Economic Fluctuations, Cyclical Regularities and Technological Change: The U.S. Food Sector (1958–2006)

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Abstract

Despite the fact that the U.S. food sector is a key component of U.S. manufacturing, it has attracted limited attention in the literature, so far. In fact, the recent food crisis shed some light on different aspects of the food sector, its products and its influence on millions of people. The sector is characterised by increasing concentration, changes in relative prices, shifts in consumer preferences and changes in government regulations. However, key issues related to technological change and the cyclical regularities of economic time series in the sector have been neglected or even unexplored in the literature. Our study provides robust evidence supporting the fact that technological change has explanatory power for output and profitability in the Granger-causal sense at various leads or lags. Also, the timing pattern of technological change indicates that the peak correlations appear at moderate lags. This implies that the technology shocks are transmitted in the economy relatively quickly. Also, the various economic time series in the sector seem to follow a cyclical pattern characterized by periodicities exhibiting a short-term cycle, a mid-term cycle and a long-term cycle.

Keywords: profitability, output, technology, fluctuations, US food sector

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1.   Introduction

The food manufacturing sector is one of the largest in United States (U.S.) manufacturing and in U.S. economy in general. However, it has attracted limited attention in the literature, so far. According to the Annual Survey of Manufacturers, around 28.000 establishments exist in the sector employing about 1.500.000 people or 11% of the manufacturing sector and more than 1% of total U.S. economy (2006). Meanwhile, it contributes more than 10.5% in total manufacturing output and approximately 2% of U.S. output (2006). The food production, processing, wholesale distribution, and retailing system are important components of the U.S. economy accounting for 12.8 % of U.S. gross domestic product (GDP) in 2000. Furthermore, the sector exports products accounting for about 33 billion dollars. Also, the sector is one of high concentration, and food processing industries are among the most profitable industries in the U.S. (Wang et *al.* 2006). Finally, market structure in the industry has changed significantly over the last fifty years and is mainly the result of mergers and acquisitions. In fact, the period 1977–1987 coincides with one of the four U.S. merger movements.

The typical features characterizing the sector are: increased consolidation and concentration, changes in relative prices, shifts in consumer preferences and changes in government regulations (Adelaja et *al.* 1999, Morrison 1997, Rogers, 2001). It is a capital intensive sector, where materials contribute about 60% of total output (Huang 2002), it is responsive to new technologies in processing, packaging and marketing of food product and has become increasingly high tech over the past decades (Morrison 1997). Also, it experienced low productivity growth rates compared to other sectors (Huang, 2002) and Total Factor Productivity (TFP) behaved cyclically (Heien 1983).

In this context, there are several reasons for studying the U.S. food manufacturing sector: first, there are limited studies on topics such as economic fluctuations and crises at the sectoral level; second, it is a very important sector for the U.S. economy; third, the recent food crisis shed some light on different aspects of the food sector, its products and its influence on millions of people; fourth, the impact of the current crisis on the food manufacturing sector is of great interest taking into account its high income inelasticity. At first, the food manufacturing sector did not seem to be seriously affected by the recent economic crisis because of the high income inelasticity of food products. However, no doubt a closer look would be of great interest. After all, judging from previous crises, and knowing that profitability practically collapses during or after the crisis period (e.g. Dumenil and Lévy, 2002; Wolff 2003; Mohun, 2005), it is quite reasonable to expect a downward trend in profitability.

This paper investigates how technological change affects indicators of economic and social welfare, such as profitability and output in the US food manufacturing sector, in the time period 1958-2006. We begin by analysing the stylised facts of the fundamentals in the food manufacturing sector for the time period 1958-2006. In order to investigate the stationarity properties of each time series we test the existence of unit roots. Given that the economic series usually contain a trend, de-trending is highly recommended. Moreover, we use spectral analysis to extract periodograms which indicate the lengths of the business cycle based on the available data and then we test whether the various de-trended economic time series tend to follow a cyclical pattern, or their evolution is white noise. Next, we focus on answering some fundamental economic questions regarding the interpretation of the cyclical behaviour of underlying economic variables in the sector. For instance, how does technology affect the behaviour of variables, such as real output and profitability over time?

The paper is organized as follows: section 2 offers a brief review of the literature on the U.S. food manufacturing sector; section 3 sets out the methodology; section 4 presents and discusses the empirical results; finally, section 5 concludes the paper.

2.   Review of the Literature

Supply oriented shock models dominate studies in the food manufacturing sector; TFP, productivity and market structure studies are among them. As we know, TFP growth is, among other things, typically used as a proxy for technological change (Morisson 1992). Some studies on TFP growth use the conventional method of growth accounting, defined as the rate of aggregate output minus the rate of growth of aggregate inputs. This method usually assumes constant returns to scale and perfect competition.

Heien (1983) was probably the first who tried to measure productivity in the food manufacturing sector. The paper measured TFP using Theil–Törnqvist indexes of total outputs and total inputs, finding evidence of cyclical behaviour. Furthermore, the paper provided an explanation for the decrease in TFP in the time period 1973 – 1977 as the result of (a) an increase in energy costs, (b) the stricter government regulation, (c) the erratic money and fiscal policy, and (d) the demographic changes in labour force.

Huang (2002) measured TFP and labour productivity growth in the time period 1975 – 1997. The paper concluded that an important characteristic of the sector is its weak TFP growth compared to other sectors of U.S. manufacturing, and this, the paper argues, is due to the low investment rate in R&D. As a result, the slow growth

in productivity signifies (a) the expansion of combined factor inputs to food manufacturing output instead of productivity growth; (b) a limited contribution on price declines in food products in recent years, which is attributed to cheaper input prices.

Gopinath and Carver (2002) used data for thirteen (13) countries to examine the effects of productivity growth in agriculture on the processed food sector. One of their findings is that U.S. has the lowest food TFP growth level among the countries investigated with the exception of Japan. Finally, they argued that public policies protecting primary agriculture can adversely affect processed food sectors, while those supporting Research and Development (R&D) efforts can bring about dynamic comparative advantage.

According to Azzam et *al.* (2002) the most important source of TFP growth in the food industry was demand growth, whereas the most important negative contributor to TFP growth was disembodied technological change. Also, Hossain et *al.* (2005) argued that the use of debt financing increased sharply resulting in changes either in productivity or performance, while increased debt use reduced productivity growth.

Morrison and Siegel (1997) investigated whether technological change and international competitiveness are responsible for the observed changes in productivity and input composition in the U.S. food manufacturing sector. The study suggested that the cost reduction was the result of increased competitiveness (trade) and knowledge capital (general technological advance or automation).

Morrison (1999) examined the impact of capital investment and import penetration on firms' costs and prices. The analysis concluded that the increased cost efficiency arises from reduced labour use. In fact, scale economies and increased high – tech capital are labour saving, energy and materials using.

In a recent study, Geylani and Stefanou (2008) examined the relationship between productivity and investment spikes for the food manufacturing industry in the 1972-1995 time span. Their key results may be summarized as follows: first, there is a significant variation in productivity growth; second, the learning period associated with investment spikes differs among quartile groups; third, there is a decreasing probability of an investment spike as the time since the last spike increases.

Galo (1992) found that aggregate profitability of the sector, when measured as a return on the assets and stockholders' equity, is one of the highest in manufacturing. However, aggregate profitability on sales for food manufacturing is below the average for nondurable manufacturing because of a high sales turnover rate.

Finally, market structure has attracted increasing attention among researchers in the field (e.g. Röder et *al.* 1999). For instance, Goodwin and Brester (1995) found that the structural changes in the sector resulted in the following: (a) the demand for raw food materials and energy became more elastic; (b) the demand for labour became less elastic; (c) nearly all input factors can be regarded as substitutes, and (d) the degree of the substitutability has significantly increased in recent years, due to technical change. In a similar vein, Röder et *al.* (1999) found a typical U – type effect of concentration on innovations and the number of firms. Additionally, the degree of existing product differentiation and the market size positively affected the number of innovations. Finally, in a recent study Wang et *al.* (2006) analysed the relationship between market concentration and other variables and one of their main findings was the increasing significance of the role of high - tech capital and the changes in production technology.

To sum up, there are several studies that make an attempt to link productivity growth in the U.S. food manufacturing sector to some key variables. Most of them focus on technological change, while others emphasise on market structure. However, no study, to the best of our knowledge, deals with the questions of instability and crisis and the role of technological change.

3. Methodology

According to this section, which is based on Michaelides et *al.* (2007), the business cycle component is regarded as the movement in the time series that exhibits periodicity within a certain range of time duration. This approach is often called the "classical business cycles" approach and is based on Burns and Mitchell (1946) and the National Bureau of Economic Research (NBER). This approach argues that business cycles are characterized by the "turning point" which indicates, roughly speaking, the beginning of an expansionary period at the end of a recession. Another popular approach regards business cycles as fluctuations around a trend, the so-called "deviation cycles" (Lucas 1997). The estimation of this trend for each time series is of great importance because it is necessary for the extraction of the cyclical component. In this study we adopt both these approaches.

First, we examine the stationarity characteristics of each time series. As we know there are several ways to test for the existence of a unit root. In this paper, we use the Augmented Dickey – Fuller methodology (ADF) (Dickey and Fuller, 1979).[1]

If the results suggest that the time series are stationary in their first differences then, de-trending is highly suggested.

The ADF test is based on the following regression (Kaskarelis 1993):

$$\Delta Y_t = a + bt + \rho Y_{t-1} + \sum_{i=1}^{m} \gamma_i \Delta Y_{t-i} + \varepsilon_t \quad (1)$$

where Δ is the first difference operator, t is time and ε_t is the error term.

(a) If b≠0 and ρ=-1 implies a trend stationary (TS) model.

(b) If b=0 and -1<ρ<0 implies an ARMA Box/Jenkins class of models.

(c) If b=0 and ρ=0 implies a difference stationary (DS) model where Y variable is integrated of degree one I(1). If we assume that the cyclical component is stationary, the secular component has a unit root and Y follows a random walk process (i.e. it revolves around the zero value in a random way (Heyman and Sobel 2004, p. 263). Furthermore, if α≠0 Y follows a random walk process with a drift. The lag dependent polynomial is inserted in order to deal with the potential serial correlation of the residuals.

The trend is important for the propagation of shocks (Nelson and Plosser 1982). Linear, exponential and quadratic de-trending is highly recommended and the estimated residuals constitute the de-trended data series.

A time series x_t with a linear deterministic trend is as follows:

$$x_t = a + bt + \varepsilon_t \quad (2)$$

where a and b are parameters, t is time and ε_t is white noise.

A time series x_t with an exponential deterministic trend is as follows:

$$\log x_t = a + bt + \varepsilon_t \quad (3)$$

where a, b are parameters, t is time and ε_t is white noise.

A time series x_t with a quadratic deterministic trend is as follows:

$$x_t = a + bt + ct^2 + \varepsilon_t \quad (4)$$

where a, b, c are parameters, t is time and ε_t is white noise.

Besides these methods we also use the following, widely used, alternative approaches:

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1 Alternatively, the test of Zivot and Andrews (1992) could have been used or some other unit root tests such as the IPS test (Im et *al.* 1997), the MW test (Maddala and Wu 1999), or the Choi test (Choi, 2001).

(a) The Hodrick-Prescott Filter

The linear, two-sided HP-filter approach is a widely used method by which the long-term trend of a series is obtained using only actual data. The trend is obtained by minimizing the fluctuations of the actual data around it, i.e. by minimizing the following function:

$$\sum \left[\ln y(t) - \ln y*(t) \right]^2 - \lambda \sum \left[\left[\ln y*(t+1) - \ln y*(t) \right] - \left[\ln y*(t) - \ln y*(t-1) \right] \right]^2 \quad (5)$$

where y* is the long-term trend of the variable y and the coefficient λ>0 determines the smoothness of the long-term trend.

This method decomposes a series into a trend and a cyclical component. The parameter used for annual data is equal to λ=100 (Hodrick and Prescott 1997, Kydland and Prescott 1990, Canova 1998).

A large number of studies has used the HP filter de-trending method for different purposes (e.g. Danthine and Girardin 1989, Blackburn and Ravn 1992, Backus and Kehoe 1992, Fiorito and Kollintzas 1994). The Hodrick and Prescott Filter is able to extract the same trend from all time-series which is considered a significant advantage since many real business cycle models indicate that all variables will have the same trend.[2]

(b) The Baxter-King Filter

Another popular method for extracting the business cycle component of macroeconomic time series is the Baxter-King Filter (Baxter and King 1999). The Baxter King filter is based on the idea to construct a band-pass linear-filter that extracts a frequency range $\left[\omega_{min}, \omega_{max} \right]$ dictated by economic reasoning. Here, this range corresponds to the minimum and maximum frequency of the business cycle.

The algorithm consists in constructing two low-pass filters, the first passing through the frequency range $\left[0, \omega_{max} \right]$ (denoted as $\bar{a}(L)$, where L is the lag operator) and the second through the range $\left[0, \omega_{min} \right]$ (denoted as $\underline{a}(L)$). Subtracting these two filters, the ideal frequency response is obtained and the de-trended time series is:

$$y^{BP}(t) = \left[\bar{a} - \underline{a} \right] y(t) \quad (6)$$

Two of the main advantages of this approach are: first, it leaves the properties of the extracted component unaffected and, secondly, it does not change the timing of the "turning points". There is widespread agreement that a business cycle lasts

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[2] However, there are shortcomings as well in this approach. For overviews of the HP filtering method shortcomings see Harvey and Jaeger (1993), King and Rebelo (1993), Cogley and Nason (1995) and Billmeier (2004).

between 8 and 32 quarters and the length of the (moving) average is 12 quarters (Baxter and King 1999). This is due to the seminal works of Burns and Mitchell (1946).[3] Consequently, these are the values (2 to 8 years) that we use in the de-trending methods described above.

A large number of studies have used the Baxter-King filtering method (see e.g. Stock and Watson 1999, Wynne and Koo 2000, Agresti and Mojon 2001, Benetti 2001, Massmann and Mitchell 2004).

As it is well-known, white noise does not permit any temporal dependence[4] and so its autocovariance function is trivially equal to zero for the various lags. The sample autocorrelation function measures how a time series is correlated with its own past history. Its graphical illustration is the correlogram. In order to test for autocorrelation we use the Ljung and Box (1978) test (Q-stat) which practically tests the null hypothesis of white noise for a maximum lag length k. The alternative hypothesis is that at least one of theses autocorrelations is nonzero, so that the series is not white noise. In case the null hypothesis is rejected then the underlying time series is clearly not white noise and can be considered a cycle. In case we are dealing with a trending time series, then we study and test not the raw series but its deviations from trend, i.e. the residuals from which sample autocorrelations can be computed.

Here we investigate the periodicities of business cycles assuming that the actual fluctuations of the data are chiefly of a periodic character. We are supposing that the presence of periodic elements in the given fluctuations is possible. It is the object of this section to isolate those elements and indicate the approximate length of the cycle. The length of the period in an economic series may, in general, be variable. Therefore, we understand by the term "period" the average length of the cycles and the periodogram can assist in finding these average lengths.

The period is measured by constructing a graphical illustration of the value R in the time frequency and checking for the highest pick:

$$R_i = \sqrt{a_i^2 + b_i^2} \ , \ \alpha_i = \frac{2}{n}\sum_{t=1}^{n} X_t \cos(2\pi t/i) \ , \ b_i = \frac{2}{n}\sum_{t=1}^{n} X_t \sin(2\pi t/i) \ , i = 1, 2, ...m \ , \ m = n/2 \quad (7)$$

where a_i, b_i are the coefficients of the Fourier-transformed function X_t (Rudin 1976).

Next, we investigate whether technological change has predictive power for profitability and output growth, respectively, in the Granger-causal sense. Thus, we conduct bi-variate (Granger) causality tests between:

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[3] For a critique to this approach see Agresti and Mojon (2001).
[4] Actually, white noise is a data generating process where autocorrelation is zero between lagged versions of the signal (except when the lag is zero).

(a)   Technological change (TFP) and real output (GDP)

(b)   Technological change (R&D) and real output (GDP)

(c)   Technological change (TFP) and Profitability (Profit Rate)

(d)   Technological change (R&D) and Profitability (Profit Rate)

(e)   Technological change (Labour Productivity) and Profitability (Profit Rate)

No doubt, profitability is the cornerstone of economic theory in a capitalist economy. A relevant measure that is convenient because it expresses profitability as a percentage rate is the so-called rate of profit which expresses the rate of return on capital invested (Moseley 2003, and Zachariah 2009).

Meanwhile, technology constitutes a very crucial determinant of sectoral competitiveness. A major problem in examining technological change and one that makes it difficult to define or characterize it is that it can take many different forms (Rosenberg, 1982: 3). In that sense, there is no generally accepted measure of technological change and all measures are imperfect, so, we decided to use three of them to quantify technological change. TFP is based upon strong assumptions and approximates technological change as the residual of the growth equation. As a result this measure could lead to misleading interpretations of technology. Alternatively, it is widely argued that there is convincing evidence that cumulative R&D is an important determinant of technology. Finally, several theoreticians, usually Marxists, argue that labour productivity expresses, in a nut-shell, technology as a productive force.

The concept of causality, introduced by Granger (1969) has been widely used in economics. In general, we say that a variable X causes another variable Y if past changes in X help to explain current change in Y with past changes in Y. Thus, the empirical investigation of (Granger) causality is based on the following general autoregressive model (Karasawoglou and Katrakilidis 1993):

$$\Delta Y_t = a_0 + \sum_{i=1}^{m} a_{1i} \Delta Y_{t-i} + \sum_{i=0}^{n} a_{2i} \Delta X_{t-i} + \varepsilon_t \quad (8)$$

where Δ is the first difference operator, ΔY and ΔX are stationary time series and ε_t is the white noise error term with zero mean and constant variance.

The null hypothesis that X does not Granger-cause Y is rejected if the coefficient a_{2i} is statistically significant. Various lag-lengths are tested in order to identify the optimal value. The optimal lag could be selected using one of the following criteria: (a) FPE (final prediction error), (b) AIC (Akaike information criterion) and (c) Hannan – Quinn information criterion.

The most frequently used testable hypotheses are expressed as follows: (a) Y Granger-causes X, (b) X Granger-causes Y (c) Y and Granger cause each other, and (d) neither variable Granger–causes the other.

4. Empirical Investigation

We implement the aforementioned techniques in order to investigate empirically the cyclical behaviour of relevant economic time series in the U.S. food manufacturing sector. The data used are on an annual basis and come from the National Bureau of Economic Research (NBER) database and from the U.S. Census Bureau, Department of Manufacturers and cover the period 1958-2006, just before the first signs of the global economic recession made their appearance. The data on capital stock stopped in 1996, and we estimated the rest of the time series based on the popular methodology employed in Huang (2002).

To begin with, the stationarity properties of the various macroeconomic variables were checked. Table 1 shows the results of the Augmented Dickey-Fuller test regarding the following time series : labour (L) i.e. number of employees, real output (Y) i.e. output in dollars at constant prices, stock of fixed capital (K) i.e. in dollars, total factor productivity (TFP) i.e. in percentage change, real wages (W) i.e. total amount of wages to L in dollars, labour productivity (Y/L), research and development (R&D) expenditures, i.e. in dollars and the profit rate (Π), defined as percentage rate: $\Pi = \dfrac{Y-W}{K}$ (Duménil and Lévy 2004).

All macroeconomic variables are non-stationary, however their first differences are stationary (Table 2). The next step was to de-trend the variables. Various de-trending approaches were employed and the graphs of the residuals are depicted in Fig. 1. Also, the results of the analysis based on the correlograms for the various economic time series are shown in Tables 3-10. The results of the Ljung/Box test indicate a rejection of the null hypothesis of white noise for all the de-trended variables under investigation. In other words, the existence of cyclical regularities is a valid hypothesis from a statistical viewpoint.

The periodograms reveal the periodicity of the cycles and are shown in Figs. 2-9. The de-trended real output seems to follow a short-term (1 year), two mid-term (3 and 5 years) and one long-term cycle (7 years) (Fig. 3). The spectral content of the cyclical component of R&D (Fig. 5) exhibits local maxima at the frequencies of 3, 5 and 7 years. Accordingly, the de-trended labour productivity is characterized by the same frequency peaks (Fig. 8) (1, 3 and 7 years) giving credit to the belief that the

cyclical movements of R&D and labour productivity seem to be synchronized, at least to a great extent. Also, the cycle of the profit rate is characterized by periodicities of 1, 3 and 7 years. Finally, an interesting observation is that most economic time series exhibit, roughly speaking, a similar pattern characterized by periodicities exhibiting a short term cycle (approximately 1 year), a mid-term cycle (approximately 3 years) and a long term cycle (approximately 7 years), same as the periodisation of output. These results can be interpreted by economic theory as indications for the existence of cycles with different lengths (i.e. periods) that are also synchronized for the different variables within the total economy.

Tables 11-15 show the correlation coefficients between the variables under discussion. It can be seen that in all cases peaks occur at moderate lags (and leads) implying a relatively rapid transmission process of technological shocks throughout the food manufacturing industry.

Table 16 presents the results of the Granger causality tests. As can be inferred, the profit rate seems to be caused (in the Granger sense of the term) by TFP, R&D and labour productivity, while TFP and R&D cause, independently, real output.

Our findings are consistent with the majority of studies in the relevant literature. For instance, the cyclical behaviour of certain key variables such as profit rate and total factor productivity is consistent with the findings by other researchers (e.g. Heien 1983; Galo 1992). Also, according to our findings technological change goes hand in hand with output and profitability as (e.g. Goodwin and Brester, 1995; Morrison, 1999; Morrison and Siegel, 1997).

5. Result Analysis and Discussion

To begin with, from a mere visual inspection, we note that output fluctuations in the US food manufacturing sector are not very sharp although trends, upswings and falls do exist (Fig. 1a). Also, one can infer that the output of the U.S. food manufacturing sector seems to behave in a way analogous to U.S. GDP (Bureau of Economic Analysis, U.S. Department of Commerce). Analytically, the collapse of output following the first "oil crisis" is common in the U.S. food manufacturing sector and the US economy in total. Between 1963 and 1972, there is a clear upward trend in the output of the industry that was stopped by the "oil crisis", the effect of which is evident in the de-trended time series irrespectively of the filter used. Furthermore, the cyclical component follows the same pattern both in the economy and the sector between 1979-1982 and 1990-1991. The 1990's began with a shallow recession (Basu et *al.,* 2001) and, according to the economic report of the President (1994), the speed

of recovery was very slow[5]. Furthermore, between 1991 and 1997 – the so-called "new economy" period – a sharp increase of output took place. Also, productivity growth in the sector coincided with an exceptionally good performance of the U.S. economy (Mankiw, 2001)[6]. Of course, differences exist with respect to the magnitude of the fluctuations. Attempting to decompose fluctuations in industrial output, the possible sources seem to be aggregate (national) shocks, industry group specific shocks and idiosyncratic factors (Norrbin and Schlagenhauf, 1990).

Regarding the de-trendeded profit rate (figure 1h) it reached its highest level in 1972 and then it was affected by the negative macroeconomic environment of the 1970's and chiefly the oil crisis. This period is often documented as the second period of great decrease in the U.S. profit rate after WWII. Finally, an upward movement occurred in the beginning of the 1980's until 1986 reaching its peak in 1988 and 1997. This rise coincides with the third period of the U.S. economy characterised by a period when profitability rose as a result of the rapid rise in the productivity of labour.[7]

As for the labour force, during the 1970s and 1980s a structural change occurred, when huge numbers of workers entered the U.S. labour force: baby boomers, women, immigrants, etc. The American economy gave jobs to all of them. Unemployment peaked during the lowest point of the business cycle, 1982 – 1983, reaching a high 10.8%. At the same time, there was an obvious trend of diminishing the number of employees in the food manufacturing industry beginning in the 1980-1986 time span (fig. 1c). The principal constraint on reducing unemployment was the fear of the Federal Reserve that too low an unemployment rate would lead to accelerating inflation. However, after 1983 there was a gradual decline in the unemployment rate reaching a minimum in 1989, a fact that is reflected in the increase of employment in the industry. This could be attributed to the introduction of flexible forms of labour, as a result of the Reagan economic policies, that reduced the official unemployment records. Finally, a slight increase in the number of unemployed took place right after the terrorist attacks of September 2001, which is depicted in the sectors' employment.

The value of labour power has a downward trend falling continuously from 1978 onwards (Mohun 2005). Wages are squeezed on profits from the mid 1960's to

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[5] The speed of recovery was very slow both for output and labor, between the peak in the second quarter of 1990 and the trough of the first quarter of 1991. See Economic Report for the President (1991).

[6] Mankiw (2001) argued that the macroeconomic performance of the 1990's was exceptional, food and energy prices were well behaved and productivity growth experienced an unexpected acceleration, i.e. the so-called "new economy" which was characterized by the increasing role of I.T.

[7] Most economists define 3 broad periods in the U.S. economy after WWII. According to Wolff (2003), these are: (a) 1947-1966, (b) 1966-1979 and (c) 1979-1997, the first as a period of rising profitability, the second as a decreasing one and the third as a recovery one.

the early 1980's and the wage share rose some 10% of money value added. The cyclical component of wages (fig. 1g) has its peak in 1978 and its lowest point in 1997. Between 1981 and 1987 de-trended wages remained at low levels a fact that may be related to Reagan's program for steady wages. After 1997, there is an upward trend.

Fig. 1b shows the fluctuations of the net capital stock invested in the U.S. food manufacturing. According to Basu et *al.* (2001) the 1990's experienced a boom in business investment of unprecedented size and duration. The 1970's was a decade characterized by an investment boom (just like the 1990's) but less prolonged. Furthermore, the authors showed that a large part of that increase was due to investment in information technology (I.T.) equipment (computers plus communications equipment). Our findings follow the same patterns as the cyclical components described earlier. Finally, a clear decreasing pattern is evident after 2001, which may be related to the IT technology bubble and the terrorist attacks of 2001.

Meanwhile, TFP quantifies the evolution of technological change (fig. 1d). The TFP time series stops in 1996 due to data availability (NBER). Except for TFP, R&D expenditures are also used in order to quantify technological change (fig. 1e). The cyclical component of TFP in the food manufacturing has two obvious trends one downward from 1973 to 1980 and one upward from 1981 to 1988. Between 1948 and 1973 TFP grew annually in the US by 2.13% one of the highest growth rates ever recorded in U.S. history. Also, U.S. net investment grew substantially in the 1950's and the 1960's as U.S. corporations went multinational (Krugman 1990). This increase may be a reason for the high increase of TFP. After the "oil crisis" of 1973, the rate went down to 0.53% per year for the years 1973 – 1989. After 1989 there is a gradual increase going to 0.93% per year until 2000 and to 1.83% for 2000 -2005. Also, the "oil crisis" caused the contraction of R&D expenditures until 1983. The tax cut policy introduced by the Reagan government pushed profitability upwards and gave motives for investment. The increase in the U.S. food sector R&D expenditures might be related to this policy.

Labour productivity was more or less steady from 1958 to 1970 and increased until 1973, whereas the 1973 shock put an end to this upward trend (fig. 1f). After 1974, fluctuations were more acute. From a visual inspection of the graphs in figs. 1g, 1e and 1f, it is obvious that the cyclical movements of labour productivity, TFP and R&D go hand in hand, as expected. This observation is consistent with the noted improvement in the investment performance in the food manufacturing sector and the more high–tech nature of the sector (Morrison 1997), and, of course, the increase in total investment in the U.S. in the 1950's and 1960's (Krugman, 1990).

6. Conclusions

This paper made an attempt to answer some fundamental economic questions regarding the interpretation of the cyclical behaviour of economic time series in the U.S. food manufacturing industry (1958-2006). The main findings of the paper can be summarized as follows: The cyclical components of real output and the measure of technological change move in the same direction in the U.S. food manufacturing industry. Moreover, the timing pattern of technological change indicates that the peak correlations of variables appear at relatively moderate lags. This implies that the technology shocks are transmitted in the economy relatively quickly. Also, we provide robust evidence supporting the fact that technological change has explanatory power for output and profitability growth in the Granger-causal sense at various lags. As regards technological change for the food industry, there is clear bidirectional causality in the Granger sense between technology and output or profitability, which can be interpreted as indicating an ambivalent relationship in the flow of cause and effect. The significance of the role of technological change in the productivity growth which is denoted from our findings is consistent with the majority of studies in the U.S. food manufacturing sector. Additionally, the economic time series in the sector under investigation seem to follow patterns followed the total economy, respectively. Finally, another interesting observation is that most economic time series exhibit, roughly speaking, a similar pattern characterized by periodicities exhibiting a short term cycle (approximately 1 year), a mid-term cycle (approximately 3 years) and a long term cycle (approximately 7 years). Finally, regarding the detrendeded profit rate (figure 1h) it reached its highest levels in 1972 and then it was adversely affected by the negative macroeconomic environment of the 1970's. A downward movement occurred in the beginning of the 1980's until 1986 reaching its peak levels (historical high) 1988 and 1997. Clearly future and more extended research would be of great interest.

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Appendix 1: ADF Statistics

Table 1: Variables (original)

VARIABLE	LAGS	T-STAT	PROBABILITY	STATIONARY	NON STATIONARY
L	0-10	-1.4315	0.5592	NO	YES
Y	0-10	-1.9728	0.2975	NO	YES
K	1-10	0.1634	0.9673	NO	YES
TFP	0-10	-1.2786	0.6295	NO	YES
R&D	0-10	-0.6943	0.8380	NO	YES
W	1-10	-0.4993	0.8822	NO	YES
Y/L	0-10	-1.9215	0.3200	NO	YES
PROFIT RATE	0-10	-0.8313	0.8010	NO	YES

Table 2: Variables (1st differences)

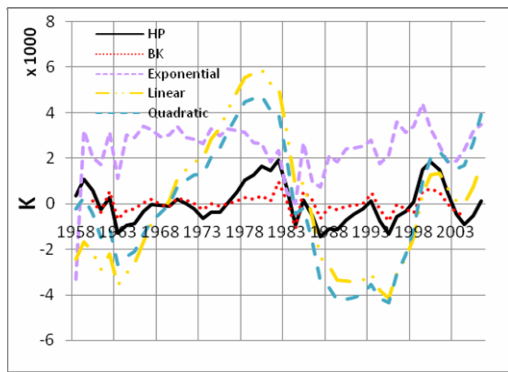| VARIABLE	LAGS	T-STAT	PROBABILITY	STATIONARY	NON STATIONARY
ΔL	0-10	-6.4966	0.0000	YES	NO
ΔY	0-10	-5.9666	0.0000	YES	NO
ΔK	1-10	-4.0598	0.0026	YES	NO
ΔTFP	0-10	-6.7144	0.0000	YES	NO
ΔR&D	0-10	-7.1683	0.0000	YES	NO
ΔW	0-10	-5.9564	0.0000	YES	NO
ΔY/L	0-10	-5.5167	0.0000	YES	NO
ΔPR	0-10	-5.8762	0.0000	YES	NO

Appendix 2: Figures of Cyclical Regularities
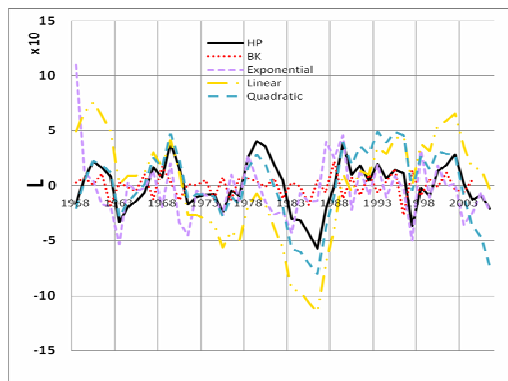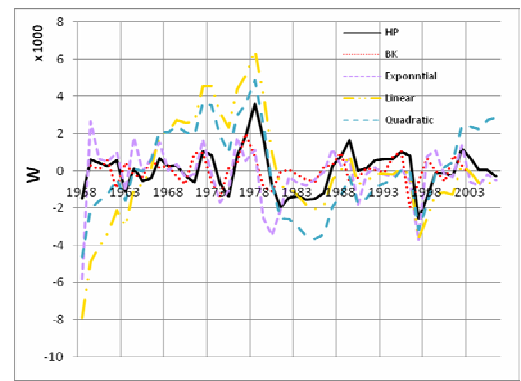

(a)

(e)

(b)

(f)

(c)

(g)

(d)

(h)

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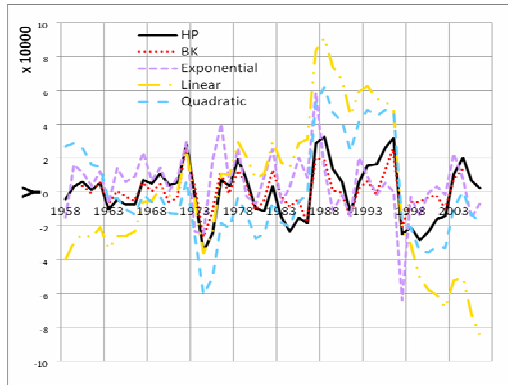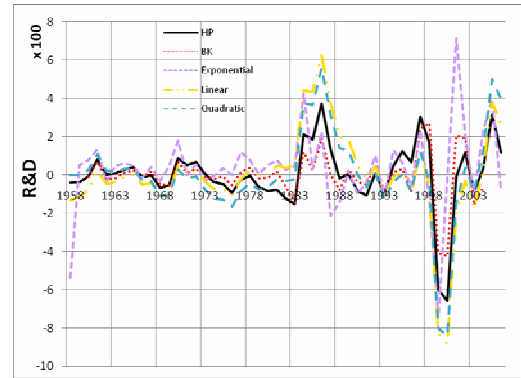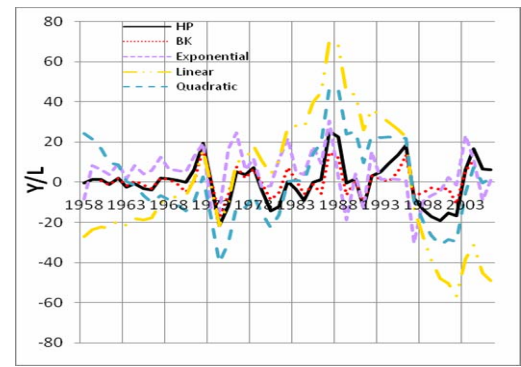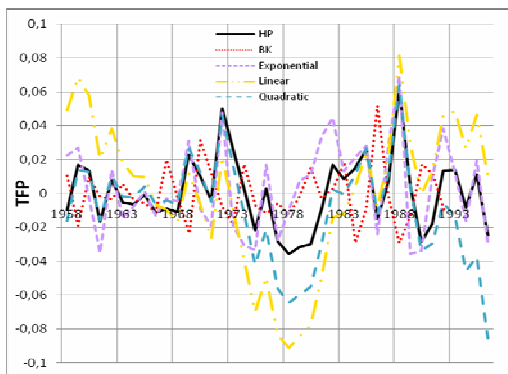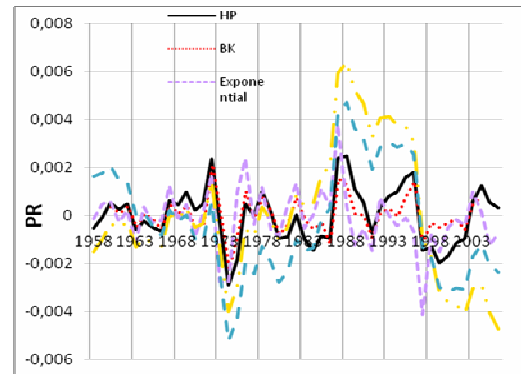
Appendix 3: White Noise Tests and Correlograms

LAG	AC	PAC	Q-Stat	Prob
1	0.548	0.548	15.654	0.000
2	0.219	-0.116	18.216	0.000
3	-0.187	-0.373	20.113	0.000
4	-0.414	-0.215	29.619	0.000
5	-0.424	-0.041	39.814	0.000
6	-0.464	-0.335	52.331	0.000
7	-0.294	-0.117	57.472	0.000
8	-0.147	-0.127	58.794	0.000

Table 3: White Noise test for L

LAG	AC	PAC	Q-Stat	Prob
1	0.486	0.486	12.306	0.000
2	0.006	-0.302	12.308	0.002
3	-0.200	-0.082	14.482	0.002
4	-0.296	-0.192	19.340	0.001
5	-0.190	0.029	21.388	0.001
6	0.025	0.069	21.423	0.002
7	0.039	-0.135	21.514	0.003
8	0.015	0.002	21.527	0.006

Table 4: White Noise test for Y

LAG	AC	PAC	Q-Stat	Prob
1	0.725	0.725	27.341	0.000
2	0.405	-0.254	36.048	0.000
3	0.182	-0.003	37.854	0.000
4	-0.074	-0.306	38.161	0.000
5	-0.219	0.046	40.891	0.000
6	-0.204	0.067	43.317	0.000
7	-0.196	-0.102	45.604	0.000
8	-0.145	0.047	46.889	0.000

Table 5: White Noise test for K

LAG	AC	PAC	Q-Stat	Prob
1	-0.169	-0.169	10.914	0.296
2	-0.569	-0.615	13.792	0.001
3	0.166	-0.155	14.910	0.002
4	0.263	-0.129	17.798	0.001
5	-0.121	-0.055	18.426	0.002
6	-0.099	-0.005	18.861	0.004
7	0.090	0.028	19.232	0.007
8	-0.131	-0.252	20.051	0.010

Table 6: White Noise test for TFP

AG	AC	PAC	Q-Stat	Prob
1	0.394	0.394	80.804	0.004
2	-0.165	-0.380	95.357	0.008
3	-0.199	0.056	11.680	0.009
4	-0.196	-0.242	13.820	0.008
5	-0.180	-0.060	15.661	0.008
6	-0.067	-0.062	15.924	0.014
7	-0.074	-0.180	16.247	0.023
8	0.005	0.073	16.248	0.039

Table 7: White Noise test for R&D

LAG	AC	PAC	Q-Stat	Prob
1	0.510	0.510	13.526	0.000
2	-0.014	-0.369	13.536	0.001
3	-0.187	0.017	15.438	0.001
4	-0.200	-0.128	17.654	0.001
5	-0.116	0.017	18.423	0.002
6	0.040	0.075	18.516	0.005
7	0.034	-0.130	18.583	0.010
8	0.021	0.094	18.611	0.017

Table 8: White Noise test for Y/L

LAG	AC	PAC	Q-Stat	Prob
1	0.489	0.489	12.441	0.000
2	0.017	-0.291	12.457	0.002
3	-0.212	-0.115	14.895	0.002
4	-0.250	-0.092	18.373	0.001
5	-0.101	0.061	18.950	0.002
6	-0.138	-0.257	20.058	0.003
7	-0.224	-0.157	23.055	0.002
8	-0.294	-0.228	28.328	0.000

Table 9: White Noise test for W

LAG	AC	PAC	Q-Stat	Prob
1	0.494	0.494	12.681	0.000
2	0.001	-0.321	12.681	0.002
3	-0.174	-0.024	14.317	0.003
4	-0.245	-0.179	17.660	0.001
5	-0.149	0.051	18.929	0.002
6	0.023	0.038	18.961	0.004
7	0.040	-0.086	19.055	0.008
8	0.016	0.010	19.070	0.014

Table 10: White Noise test for PR

Appendix 4: Periodograms
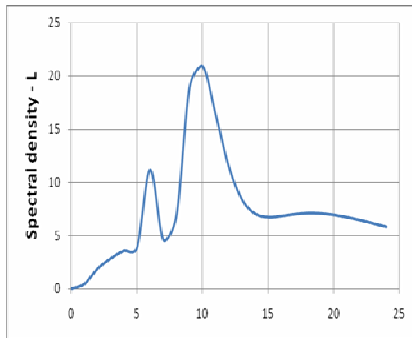
Figure 1: Periodogram for L (10³)

Figure 2: Periodogram for Y (10⁶)

Figure 3: Periodogram for K (10²)

Figure 4: Periodogram for Y/L (10²)

Figure 5: Periodogram for R&D (10⁶)
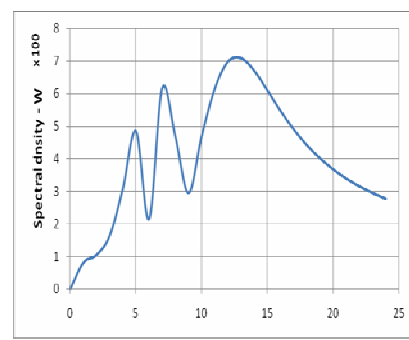
Figure 6: Periodogram for W (10⁶)
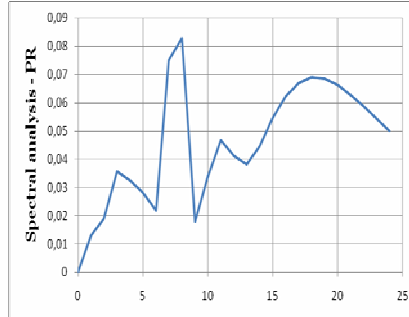
Figure 7: Periodogram for Profit Rate

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Appendix 5: Correlation of De-trended Time Series

i	Y and TFP		
	Quadratic	**HP**	**BK**
8	-0.2188	-0.3231	-0.3095
7	-0.1722	-0.1522	-0.1151
6	-0.0795	0.0869	0.1667
5	0.0040	0.2002	0.1745
4	-0.0229	0.0530	0.0801
3	-0.0659	-0.0578	-0.0819
2	-0.0880	-0.2030	-0.4282
1	0.0295	0.0507	0.1629
0	0.0948	0.2418	0.5658
-1	0.0231	-0.1089	-0.3215
-2	0.0418	-0.1299	-0.2148
-3	0.1085	0.0205	0.0387
-4	0.1254	0.1021	0.0428
-5	0.1254	0.1826	0.0582
-6	0.1124	0.2561	0.1299
-7	0.0469	0.2385	0.0038
-8	-0.0774	0.1163	-0.1352

Table 11: Correlation coefficients for Y and TFP

i	Y and R&D		
	Quadratic	**HP**	**BK**
8	-0.0708	0.1183	-0.0027
7	-0.1731	0.0855	0.0970
6	-0.3223	0.0501	0.0383
5	-0.3320	-0.0806	-0.4350
4	-0.3041	-0.0607	-0.0400
3	-0.0953	-0.0082	0.0364
2	0.1254	0.1387	0.1268
1	0.2163	0.2219	0.1003
0	0.2484	0.1604	-0.2305
-1	0.3953	0.2461	-0.0082
-2	0.4128	0.2415	0.3955
-3	0.3856	-0.0657	-0.0392
-4	0.2891	-0.3177	-0.3514
-5	0.2739	-0.1917	0.0649
-6	0.3014	-0.1241	-0.1252
-7	0.2752	0.0933	-0.0582
-8	0.2468	0.1949	0.0995

Table 12: Correlation coefficients for Y and R&D

	PROFIT RATE and TFP		
i	Quadratic	HP	BK
8	-0.2569	-0.3458	0.0767
7	-0.2002	-0.1810	-0.0311
6	-0.1000	0.0449	-0.1214
5	0.0101	0.1943	-0.0212
4	0.0199	0.0733	0.1148
3	0.0078	-0.0355	0.0410
2	0.0159	-0.1527	-0.2021
1	0.1485	0.1301	-0.2014
0	0.2183	0.3145	0.0044
-1	0.1251	-0.0743	0.1467
-2	0.1316	-0.0756	0.2063
-3	0.1672	0.0694	-0.2284
-4	0.1401	0.0989	-0.0134
-5	0.1032	0.1437	0.1973
-6	0.0590	0.1967	0.0338
-7	-0.0281	0.1669	-0.0307
-8	-0.1665	0.0174	-0.0362

Table 13: Correlation coefficients for PR and TFP

	PROFIT RATE - R&D		
i	Quadratic	HP	BK
8	-0.2188	-0.3231	-0.3095
7	-0.1722	-0.1522	-0.1151
6	-0.0795	0.0869	0.1667
5	0.0040	0.2002	0.1745
4	-0.0229	0.0530	0.0801
3	-0.0659	-0.0578	-0.0819
2	-0.0880	-0.2030	-0.4282
1	0.0295	0.0507	0.1629
0	0.0948	0.2418	0.5658
-1	0.0231	-0.1089	-0.3215
-2	0.0418	-0.1299	-0.2148
-3	0.1085	0.0205	0.0387
-4	0.1254	0.1021	0.0428
-5	0.1254	0.1826	0.0582
-6	0.1124	0.2561	0.1299
-7	0.0469	0.2385	0.0038
-8	-0.0774	0.1163	-0.1352

Table 14: Correlation coefficients for PR and R&D

	PR and Y/L		
i	**Quadratic**	**HP**	**BK**
8	-0.1320	0.0312	0.0874
7	-0.0645	0.0858	-0.2093
6	-0.0055	0.0834	-0.1677
5	-0.0250	-0.0957	-0.1148
4	0.1480	-0.1956	0.2201
3	0.3126	-0.1722	0.2784
2	0.4726	-0.8090	-0.1056
1	0.7146	0.4226	0.3522
0	0.9246	0.9199	0.0116
-1	0.8405	0.5019	0.2113
-2	0.7101	0.0428	0.3725
-3	0.5553	-0.1595	-0.0331
-4	0.4205	-0.1904	-0.3892
-5	0.3172	-0.1014	-0.1269
-6	0.2940	0.0474	0.2154
-7	0.2211	0.0219	0.1073
-8	0.1535	0.0115	0.0935

Table 15: Correlation coefficients for PR and Y/L

Appendix 6: Granger Causality Test

Table 16: Granger causality test results

Hypothesis to be Tested	CRITERIA FOR LAG SELECTION			LAGS	OBS	F-STATISTIC	PROBABILITY
	FPE	AIC	HQ				
TFP does not Granger Cause Y Y does not Granger Cause TFP	2	2	1	2	37	2.81083 2.85707	0.07506 0.07217
R&D does not Granger Cause Y Y does not Granger Cause R&D	1	3	1	1	48	2.76128 2.11861	0.10352 0.15246
Y/L does not Granger Cause PROFIT RATE PROFIT RATE does not Granger Cause Y/L	14	15	15	15	34	5.71204 4.93451	0.08840 0.10706
TFP does not Granger Cause PROFIT RATE PROFIT RATE does not Granger Cause TFP	2	2	1	2	37	3.84397 1.71500	0.03191 0.19609
R&D does not Granger Cause PROFIT RATE PROFIT RATE does not Granger Cause R&D	3	3	3	3	34	6.11292 0.96827	0.08079 0.59372