as a proxy for unobserved productivity shocks as mentioned in the (LP 2003) methodology detailed above. However, in some industries, when firms experience large positive productivity shocks, they may react by making use of more inputs. Based on this intuition, the estimated parameters yielded from the OLS approach can suffer from prejudice. The intermediates inputs – as a valid proxy for the productivity shocks – offer an advantage by linking the economic theory and the estimation strategy quite simply because they cannot as a state variable. This is where more productive firms – given their profit maximising behaviour – will tend to use more intermediate inputs, and any increase in productivity is meant to result in a rise in the marginal productivity of the intermediate inputs, which in turn will increase in the amount of intermediate inputs used in production.

Table (2) also shows that the labour hours estimated coefficients in both techniques are similar, but capital services coefficients are different. This is where the OLS capital services estimates appear to be more inflated than those estimated via LP. There is no consensus as to which is the best way to implement the proxy methodology, but the choice of the proxy needs to hinge on the data details and the industry, and the scale of the missing observations in the total sample – for the proxy – needs to be as low as possible.

Table (2) The OLS and LP productivity estimates for 13 manufacturing industries in the U.S economy during the period 1998-2019

Dependent Variable: Sectoral Output (Value-Added)	**Models Estimated**	
	Cobb-Douglas Production Function OLS	**(LP 2003) Productivity Estimator**
Independent variables		
Ln Labour Hours Worked	.675*** (.151)	.663*** (.103)
Ln Capital Services	.539*** (.131)	.311*** (.146)
Constant	.171 (.304)	-
R-Squared	0.12	-
F (3, 282)	14.68	-
Prob > F	0.000	-
Number of Observations	286	286
	Notes: **1-** OLS = Ordinary Least Squares estimator. **2-** LP = Levinsohn and Petrin productivity estimator. **3-** (**) indicates confidence level at 95% confidence. (No *) indicates no confidence at any 90%, 95%, or 99%. **4-** (*) indicates confidence level at 90%, (***) indicates confidence level at 99%. **5-** Figures in parentheses are robust standard errors.	

It is also crucial that the monotonicity condition must hold. The two estimation strategies for productivity dynamics clearly indicate that when productivity is positive OLS overestimates productivity gains in some years, and when productivity is negative in certain years OLS also demonstrates larger falls in productivity in comparison with the LP estimates, and that is evident in most industries in the selected sample – as can be seen in figures 1 – 13. If this bias is not corrected, it is highly likely that similar mistakes would occur when computing productivity estimates.

The value of the $\mathbf{R^2}$ reported in table (2) supports the fact that the specified model does not explain more than 12% of the variations in the dependent variable in this case, but again the three principal variables required to perform reasonable and logical estimation of TFP – as far as the literature is concerned - are the ones which indeed had been factored in the model as stated above. In economic terms, and based on the figures from (1) to (13) which illustrate the changes in productivity over the period from 1998 to 2019, It can be clearly seen that productivity declined during the Great Recession from 2007 to 2009, and its growth slowed down during the years that followed. In fact, productivity in most cases did not recover to grow in a similar pace as occurred in the pre-Great Recession period. Several factors played pivotal role in this deceleration in productivity, such as technical change, decrease in investments, decline in capital intensity and capital deepening, significant fall in the de novo firms share in the total number of enterprises across the U.S. economy during the same period.

Table (3) Diagnostic robustness and goodness of fit tests

Test	Results	Interpretation
Heteroscedasticity (Breusch-Pagan/ Cook-Weisberg test)	H0: Constant variance accepted.	There is no Heteroscedasticity problem in the estimated model.
Omitted variables (Ramsey Reset test) using powers of the fitted values of ln. Value-Added Output.	Prob > F = .343	The null hypothesis of no omitted variables in the model is rejected.
Multicollinearity test	Mean VIF = 2.13	There is no Multicollinearity problem because the Mean VIF is less than 10.
Joint Significance (F – test)	Prob > F = 0.0000	All variables included in the model have significant impact on the dependent variable (ln. value-added output).

Note: the tests' results in this table are conducted after running the STATA commands provided in the models' section to check the models' goodness of fit and robustness.

Table (3) shows the diagnostic tests that had been conducted after the estimation procedures, and their results appear to be good as far as the statistics and econometrics are concerned, apart from the omitted variables test which indicated – from an econometric point of view - that more independent variables need to be included in the estimated models, but from an economic point of view the three independent variables that had been already included – capital services, labour hours, and materials inputs – are what is essentially needed to estimate TFP according to the literature on production function different estimation methodologies.

11. The Causes of the Productivity Slowdown:

During the period from 2004 to 2016 productivity in the manufacturing sector declined by average of 0.3% per year. This is where semiconductors and electrical components manufacturing industries along with computer and peripheral equipment manufacturing contributed the most to this decline. Whereas productivity grew by an average of 0.2% during the period from 1992 to 2004 mainly due to the significant positive contribution of the ICT industries. The important thing is that productivity grew by just 0.7% at an annual average rate during the aftermath of the recession between 2010 and 2014. The employment growth in the U.S. during the period 2007-2013 was the worst since the years that followed the end of World War II with an average of (-0.5%) per year which manifests itself in the weak and subdued growth in productivity in recent years.

During the shorter term over the period 2007-2017 the contribution of capital intensity – the amount of fixed real capital share in relation to other production factors such as labour – to productivity is 0.5 percentage point (42% of the total), whereas the contribution of labour composition – the shift in the age, education, and gender in the work force as a measure that affects labour inputs – is 0.2 percentage point (16% of the total) therefore, (58% is the aggregate contribution of capital intensity and labour composition), and the contribution of TFP is 0.5 percentage point (42% of the total). The growth in capital intensity and capital deepening – where the former refers to the amount of capital (the flow of capital services) available per worker/hour worked, while the latter refers to the annual rate of change in capital intensity – declined in recent years in the U.S. economy which means that the sufficient level of aggregate demand that is supposed to motivate more investments to produce goods and services in the economy is neither encouraging nor incentivising for businesses to invest. This resulted in a decrease in output and hence caused the ratio of capital per output (capital/output) to increase and led to constraints on credit in the capital markets.

That might be explained by the fact that when TFP is growing, more opportunities for businesses arise and more capital accumulation becomes available for investments resulting in more capital per hour worked and therefore greater share of capital's contribution to productivity growth. But in the same time this can cause the growth in capital supply sourced from the capital markets to shrink which in turn can be justified by the pre-existing overabundance of capital in the economy.

Table (4) shows that in most industries the average TFP growth contributions to VA output during the prior-recession period between 1998-2006 was better than those during and post-recession periods. For instance, the TFP growth contribution in the computer and electronic products industry was about 33.2% during the years from 1998 to 2006, it then decreased to about 17.4% during the recession years (2007-2009), and decelerated to only 7.4% in the post-recession era from 2010 to 2019. In some industries the TFP growth contributions to VA output were negative during the recession and post-recession years such as: food, petroleum, chemical, and paper products.

Table (4) the industry-level TFP growth (%) contributions to aggregate value-added output growth from 1998 to 2019

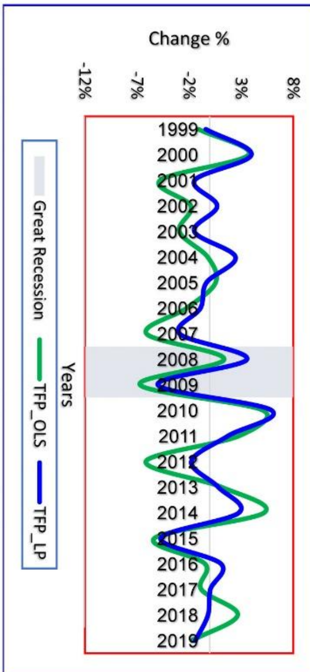
Industry-level Production Account: TFP Growth Contributions to Aggregate Value-Added Growth	1998-2006	2007-2009	2010-2019
Apparel and leather and allied products	0.002	-0.001	0.001
Chemical products	0.010	-0.084	-0.047
Computer and electronic products	0.332	0.174	0.074
Electrical equipment, appliances, and components	0.009	-0.011	0.001
Fabricated metal products	0.005	-0.049	0.003
Food and beverage and tobacco products	0.011	-0.019	-0.023
Machinery	0.022	-0.019	0.000
Paper products	0.004	-0.003	-0.003
Petroleum and coal products	0.020	-0.015	-0.023
Plastics and rubber products	0.012	-0.001	0.001
Primary metals	0.012	0.013	0.013
Textile mills and textile product mills	0.008	-0.002	0.001
Wood products	0.002	0.011	0.002
Average TFP growth Contributions for all 13 industries	**0.034**	**-0.001**	**0.000**

Sources: US Bureau of Labor Statistics. Data extracted on 05/06/2023.

The decline and slowdown in TFP growth, potential output and labour productivity can be also partly explained by the deterioration in business dynamism in the U.S. One way to measure business dynamism is by the number of the start-ups (the share of new firms entering the marketplace as a percentage of the total number of firms in the marketplace) during certain period. Start-ups can play important role in promoting output by bringing new ideas into the mixture of firms that are already operating in the market.

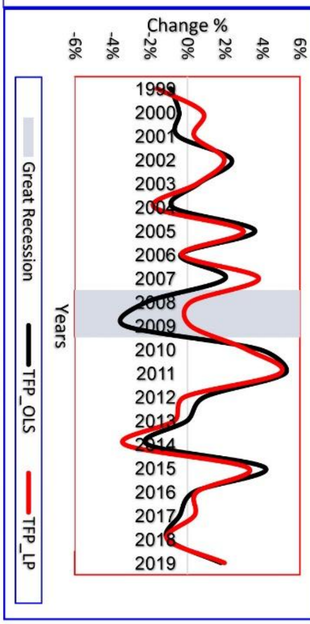
The following figures from 1 to 13, depict the OLS and LP (2003) TFP estimates calculated by Stata software for the 13 manufacturing industries over the period from 1998 to 2019.

Figure (1) Apparel and leather and allied products



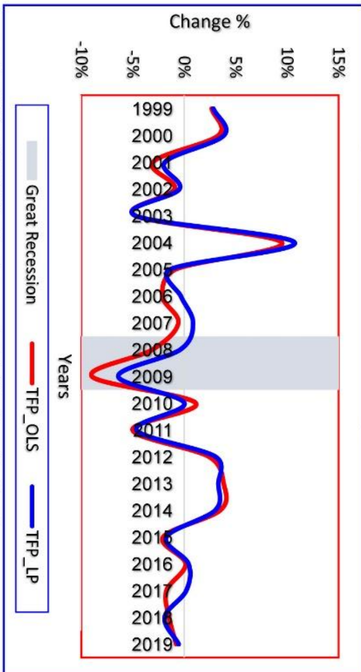
Source: the OLS and LP TFP estimates are calculated by the author based on the econometric results obtained using the STATA Statistical Software.

Figure (2) Wood Products



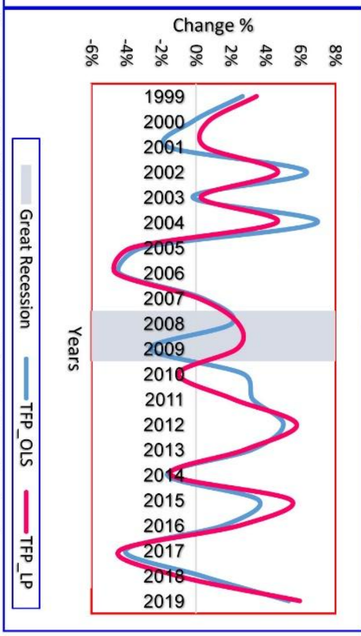
Source: the OLS and LP TFP estimates are calculated by the author based on the econometric results obtained using the STATA Statistical Software.

Figure (3) Textile mills and textile product mills



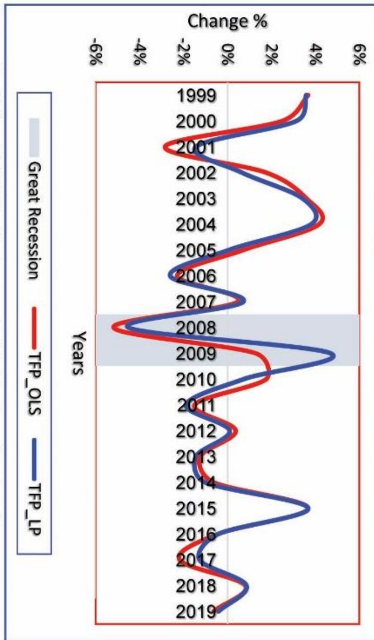
Source: the OLS and LP TFP estimates are calculated by the author based on the econometric results obtained using the STATA Statistical Software.

Figure (4) Primary metals



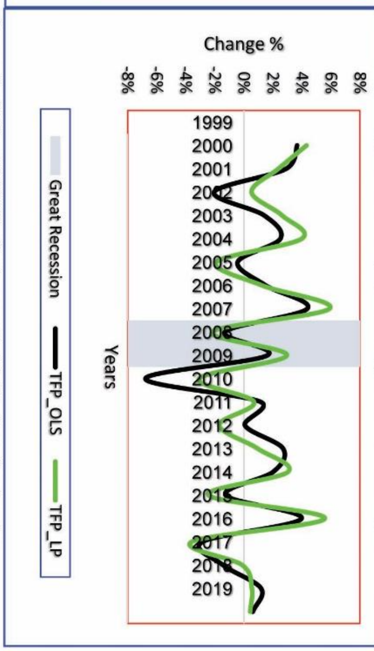
Source: the OLS and LP TFP estimates are calculated by the author based on the econometric results obtained using the STATA Statistical Software.

Figure (5) Plastics and rubber products



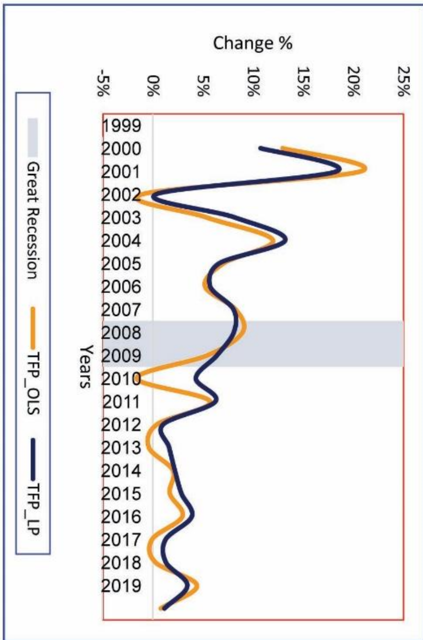
Source: the OLS and LP TFP estimates are calculated by the author based on the econometric results obtained using the STATA Statistical Software.

Figure (6) Electrical equipment, appliances, and components



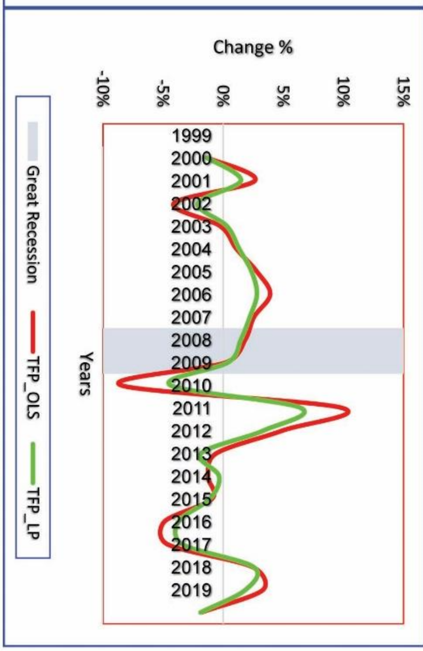
Source: the OLS and LP TFP estimates are calculated by the author based on the econometric results obtained using the STATA Statistical Software.

Figure (7) Computer and electronic products



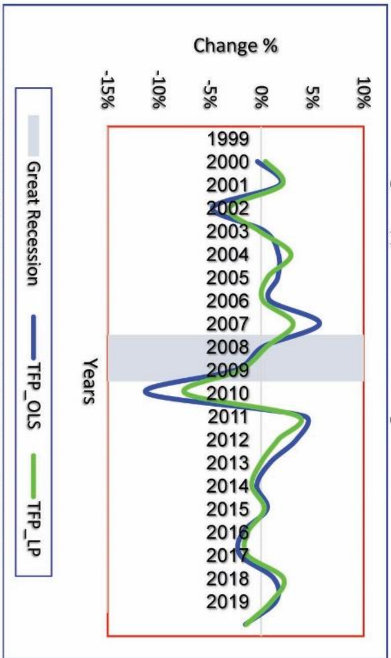
Source: the OLS and LP TFP estimates are calculated by the author based on the econometric results obtained using the STATA Statistical Software.

Figure (8) Machinery



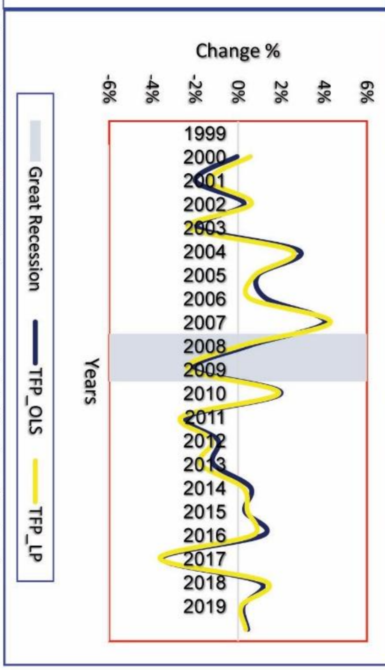
Source: the OLS and LP TFP estimates are calculated by the author based on the econometric results obtained using the STATA Statistical Software.

Figure (9) Fabricated metal products



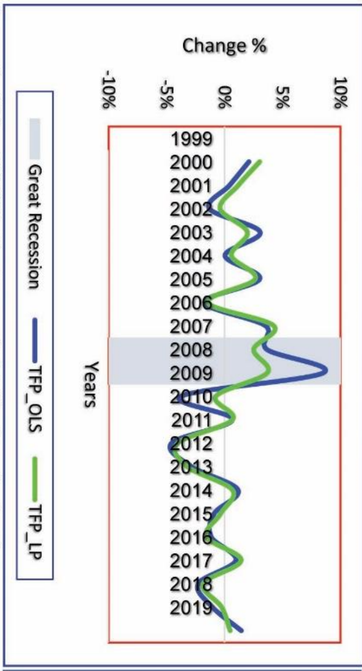
Source: the OLS and LP TFP estimates are calculated by the author based on the econometric results obtained using the STATA Statistical Software.

Figure (10) Food and beverage and tobacco products



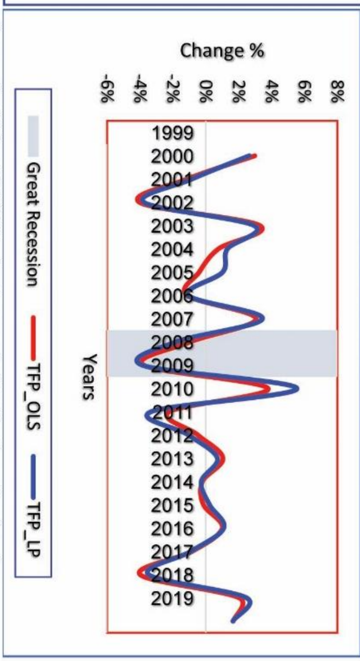
Source: the OLS and LP TFP estimates are calculated by the author based on the econometric results obtained using the STATA Statistical Software.

Figure (11) Chemical products



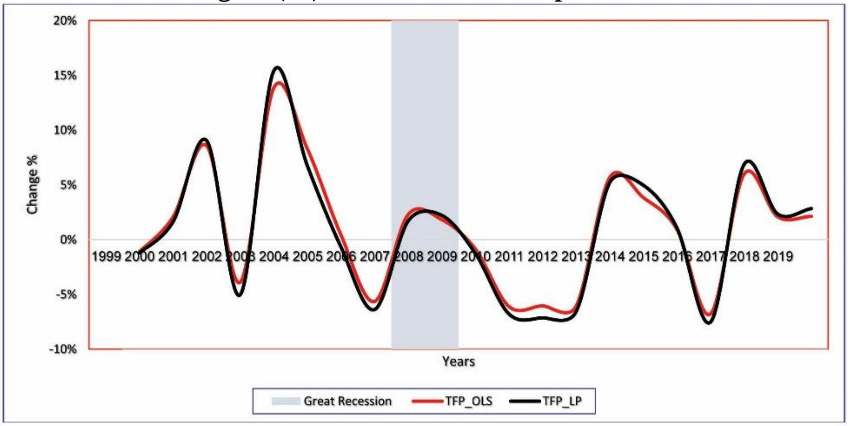
Source: the OLS and LP TFP estimates are calculated by the author based on the econometric results obtained using the STATA Statistical Software.

Figure (12) Paper products



Source: the OLS and LP TFP estimates are calculated by the author based on the econometric results obtained using the STATA Statistical Software.

Figure (13) Petroleum and coal products



Source: the OLS and LP TFP estimates are calculated by the author based on the econometric results obtained using the STATA Statistical Software.

During the period from 1977 to 2015 there was a continuous decline in the share of newly born firms (less than a year-old firm) as shown in the line graph above. The share of start-ups number of the total number of firms in the U.S. economy has declined markedly since 1977. It decreased continuously from 16.5% in 1977 to 13.1% in 1987 and to 10.9% in 1997 to 8% in 2009.

Table (5) the start-ups share (%) of the total number of firms in the U.S. economy during the period 1977-2015

Years	The start-ups share of the total number of firms (%)
1977	16.5
1987	13.4
1997	10.9
2009	8
2015	8.1

Source: Figures in this table extracted from the U.S. Census Bureau. (Accessed in May 2018)

However, the data sourced from the U.S. Census Bureau show some improvement in 2015 to 8.1% of the total number of firms with different age yet it still below its level before the financial crisis in 2006 at 10.8%. The decline in start-ups age points to the relatively weaker firm dynamics in the U.S. economy. Market power makes it difficult for small new ventures to compete with the existing corporations.

There are several reasons and explanations as to why TFP has been declining and slowing down in the U.S. economy for more than a decade. One of which is that innovations that have been taking place in recent years might not be as important as the innovations that had been accomplished and used during the eighties and nineties, in terms of the scale of their effects on productivity and growth, and based on the diminishing returns to scale, in spite of the fact that many of the innovations achieved in the last decade played significant role as productivity enhancer. The slowdown in R&D intensity is another determinant of TFP growth because it is partly responsible for creating new ideas, innovation and new technology which is partly captured by TFP.

The contribution of R&D intensity did not grow by more than 0.1 percentage point over the period from 1987 to 2017 according to the BLS 2018. Another explanation is that licensing over-restriction on innovations, could have played a negative role by preventing them from being diffused and spread out in the mainstream, which does not allow the stragglers and the less productive firms in the middle and the bottom of the distribution to pick and adopt new technologies, in order to raise their productivity, and converge, and close the gap, with the more productive firms. However, even with the available innovations and new technologies that are already in the public use, it tends to be the case, at times, that some of the less efficient firms, find it difficult to deploy these information technologies and innovations, because they lack the managerial expertise, and the adequate skills embodied in their labour force, in order to adopt and adapt to the best practices by the frontier firms, bearing in mind the necessity for the frontier firms to protect themselves, and stay one step ahead of the competition, where they need to patent and license their new and cutting-edge innovation and technology, so as to receive the economic reward for their investments, which will keep them incentivised, and encouraged to generate more new ideas and new innovations. In addition to the lack of access to innovations, and the lack of ability to use these innovations efficiently, the slowdown can be also attributed to policies and regulations that are restricting and limiting the competition in the market economy, which to some extent, affects the process of dynamism and resources reallocation to the best level possible.

12. Conclusions:

To conclude, the percentage with which an industry can contribute to the growth of total manufacturing TFP is principally determined by the growth rate of TFP in that industry along with its share of output out of the total manufacturing sector output. With that being said it seems to be the case that there is a variety of reasons for why productivity has been slowing down since the Great Recession, and not just because of the recession itself but due to a number of factors which have been playing crucial role in this productivity deceleration.

Throughout the period during which productivity has been booming – from 1992 to 2004 – the contribution of the IT-related industries such as semiconductors and other electronic components, and computers and peripheral equipment manufacturing was significant. Both industries accounted for about 60% of the TFP growth in the manufacturing sector during the above-mentioned period. On the other hand, the TFP decline in the petroleum and coal products along with pharmaceutical and medicine manufacturing had exerted the greatest influence on the slowdown in the total manufacturing TFP growth during the period (2004 – 2016). The average growth of TFP contributions to value-added output during the period from 1998 to 2006 was 3.4%, it then plummeted to 0.1% during the recession years from 2007 to 2009, and remained at the level of 0% during the period from 2010 to 2019. However, this slowdown does not appear to be incurable, and productivity can recover and pick up pace especially if the long-term aggregate demand and investment enhancing economic policies were to be applied, such as tax reforms to encourage businesses.

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