Does Productivity Affect Unemployment? A Time-Frequency Analysis for the US

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Abstract The effect of increased productivity on unemployment has long been disputed both theoretically and empirically. Although economists mostly agree on the long run positive effects of labor productivity, there is still much disagreement over the issue as to whether productivity growth is good or bad for employment in the short run. Does productivity growth increase or reduce unemployment? This paper try to answer this question by using the property of wavelet analysis to decompose economic time series into their time scale components, each associated to a specific frequency range. We decompose the relevant US time series data in different time scale components and consider co-movements of productivity and unemployment over different time horizons. In a nutshell, we conclude that, according to US post-war data, productivity creates unemployment in the short and medium terms, but employment in the long run.

1 Introduction

Productivity growth is recognized as a major force to increase the overall performance of the economy, as measured for example by the growth of output, real wages, and cost reduction, and a major source of the observed increases in the standard of

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living (Landes 1969). Economists in the past, from Ricardo to Schumpeter to Hicks, have explored the phenomenon of whether new technology and productivity in fact increase unemployment. The relationship between productivity and employment is also very important in the theoretical approach followed by the mainstream models: Real Business Cycle (RBC) and DSGE. In particular, RBC theorists have postulated technology shocks as the main driving force of business cycles. In RBC models technology shocks, either to output and employment (measured as hours worked) are predicted to be positively correlated.[1] This claim has been made the focus of numerous econometric studies.[2] Employing the Blanchard and Quah (1989) methodology Gali (1999), Gali and Rabanal (2005), Francis and Ramey (2005) and Basu et al. (2006) find a negative correlation between employment and productivity growth, once the technology shocks have been purified taking out demand shocks affecting output.

Although economists mostly agree on the long run positive effects of labor productivity, significant disagreements arise over the issue as to whether productivity growth is good or bad for employment in the short run. Empirical results have been mixed (e.g. in Muscatelli and Tirelli 2001, where the relationship between productivity growth and unemployment is negative for several G7 countries and not significant for others) and postulate a possible trade-off between employment and productivity growth (Gordon 1997). Such empirical findings have been also complicated by the contrasting evidence emerging during the 1990s between the US and Europe as to the relationship between (un)employment and productivity growth. Whereas the increase in productivity growth in the US in the second half of the 1990s is associated with low and falling unemployment (Staiger et al. 2001), in Europe the opposite tendency was visible. Productivity growth appears to have increased unemployment.

The labor market provides an example of a market where the strategies used by the agents involved, firms and workers (through unions), can differ by time scale. Thus, the "true" economic relationships among variables can be found at the disaggregated (scale) level rather than at the usual aggregate level. As a matter of fact, aggregate data can be considered the result of a time scale aggregation procedure over all time scales and aggregate estimates a mixture of relationships across time scales, with the consequence that the effect of each regressor tends to be mitigated by this averaging over all time scales.[3] Blanchard et al. (1995) were the first ones to hint at such a research agenda. They stressed that it may be useful to distinguish between the short, medium and long-run effects of productivity growth, as the effects of productivity growth on unemployment may show different

[1] See the volume by Cooley (1995), and see also Backus and Kehoe (1992) among the others.

[2] For details of the evaluations, see Gong and Semmler (2006, ch.6).

[3] For example in Gallegati et al. (2011) where wavelet analysis is applied to the wage Phillips curve for the US.

co-movements depending on the time scales.[4] Similar thoughts are also reported in Solow (2000) with respect to the different ability of alternative theoretical macroeconomic frameworks to explain the behavior of an economy at the aggregate level in relation to their specific time frames[5] and, more recently, the idea that time scales can be relevant in this context has also been expressed by Landmann (2004).[6]

Following these insights, studies are now emerging arguing that researchers need to disentangle the short and long-term effects of changes in productivity growth for unemployment. For example, Tripier (2006), studying the co-movement of productivity and hours worked at different frequency components through spectral analysis, finds that co-movements between productivity and unemployment are negative in the short and long run, but positive over the business cycle.[7] This paper is related to the above mentioned literature by focussing on the relationship of unemployment and productivity growth at different frequency ranges. Indeed, wavelets with respect to other filtering methods are able to decompose macroeconomic time series, and data in general, into several components, each with a resolution matched to its scale. After the first applications of wavelet analysis in economics and finance provided by Ramsey and his co-authors (1995; 1996; 1998a; 1998b), the number of wavelet applications in economics has been rapidly growing in the last few years as a result of the interesting opportunities provided by wavelets in order to study economic relationships at different time scales.[8]

The objective of this paper is to provide evidence on the nature of the time scale relationship between labor productivity growth and the unemployment rate using wavelet analysis, so as to provide a new challenging theoretical framework, new empirical results as well as policy implications. First, we perform wavelet-based exploratory analysis by applying the continuous wavelet transform (CWT) since tools such as wavelet power, coherency and phase can reveal interesting features

[4]Most of the attention of economic researchers who work on productivity has been devoted to measurement issues and to resolve the problem of data consistency, as there are many different approaches to the measurement of productivity linked to the choice of data, notably the combination of employment, hours worked and GDP (see for example the OECD Productivity Manual, 2001).

[5]"At short term scales, I think, something sort of Keynesian is a good approximation, and surely better than anything straight neoclassical. At very long scales, the interesting questions are best studied in a neoclassical framework.... At the 5–10 years time scale, we have to piece things together as best as we can, and look for an hybrid model that will do the job" (Solow 2000, p. 156).

[6]"The nature of the mechanism that link [unemployment and productivity growth] changes with the time frame adopted" because one needs "to distinguish between an analysis of the forces shaping long-term equilibrium paths of output, employment and productivity on the one hand and the forces causing temporary deviations from these equilibrium paths on the other hand" (Landmann 2004, p. 35).

[7]Qualitative similar results are also provided using time domain techniques separating long-run trends from short run phenomena.

[8]For example Gençay et al. (2005), Gençay et al. (2010), Kim and In (2005), Fernandez (2005), Crowley and Mayes (2008), Gallegati (2008), Ramsey et al. (2010), Gallegati et al. (2011).

about the structure of a process as well as information about the time-frequency dependencies between two time series. Hence, after decomposing both variables into their time-scale components using to the maximum overlap discrete wavelet transform (MODWT), we analyze the relationship between labor productivity and unemployment at the different time scales using parametric and nonparametric approaches. The results indicate that in the medium-run, at business cycle frequency, there is a positive relationship of productivity and unemployment, whereas in the long-run we can observe a negative co-movement, that is productivity creates employment.

The paper proceeds as follows. In Sect. 2 a wavelet-based exploratory analysis is performed by applying several CWT tools to labor productivity growth and the unemployment rate. In Sect. 3, we analyze the "scale-by-scale" relationships between productivity growth and unemployment by means of parametric and nonparametric approaches. Section 4 provides interpretation of results according to alternative labor market theories and Sect. 5 concludes the paper.

2 Continuous Wavelet Transforms

The essential characteristics of wavelets are best illustrated through the development of the continuous wavelet transform (CWT).[9] We seek functions $\psi(u)$ such that:

$$\int \psi(u)\, du = 0 \tag{1}$$

$$\int \psi(u)^2\, du = 1 \tag{2}$$

The cosine function is a "large wave" because its square does not converge to 1, even though its integral is zero; a wavelet, a "small wave" obeys both constraints. An example would be the Haar wavelet function:

$$\psi^H(u) = \begin{cases} -\frac{1}{\sqrt{2}} & -1 < u < 0 \\ \frac{1}{\sqrt{2}} & 0 < u < 1 \\ 0 & otherwise \end{cases} \tag{3}$$

Such a function provides information about the variation of a function, $f(t)$, by examining the differences over time of partial sums. As will be illustrated below

[9]Wavelets, their generation, and their potential use are discussed in intuitive terms in Ramsey (2010), while Gençay et al. (2001) generate an excellent development of wavelet analysis and provide many interesting economic examples. Percival and Walden (2000) provide a more technical exposition with many examples of the use of wavelets in a variety of fields, but not in economics.

general classes of wavelet functions compare the differences of weighted averages of the function $f(t)$. Consider a signal, $x(u)$ and the corresponding "average":

$$\frac{1}{b-a}\int_a^b x(u)\,du = \alpha(a,b) \tag{4}$$

Let us choose the convention that we assess the value of the "average" at the center of the interval and let $\lambda \equiv b-a$ represent the scale of the partial sums. We have the expression:

$$\begin{aligned} A(\lambda,t) &\equiv \alpha(t-\lambda/2,\ t+\lambda/2) \\ &= \frac{1}{\lambda}\int_{t-\lambda/2}^{t+\lambda/2} x(u)\,du \end{aligned} \tag{5}$$

A(λ,t) is the average value of the signal centered at "t" with scale λ. But what is of more use is to examine the differences at different values for λ and at different values for "t". We define:

$$\begin{aligned} D(\lambda,t) &= A(\lambda,t+\lambda/2) - A(\lambda,t-\lambda/2) \\ &= \frac{1}{\lambda}\int_t^{t+\lambda} x(u)\,du - \frac{1}{\lambda}\int_{t-\lambda}^{t} x(u)\,du \end{aligned} \tag{6}$$

This is the basis for the continuous wavelet transform, CWT, as defined by the Haar wavelet function. For an arbitrary wavelet function, $W(\lambda\ t)$, the wavelet transform, ψ is:

$$\begin{aligned} W(\lambda,\ t) &= \int_{-\infty}^{\infty} \psi_{\lambda,\,t}(u)x(u)\,du \\ \psi_{\lambda,\,t}(u) &\equiv \frac{1}{\sqrt{\lambda}}\left(\frac{u-t}{\lambda}\right) \end{aligned} \tag{7}$$

where λ is a scaling or dilation factor that controls the length of the wavelet and t a location parameter that indicates where the wavelet is centered (see Percival and Walden 2000).

2.1 Wavelet Power Spectrum

Let $W_x(\lambda,t)$ be the continuous wavelet transform of a signal $x(.)$, $|W_x|^2$ represents the wavelet power and can be interpreted as the energy density of the signal in the time-frequency plane. Among the several types of wavelet families available, that is Morlet, Mexican hat, Haar, Daubechies, etc., the Morlet wavelet is the most widely used because of its optimal joint time frequency concentration. The Morlet wavelet is a complex wavelet that produces complex transforms and thus can provide us with information on both amplitude and phase. It is defined as

$$\psi_\eta(t) = \pi^{-\frac{1}{4}} e^{i\omega_0 \eta} - e^{-\frac{\eta^2}{2}}. \tag{8}$$

where $-1/4$ is a normalization term, $\eta = t/\lambda$ is the dimensionless time parameter, t is the time parameter, λ is the scale of the wavelet. The Morlet coefficient ω_0 governs the balance between time and frequency resolution. We use the value $\omega_0 = 6$ since this particular choice provides a good balance between time and frequency localization (see Grinsted et al. 2004) and also simplifies the interpretation of the wavelet analysis because the wavelet scale, λ, is inversely related to the frequency, $f \approx 1/\lambda$.

Plots of the wavelet power spectrum provide evidence of potentially interesting structures, like dominant scales of variation in the data or "characteristic scales" according to the definition of Keim and Percival (2010).[10] Since estimated wavelet power spectra are biased in favor of large scales, the bias rectification proposed by Liu et al. (2007) is applied, where the wavelet power spectrum is divided by the scale coefficient so that it becomes physically consistent and unbiased. Specifically, the adjusted wavelet power spectrum is obtained by dividing the power at each point in the spectrum by the corresponding scale based on the energy definition (the transform coefficient squared is divided by the scale it associates). This allows for a comparison of the spectral peaks across scales.

Time is recorded on the horizontal axis and the vertical axis gives us the periods and the corresponding scales of the wavelet transform. Reading across the graph at a given value for the wavelet scaling, one sees how the power of the projection varies across the time domain at a given scale. Reading down the graph at a given point in time, one sees how the power varies with the scaling of the wavelet (see Ramsey et al. 1995). A black contour line testing the wavelet power 5 % significance level against the null hypothesis that the data generating process is generated by a stationary process is displayed,[11] as is the cone of influence represented by a shaded area corresponding to the region affected by edge effects.[12]

[10]The CWT has been computed using the MatLab package developed by Grinsted et al. (2004). MatLab programs for performing the bias-rectified wavelet power spectrum and partial wavelet coherence are provided by Ng and Kwok at http://www.cityu.edu.hk/gcacic/wavelet.

[11]The statistical significance of the results obtained through wavelet power analysis was first assessed by Torrence and Compo (1998) by deriving the empirical (chi-squared) distribution for the local wavelet power spectrum of a white or red noise signal using Monte Carlo simulation analysis.

[12]As with other types of transforms, the CWT applied to a finite length time series inevitably suffers from border distortions; this is due to the fact that the values of the transform at the beginning and the end of the time series are always incorrectly computed, in the sense that they involve missing values of the series which are then artificially prescribed; the most common choices are zero padding extension of the time series by zeros or periodization. Since the effective support of

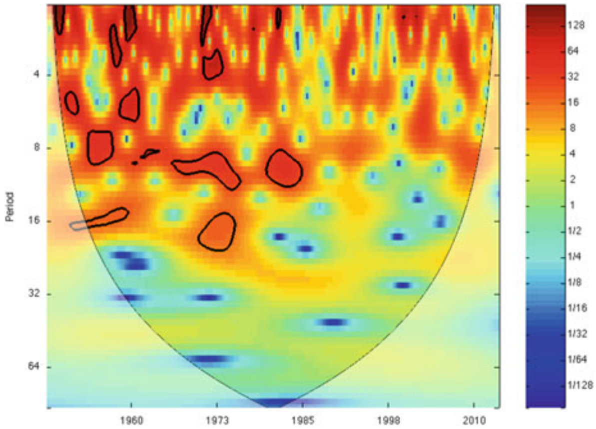

Fig. 1 Rectified wavelet power spectrum plots for labor productivity growth. Note: contours and a cone of influence are added for significance. A *black contour line* testing the wavelet power 5 % significance level against a *white* noise null is displayed as is the cone of influence, represented by a *shaded area* corresponding to the region affected by edge effects

In Figs. 1 and 2 we report estimated wavelet spectra for labor productivity growth and the unemployment rate, respectively.[13] The comparison between the power spectra of the two variables reveals important differences as to their characteristic features. In the case of labor productivity growth there is evidence of highly localized patterns at lower scales, with high power regions concentrated in the first part of the sample (until late eighties). By contrast, for the unemployment rate significant power regions are evident at scales corresponding to business cycle frequencies throughout the sample.

Although useful for revealing potentially interesting features in the data like “characteristic scales”, the wavelet power spectrum is not the best tool to deal with the time-frequency dependencies between two time-series. Indeed, even if two variables share similar high power regions, one cannot infer that their comovements look alike.

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the wavelet at scale λ is proportional to λ, these edge effects also increase with λ. The region in which the transform suffers from these edge effects is called the cone of influence. In this area of the time-frequency plane the results are unreliable and have to be interpreted carefully (see Percival and Walden 2000).

[13] We use quarterly data for the US between 1948:1 and 2013:4 from the Bureau of Labor Statistics. Labor productivity is defined as output per hour of all persons in the Nonfarm Business Sector, Index 1992 = 100, and transformed into its growth rate as $400 * ln(x_t/x_{t-1})$. Unemployment rate is defined as percent Civilian Unemployment Rate.

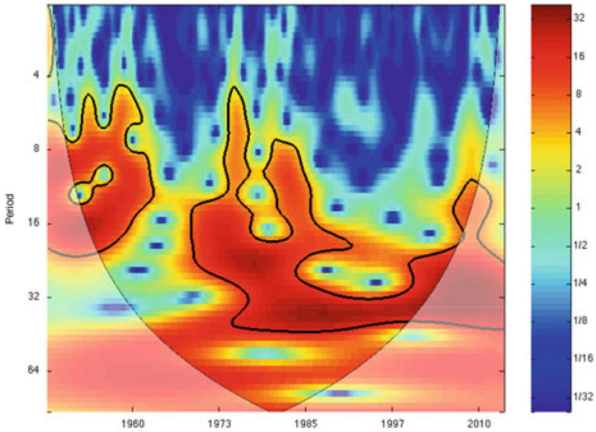

Fig. 2 Rectified wavelet power spectrum for the unemployment rate. Note: see Table 1

2.2 *Wavelet Coherence*

In order to detect and quantify relationships between variables suitable wavelet tools are the cross-wavelet power, wavelet coherence and wavelet phase difference. Let W_x and W_y be the continuous wavelet transform of the signals $x(.)$ and $y(.)$, the cross-wavelet power of the two series is given by $|W_{xy}|=|W_x W_y|$ and depicts the local covariance of the two time series at each scale and frequency (see Hudgins et al. 1993). The wavelet coherence is defined as the modulus of the wavelet cross spectrum normalized to the single wavelet spectra and is especially useful in highlighting the time and frequency intervals where two phenomena have strong interactions. It can be considered as the local correlation between two time series in time frequency space. The statistical significance level of the wavelet coherence is estimated using Monte Carlo methods. The 5 % significance level against the null hypothesis of red noise is shown as a thick black contour. The cone of influence is marked by a black thin line: again, values outside the cone of influence should be interpreted very carefully, as they result from a significant contribution of zero padding at the beginning and the end of the time series.

Complex-valued wavelets like Morlet wavelet have the ability to provide the phase information, that is a local measure of the phase delay between two time series as a function of both time and frequency. The phase information is coded by the arrow orientation. Following the trigonometric convention the direction of arrows shows the relative phasing of the two time series and can be interpreted as indicating a lead/lag relationship: right (left) arrow means that the two variables are in phase (anti-phase). If the arrows points to the right and up, it means the unemployment rate is lagging. If they points to the right and down, unemployment rate is leading. If the arrows are to the left and up, it means unemployment rate is leading and if they are to the left and down, unemployment rate is lagging. The relative phase

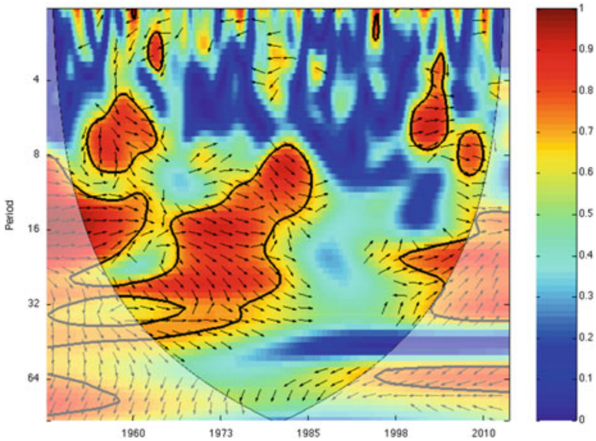

Fig. 3 Wavelet coherence between the unemployment rate and productivity growth. The color code for power ranges from *blue* (low coherence) to *red* (high coherence). A pointwise significance test is performed against an almost process independent background spectrum. 95 % confidence intervals for the null hypothesis that coherency is zero are plotted as contours in *black* in the figure. The cone of influence is marked by *black lines* (Color figure online)

information is graphically displayed on the same figure with wavelet coherence by plotting such arrows inside and close to regions characterized by high coherence, so that the coherence and the phase relationship are shown simultaneously.

In Fig. 3 regions of strong coherence between productivity and unemployment are evident at business cycle scales, i.e. at scales corresponding to periods between 2 and 8-years, except for the mid 1980s–mid 1990s period where no relationship is evident at any scale. The analysis of the phase difference reveals an interesting difference in the phase relationship of the two variables. If at scales corresponding to business cycle frequencies the two series are generally in phase, the low frequency region of the wavelet coherence reveals the presence of an anti-phase relationship between productivity and unemployment.

3 Discrete Wavelet Transform

So far we have considered only continuously labeled decompositions. Nonetheless there are several difficulties with the CWT. First, it is computationally impossible to analyze a signal using all wavelet coefficients. Second, as noted, $W(\lambda, t)$ is a function of two parameters and as such contains a high amount of redundant information. As a consequence, although the CWT provides a useful tool for analyzing how the different periodic components of a time series evolve over time, both individually (wavelet power spectrum) and jointly (wavelet coherence and phase-difference), in practice a discrete analogs of this transform is developed.

We therefore move to the discussion of the discrete wavelet transform (DWT), since the DWT, and in particular the MODWT, a variant of the DWT, is largely predominant in economic applications.[14]

The DWT is based on similar concepts as the CWT, but is more parsimonious in its use of data. In order to implement the discrete wavelet transform on sampled signals we need to discretize the transform over scale and over time through the dilation and location parameters. Indeed, the key difference between the CWT and the DWT lies in the fact that the DWT uses only a limited number of translated and dilated versions of the mother wavelet to decompose the original signal. The idea is to select t and λ so that the information contained in the signal can be summarized in a minimum number of wavelet coefficients. The discretized transform is known as the discrete wavelet transform, DWT.

The discretization of the continuous time-frequency decomposition creates a discrete version of the wavelet power spectrum in which the entire time-frequency plane is partitioned with rectangular cells of varying dimensions but constant area, called Heisenberg cells (e.g. in Fig. 4).[15] Higher frequencies can be well localized in time, but the uncertainty in frequency localization increases as the frequency increases, which is reflected as taller, thinner cells with increase in frequency. Consequently, the frequency axis is partitioned finely only near low frequencies. The implication of this is that the larger-scale features of the signal get well resolved in the frequency domain, but there is a large uncertainty associated with their location. On the other hand, the small-scale features, such as sharp discontinuities, get well resolved in the time domain, even if there is a large uncertainty associated with their frequency content. This trade-off is an inherent limitation due to the Heisenberg's uncertainty principle that states that the resolution in time and frequency cannot be arbitrarily small because their product is lower bounded. Therefore, owing to the uncertainty principle, an increased resolution in the time domain for the time localization of high-frequency components comes at a cost of an increased uncertainty in the frequency localization, that is one can only trade time resolution for frequency resolution, or vice versa.

The general formulation for a continuous wavelet transform can be restricted to the definition of the "discrete wavelet transform", the properties of which can be summarized by the equation:

$$\psi_{j,k}(t) = 2^{-j/2}\psi\left(\frac{t - 2^j k}{2^j}\right) \tag{9}$$

[14]The number of the papers applying the DWT is far greater than those using the CWT. As a matter of fact, the preference for DWT in economic applications can be explained by the ability of the DWT to facilitate a more direct comparison with standard econometric tools than is permitted by the CWT, e.g. time scales regression analysis, homogeneity test for variance, nonparametric analysis.

[15]Their dimensions change according to their scale: the windows stretch for large values of λ to measure the low frequency movements and compress for small values of λ to measure the high frequency movements.

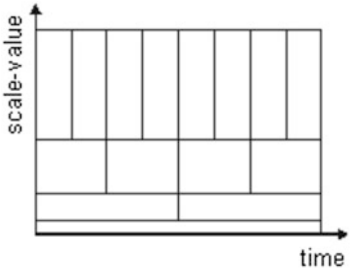

Fig. 4 DWT time-scale partition

which is known as the "mother wavelet". This function represents a sequence of rescaleable functions at a scale of $\lambda = 2^j, j = 1, 2, \ldots J$, and with time index $k, k = 1, 2, 3, \ldots N/2^j$. The wavelet transform coefficient of the projection of the observed function $f(t)$ for $i = 1, 2, 3, \ldots N, N = 2^J$ on the wavelet $\psi_{j,k}(t)$ is given by:

$$d_{j,k} \approx \int \psi_{j,k}(t) f(t)\, dt, \quad j = 1, 2, ..J \tag{10}$$

For a complete reconstruction of a signal f(t), one requires a scaling function, $\phi(.)$, that represents the smoothest components of the signal. While the wavelet coefficients represent weighted "differences" at each scale, the scaling coefficients represent averaging at each scale. One defines the scaling function, also know as the "father wavelet", by:

$$\phi_{J,k}(t) = 2^{-J/2} \phi\left(\frac{t - 2^J k}{2^J}\right) \tag{11}$$

And the scaling function coefficients vector is given by:

$$s_{J,k} \approx \int \phi_{J,k}(t) f(t)\, dt, \tag{12}$$

By construction, we have an orthonormal set of basis functions, whose detailed properties depend on the choices made for the functions, $\phi(.)$ and $\psi(.)$, see for example the references cited above as well as Daubechies (1992) and Silverman (1999). At each scale, the entire real line is approximated by a sequence of "non-overlapping" wavelets. The deconstruction of the function $f(t)$ is therefore:

$$f(t) \approx \sum_k s_{J,k} \phi_{J,k}(t) + \sum_k d_{J,k} \psi_{J,k}(t) + \sum_k d_{J-1,k} \psi_{J-1,k}(t) + \ldots + \sum_k d_{1,k} \psi_{1,k}(t) \tag{13}$$

The above equation is an example of the Discrete Wavelet Transform, DWT based on an arbitrary wavelet function, $\phi(.)$. Using economic variables, the degree of relative error is approximately on the order of 10^{-13} in many cases, so that one can reasonably claim that the wavelet decomposition is very good. While it would appear that wavelets involve large numbers of coefficients, it is also true that the number of coefficients greater than zero is very small; the arrays are said to be "sparse". In the literature quite complicated functions are approximated to a high level of accuracy with a surprisingly small number of coefficients. As a corollary to this general statement, other scholars have noted the extent to which the distribution of coefficients under the null hypothesis of zero effect, rapidly approaches the Gaussian distribution.

Further, the approximation can be re-written in terms of collections of coefficients at given scales. Define;

$$
\begin{aligned}
S_J &= \sum_k s_{J,k}\phi_{J,k}(t) \\
D_J &= \sum_k d_{J,k}\psi_{J,k}(t) \\
D_{J-1} &= \sum_k d_{J-1,k}\psi_{J-1,k}(t) \\
&\cdots\cdots \\
D_1 &= \sum_k d_{1,k}\psi_{1,k}(t)
\end{aligned}
\tag{14}
$$

Thus, the approximating equation can be restated in terms of coefficient crystals as:

$$
f(t) \approx S_J + D_J + D_{J-1} + \ldots D_2 + D_1 \tag{15}
$$

where S_J contains the "smooth component" of the signal, and the D_j, $j = 1, 2, ..J$, the detail signal components at ever increasing levels of detail. S_J provides the large scale road map, D_1 shows the pot holes. The previous equation indicates what is termed the multiresolution decomposition, MRD.

3.1 Time Scale Decomposition Analysis

The orthonormal discrete wavelet transform (DWT), even if widely applied to time series analysis in many disciplines, has two main drawbacks: (1) the dyadic length requirement (i.e. a sample size divisible by 2^J), and (2) the wavelet and scaling coefficients are not shift invariant. Because of the practical limitations of DWT wavelet analysis is generally performed by applying the *maximal overlap discrete* *wavelet transform* (MODWT), a non-orthogonal variant of the classical discrete wavelet transform (DWT) that, unlike the DWT, is translation invariant, as shifts in the signal do not change the pattern of coefficients, can be applied to data sets of length not divisible by 2^J and provides at each scale a number of coefficients equal to the length of the original series.

For our analysis we select the Daubechies least asymmetric (LA) wavelet filter of length $L = 8$ based on eight non-zero coefficients (Daubechies 1992), with reflecting boundary conditions, and apply the MODWT up to a level $J = 5$ that produces one vector of smooth coefficients s_5, representing the underlying smooth behavior of the data at the coarse scale, and five vectors of details coefficients d_5, d_4, d_3, d_2, d_1, representing progressively finer scale deviations from the smooth behavior. Through the synthesis, or reconstruction, operation we can reassemble the original signal from the wavelet and scaling coefficients using the inverse stationary wavelet transform.[16] Specifically, with $J = 5$ we reconstruct five wavelet details vectors D_5, D_4, D_3, D_2, D_1 and one wavelet smooth vector, S_5, each associated with a particular time scale 2^{j-1}. In particular, since we use quarterly data the first detail level D_1 captures oscillations between 2 and 4 quarters, while details D_2, D_3, D_4 and D_5 capture oscillations with a period of 1–2, 2–4, 4–8 and 8–16 years, respectively.[17]

The smooth and detail components obtained from the reconstruction process take the form of non-periodic oscillating waves representing the long-term trend and the deviations from it at an increasing level of detail. According to Ramsey (2002) the visual inspection between pairs of variables provides an excellent exploratory tool for discovering time varying delays or phase variations between variables. Indeed, by examining the phase relationship in a bivariate context we can obtain useful insights on the timing (lagging, synchro or leading) of the linkage between variables as well as on the existence of a fixed or changing relationship.[18]

In Fig. 5 we plot the smooth and detail components, i.e. S_5, D_5, D_4 and D_3, as a sequence of pairs where the unemployment rate (dotted lines) is plotted against labor productivity growth (solid lines). The visual inspection of the long-run components indicate an anti-phase relationship between variables, with productivity growth slightly leading the unemployment rate.[19] The pattern displayed by the top right

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[16]Since the J components obtained by the application of MODWT are not orthogonal, they do not sum up to the original variable.

[17]Detail levels D_1 and D_2, represent the very short-run dynamics of a signal (and contains most of the noise of the signal), levels D_3 and D_4 roughly correspond to the standard business cycle time period (Stock and Watson 1999), while the medium-run component is associated to level D_5. Finally, the smooth component S_5 captures oscillations with a period longer than 16 years corresponding to the low-frequency components of a signal.

[18]Although a standard assumption in economics is that the delay between variables is fixed, the phase relationship may well be scale dependent and vary continuously over time (e.g. in Ramsey and Lampart 1998a,b; Gallegati and Ramsey 2013).

[19]This leading behavior is consistent with the findings reported in the previous section using wavelet coherence.

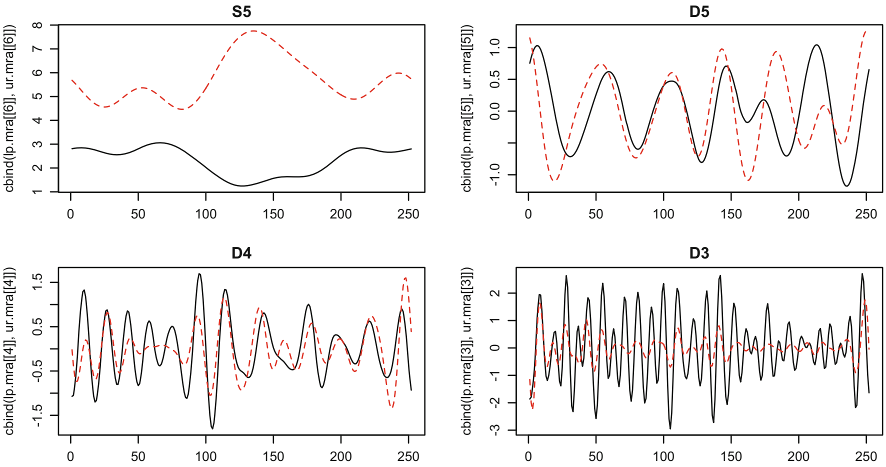

Fig. 5 Phase shift relationships of smooth and detail components for unemployment (*dotted lines*) and productivity (*solid lines*)

panel in Fig. 5 reveals that the two components are mostly in phase at the D_5 scale level, with unemployment slightly leading productivity growth. Nonetheless, the plot also shows that the two series at this level have been moving into antiphase at the beginning of the 1990s, as a consequence of a shift in the phase relationship, and then have been moving in-phase again in the last part of the sample. At the D_4 scale level unemployment and productivity are in-phase throughout the sample with the exception of the 1960s. Finally, at the lower scale levels productivity growth and unemployment rate components show very different amplitude fluctuations. This pattern suggests how a well known feature of aggregate productivity growth quarterly data, that is its very high volatility, can be ascribed to high frequency components.

3.2 Parametric Analysis

Wavelets provide a unique tool for the analysis of economic relationships on a scale-by-scale basis. Time scale regression analysis allows the researcher to examine the relationship between variables at each j scale where the variation in both variables has been restricted to the indicated specific scale. In order to perform a time scale regression analysis first we need to partition each variable into a set of different components by using the discrete wavelet transform (DWT), such that each component corresponds to a particular range of frequencies, and then run regression analysis on a scale-by-scale basis (e.g. Ramsey and Lampart 1998a,b; Kim and

Table 1 Aggregate and time scale regression analysis (1948:1–2013:4)—OLS

$ur_t = \alpha + \beta \Delta lp_t + \epsilon_t$

	Aggregate	S_5	D_5	D_4	D_3	D_2	D_1
α_j	**5.7694**	**9.8850**	−5.13e−09	7.41e−10	−3.46e−09	−5.29e−10	2.26e−10
	(0.2248)	(0.2773)	(0.0616)	(0.0530)	(0.0259)	(0.0079)	(0.0018)
β_j	0.0257	**−1.8614**	**0.6862**	**0.5217**	**0.1902**	**0.0285**	**−0.0092**
	(0.0316)	(0.1166)	(0.1496)	(0.0557)	(0.0217)	(0.0101)	(0.0022)
$\overline{R}^2$	0.0027	0.8077	0.2375	0.4247	0.3777	0.0450	0.0735
S.E.	1.6646	0.5359	0.4606	0.4197	0.2671	0.1586	0.0704

Note: *HAC* standard errors in parenthesis, *S.E.* is the regression standard error
Regressors significant at 5 % in bold

In 2005; Gallegati et al. 2011).[20] Therefore, after decomposing the regression variables into their different time scale components using the MOWDT we estimate a sequence of least squares regressions using

$$ur[S_J]_t = \alpha_J + \beta_J lp[S_J]_t + \epsilon_t \tag{16}$$

and

$$ur[D_j]_t = \alpha_j + \beta_j lp[D_j]_t + \epsilon_t \tag{17}$$

where $ur[S_J]_t$, and $lp[S_J]_t$ represent the components of the variables at the longest scale, and $ur[D_j]_t$, and $lp[D_j]_t$ represent the components of the variables at each scale j, with $j = 1, 2, \ldots, J$.

In Table 1 we present the results from least squares estimates at the aggregate and individual scale levels. First of all, we notice that although at the aggregate level the relationship between productivity and unemployment is not significant, the "scale-by-scale" regressions reveal a positive significant relationship at almost each scale level and that the effects of productivity on unemployment rate differ widely across scales in terms of sign and estimated size effect. Specifically, if at scales D_1 and D_2 the estimated size effect of productivity growth on unemployment is negligible, at business cycles and medium run scales, i.e. from D_3 to D_5, the size and significance of the estimated coefficients indicate a positive relationship that is higher for the D_4 scale level. Finally, long run trends are negatively related. A 1 % fall in the long-run productivity growth rate increases the unemployment rate by 1.86 %.[21]

[20]Thus, we test for frequency dependence of the regression parameter by using timescale regression analysis since the approaches used to detect and model frequency dependence such as spectral regression approaches (Hannan 1963; Engle 1974, 1978) present several shortcomings because of their use of the Fourier transformation. For examples of the use of this procedure in economics, see Ramsey and Lampart (1998a,b), Gallegati et al. (2011).

[21]This estimated magnitude of the impact of growth on unemployment is in line with those obtained in previous studies. For example, Pissarides and Vallanti (2007) a panel of OECD countries estimate that a 1 % decline in the growth rate leads to a 1.3–1.5 % increase in unemployment.

This finding is not new. A negative link between unemployment and productivity growth at low frequencies is also documented in Staiger et al. (2001), Ball and Moffitt (2002), where the trending behavior of productivity growth is called for in the explanation of low and falling inflation combined with low unemployment experienced by the US during the second half of the 1990s, as well as in Muscatelli and Tirelli (2001) for several G7 countries. Similar results have been also obtained in Tripier (2006), Chen et al. (2007) using different methods. In the first by using measures of co-movements in the frequency domain it is shown that co-movements between variables differ strongly according to the frequency, that is negative in the short and long run, but positive over the business cycle. In the latter, the authors, disaggregating data into their short and long-term components and using two different econometric methods (Maximum Likelihoof and structural VAR), find that productivity growth affects unemployment positively in the short run and negatively in the long run.[22]

In sum, when we consider different time frames we find that the effects of productivity growth on unemployment are frequency-dependent: in the long run an increase in productivity releases forces that stimulate innovation and growth in the economy and thus determine a reduction of unemployment, whereas at intermediate and business cycle time scales productivity gains cause unemployment to increase.

3.3 Nonparametric Analysis

In this section we apply a methodology that allows us to explore the robustness of the issues related to the relationship between productivity growth and unemployment without making any a priory explicit or implicit assumption about the form of the relationship: nonparametric regression analysis. Indeed, nonparametric regressions can capture the shape of a relationship without us prejudging the issue, as they estimate the regression function $f(.)$ linking the dependent to the independent variables directly.[23]

There are several approaches available to estimate nonparametric regression models,[24] and most of these methods assume that the nonlinear functions of the independent variables to be estimated by the procedures are *smooth* continuous functions. One such model is the locally weighted polynomial regression pioneered

[22]Recently, a negative long-run relationship between productivity growth and unemployment has also been obtained by Schreiber (2009) using a co-breaking approach and Miyamoto and Takahashi (2011) using band-pass filtering.

[23]The traditional nonlinear regression model introduce nonlinear functions of dependent variables using a limited range of transformed variables to the model (quadratic terms, cubic terms or piecewise constant function). An example of a methodology testing for nonlinearity without imposing any a priory assumption about the shape of the relationship is the smooth transition regression used in Eliasson (2001).

[24]See Fox (2000a,b) for a discussion on nonparametric regression methods.

by Cleveland (1979). This procedure fits the model $y = f(x_1, \ldots, x_k) + \epsilon$ nonparametrically, that is without assuming a parametric form for $f(x_1, \ldots, x_k)$. The low-degree polynomial, generally first or second degree (that is, either locally linear or locally quadratic), is fit using weighted least squares, so that the data points are weighted by a smooth function whose weights decrease as the distance from the center of the window increases. The value of the regression function is obtained by evaluating the local polynomial at each particular value of the independent variable, x_i. A fixed proportion of the data is included in each given local neighborhood, called the *span* of the local regression smoother (or the smoothing parameter)[25] and the fitted values are then connected in a nonparametric regression curve.

In Fig. 6 we report the scatter plots of the productivity growth-unemployment relationship at the different scale levels, from S_5 (top left panel) to D_1 (top right panel). In each panel of Fig. 6 a solid line drawn by connecting the points of the fitted values for each function against its regressor is superimposed on each scatter plot. The smooth plots represented by the solid lines depict the loess fit using a smoothing parameter value of $2/3$.[26] These lines can be used to reveal the shape of the estimated relationship between the dependent (unemployment rate) and the independent variable (labor productivity).

The loess fits shown on the plots in Fig. 6 support the conclusions obtained from the parametric results reported in Table 1. In particular, the shape of the nonparametric fitted regression function suggests a negative long-run relationship between labor productivity and unemployment. By contrast, a positive relationship is evident at lower wavelet scales, especially at the frequency band corresponding to periods of 2–8 years. To summarize, we find that unemployment is positively associated with productivity in the short and medium term, but negatively in the long term.

4 Interpretation

Notwithstanding the question of how productivity growth affects unemployment has received much attention in the recent literature, the theoretical approach is far from being uniform (e.g. in search and matching theories of the labor market in Pissarides (1990), Aghion and Howitt (1994), Mortensen and Pissarides (1998)). Theoretical predictions of the impact of productivity growth on unemployment depend on the quantitative importance of the "capitalization" and "creative destruction" effects

[25]The smoothing parameter controls the flexibility of the loess regression function: large values of produce the smoothest functions that wiggle the least in response to fluctuations in the data, the smaller the smoothing parameter is, the closer the regression function will conform to the data

[26]We use different smoothing parameters, but our main findings do not show excess sensitivity to the choice of the span in the loess function within what appear to be reasonable ranges of smoothness (i.e. between 0.4 and 0.8).

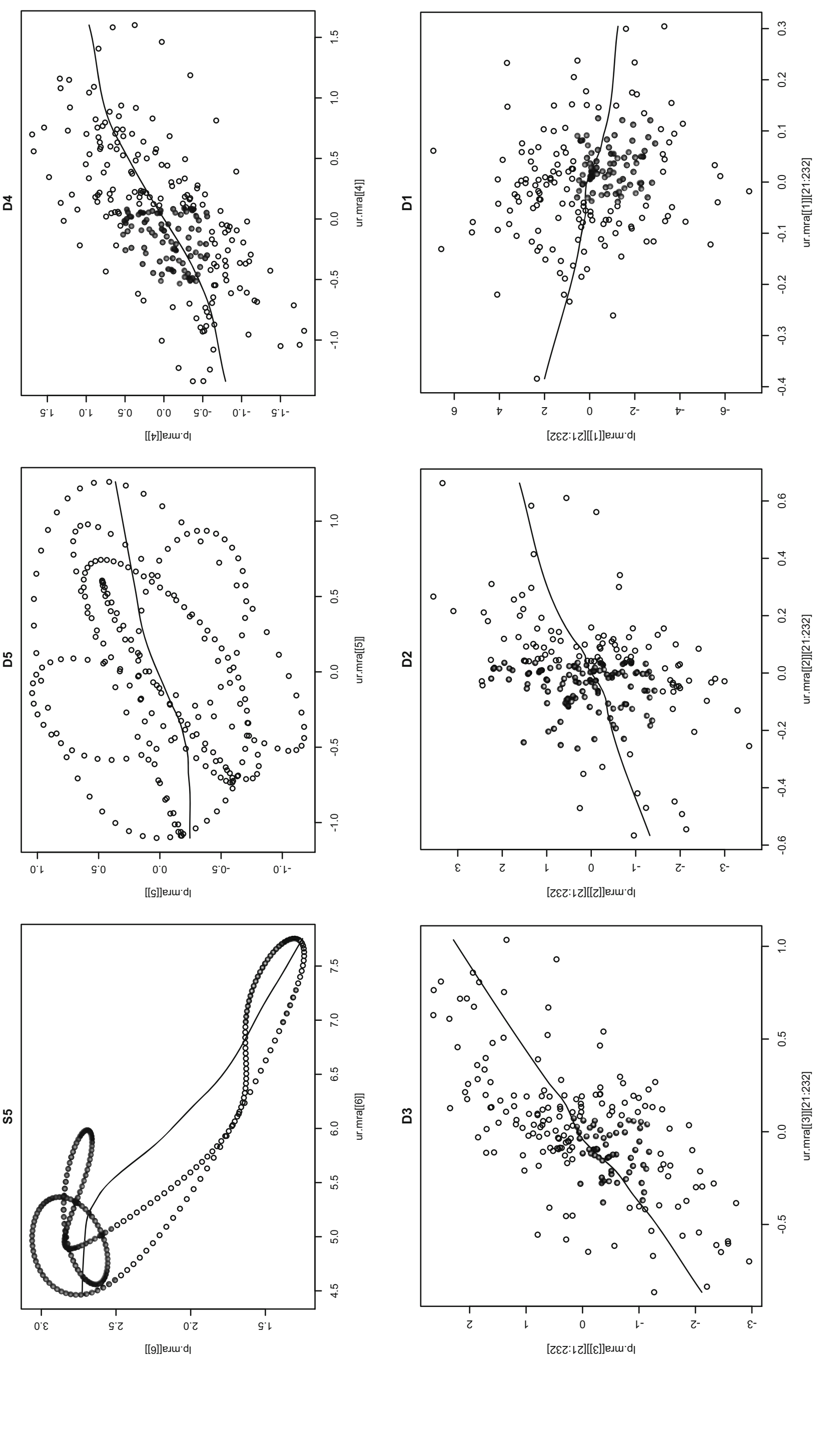

Fig. 6 Scatter plot and loess fit at different scale levels

which, in turn, reflect the extent to which the two forms of technical change discussed in this literature, that is embodied and disembodied technology,[27] are embodied in production factors.

In the model with disembodied technological progress it is suggested that higher productivity growth reduces the long run unemployment rate through the so called "capitalization effect" (Pissarides 1990, 2000). By contrast, in the model with embodied technological progress, faster technical change increases long run unemployment through a "creative destruction effect" (Aghion and Howitt 1994, 1998; Postel-Vinay 2002). Inconsistency between these findings is resolved in Mortensen and Pissarides (1998) by building up a matching model with embodied technical progress in which both types of effects, that is "capitalization" and "creative destruction", can be obtained depending on "whether new technology can be introduced into ongoing jobs, or it needs to be embodied in new job creation" (Pissarides and Vallanti 2007). As a result, whether the overall impact of productivity growth on unemployment is positive or negative is assumed to depend upon the relative strength of the "capitalization" and "creative destruction" effects.

What effect is likely to prevail is a question that can be addressed by considering the different time horizon of "capitalization" and "creative destruction" effects, and their associated effects on job creation and jobs destruction, respectively. The time horizon of job creation can be radically different from that of job destruction. Indeed, firm's time horizon when creating jobs can be very long, and definitely much longer than firm's horizon when destructing jobs, since job creation involves computing the expected present discounted value of future profits from new jobs. As a consequence, we can expect that the relevance of the capitalization effect as to the creative destruction effect (and the net effect of productivity growth on employment) could be different across different time horizons since the latter effect induces more job destruction and less job creation than the first one. In particular, we should observe a positive relationship between productivity growth and unemployment if the creative destruction effect dominates over the capitalization effect, and conversely a negative relationship if the capitalization effect dominates.

The empirical evidence provided using wavelet analysis hints that the "creative destruction" effect dominates over the "capitalization" effect at short- to medium term scales, whereas the "capitalization" effect dominates at the longest scale. In this way we can interpret the negative long-run connection between productivity growth and unemployment as consistent with models where technological progress is purely disembodied (see Pissarides and Vallanti 2007) or the positive "capitalization effect"

[27]Embodied technical change is embedded in (new) capital goods or jobs and can benefit only jobs that explicitly invest in new technology. By contrast, disembodied technical change is not tied to any factor of production and can benefit all existing jobs. According to the "capitalization" effect an increase in growth raises the capitalized value of those returns obtained from creating jobs, thereby reducing the equilibrium rate of unemployment by increasing the job-finding rate. The second effect is the creative destruction, according to which an increase in growth raises the equilibrium level of unemployment both directly, by raising the job-separation rate, and indirectly, by discouraging the creation of job vacancies.

of disembodied technological progress dominates the "creative destruction" effect of embodied technology.[28] On the other hand, the positive impact of productivity growth on unemployment at intermediate scales support the "creative destruction" hypothesis of several labour market models in which the "capitalization" effect is too weak to reverse a "creative destruction" effect.[29]

To summarize, we argue that co-movements of productivity and unemployment at short-term scales can be markedly different from those at the longest scale. In particular, our results indicate that this "opposite" relationship displayed by unemployment and productivity growth at different time frames can be determined by the relative strength of the "capitalization" and "creative destruction" effects. All in all, what emerges is a more complex picture of the relationship in which the two effects have different strengths at different time horizons and the aggregate effect is simply the interaction of the relative strength of the two effect at different time horizons.

Furthermore, these results have other relevant economic implications. First of all, as regards the Okun's (1962) law, the US employment seems to be decoupled from economic growth, the so-called "jobless growth". In the US there is a slowly recovering unemployment rate, though the annual growth rates of productivity are higher than in Europe. Due to high productivity growth rates, in the US one can observe some aspect of jobless growth. This might be a short run phenomenon. In the long term this could be turned into a negative relationship of productivity and unemployment.

Finally, as to the controversial hypothesis of the RBC models that employment is rising with positive productivity shocks, the critics (such as Basu et al. 2006) are presumably correct to state a nonsignificant relationship between technology shocks and employment, or even a negative relationship of those variables. So the RBC postulate of a positive relationship between productivity and employment seems to be incorrect in the short and medium run, but in the long run, when productivity growth makes the firms and the country more competitive, the increase in productivity may cause employment to rise.

5 Conclusion

The effect of productivity increases on unemployment is controversial. Economic theories have postulated strong comovements of productivity shocks and employment. Yet, in the 1990s, Europe was seen to suffer from higher growth rates of

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[28]These long run effects maybe also based on the sluggishness of real wage adjustments as suggested by models where wage setting depends on backward looking reservation wages (Blanchard and Katz 1999). Results compatible with this evidence are reported in Gallegati et al. (2011) where wages do not adjust fully to productivity changes in the long-run.

[29]Higher productivity growth is often accompanied by structural change wherein "old jobs" are replaced by "new ones" since technology could enhance the demands for new products.

productivity that did not show up in the labor market as higher employment. US is now viewed as suffering from jobless growth, so that the question is whether the low reaction of employment to increases in productivity is a short or long run phenomenon. The issue is therefore how does productivity affect unemployment at different time horizons. Such relationships, and, in particular, the medium and long-run relationships between productivity growth and unemployment are generally analyzed in the empirical literature looking at average aggregate data, generally decades, because from a time series perspectives the rate of growth of labor productivity is a very volatile series whose implications in terms of the movements of the other supply-side variables are difficult to interpret, particularly in the short-run and medium run.[30]

The key to the empirical results obtained in the past is to examine the empirical relationships on a "scale-by-scale" basis. This is because the result is an empirical issue and the outcome depends at each scale on the elasticity of response of demand to price, new products, and/or re-engineered products to the new technology. The results in the short and intermediate run indicate that a reduction of employment is plausible, especially if the elasticity of response of demand to price reductions is unsubstantial. But the opposite seems to be the case for the long run. However, even though the sign of the relationship between employment and productivity may well stay constant over long periods of time, one would expect there to be large differences in the relative magnitudes of the net response over time caused by different market and technology conditions.

In this paper, we use wavelets to analyze the productivity-unemployment relationship over different time frames and demonstrate the usefulness of wavelet analysis in disentangling the short, medium and long run effects of changes in productivity growth for unemployment. In a nutshell, we find a strong negative long run relationship between labor productivity and unemployment, but also a positive significant relationship at lower scales, especially at scales corresponding to business cycle frequency bands. In the medium run, new technology is likely to be labor reducing, and thus adding to unemployment,[31] as was visible in Europe during the 1990s. In the long run, however, new technology replacing labor (process innovation) increase productivity and makes firms and the economy more competitive and may reduce unemployment.[32] Finally, our results suggest some relevant implications concerning the interpretation of search-matching models of unemployment, Okun's law, the RBC hypothesis of a positive co-movement of productivity shocks and employment, and the US employment prospects.

When Thomas More (Utopia 1516) was asserting: sheep are eating men, he was, in the short run, right. Due to agricultural innovations, profits in the primary sector

[30]Indeed, the relationship between productivity and the unemployment rate may appear weaker when we reduce the time period used for aggregating data (see Steindel and Stiroh 2001).

[31]A statement like this goes back to David Ricardo who has pointed out that if machinery is substituted for labor unemployment is likely to increase.

[32]This point is made clear in a simple text book illustration by Blanchard (2005).

were rising, less labor force was employed in agriculture and more lands were devoted to pastureland. People had to "invent" new jobs, i.e. people were stimulated into creating new products that the new technology made possible.

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References

Aghion P, Howitt P (1994) Growth and unemployment. Rev Econ Stud 61:477–94
Aghion P, Howitt P (1998) Endogenous growth theory. MIT Press, Cambridge
Backus DK, Kehoe PJ (1992) International evidence on the historical evidence of business cycles. Am Econ Rev 82:864–888
Ball L, Moffitt R (2002) Productivity growth and the Phillips curve. In: Krueger AB, Solow R (ed) The roaring nineties: Can full employment be sustained? Russell Sage Foundation, New York, pp 61–90
Basu S, Fernald JG, Kimball MS (2006) Are technology improvement contractionary? Am Econ Rev 96:1418–1448
Blanchard OJ (2005) Macroeconomics, 4th edn. Prentice Hall, New Jersey
Blanchard OJ, Quah D (1989) The dynamic effects of aggregate demand and supply disturbances. Am Econ Rev 79:655–673
Blanchard OJ, Katz L (1999) Wage dynamics: reconciling theory and evidence. NBER Working Paper, No. 6924
Blanchard OJ, Solow R, Wilson BA (1995) Productivity and unemployment. MIT Press, unpublished
Chen P, Rezai A, Semmler W (2007) Productivity and Unemployment in the Short and Long Run. SCEPA Working Paper, 2007–8
Cleveland WS (1979) Robust Locally-Weighted Regression and Scatterplot Smoothing. J Am Stat Assoc 74:829–836
Cooley TF (1995) Frontiers of business cycle research. Princeton University Press, Princeton
Crowley PM, Mayes DG (2008) How fused is the euro area core? An evaluation of growth cycle co-movement and synchronization using wavelet analysis. J Bus Cycle Measur Anal 4:76–114
Daubechies I (1992) Ten lectures on wavelets. In: CBSM-NSF regional conference series in applied mathematics. SIAM, Philadelphia
Eliasson AC (2001) Detecting equilibrium correction with smoothly time-varying strength. Stud Nonlinear Dyn Econ 5:Article 2
Engle RF (1974) Band spectrum regression. Int Econ Rev 15:1–11
Engle RF (1978) Testing price equations for stability across spectral frequency bands. Econometrica 46:869–881
Fernandez VP (2005) The international CAPM and a wavelet-based decomposition of value at risk. Stud Nonlinear Dyn Econ 9(4):4
Fox J (2000a) Nonparametric simple regression: smoothing scatterplots. Sage, Thousands Oaks
Fox J (2000b) Multiple and Generalized Nonparametric Regression. Sage, Thousands Oaks CA.
Francis N, Ramey VA (2005) Is the technology-driven real business cycle hypothesis dead? Shocks and aggregate fluctuations revisited. J Monet Econ 52:1379–1399
Gali J (1999) Technology, employment, and the business cycle: Do technology shocks explain aggregate fluctuations? Am Econ Rev 89:249–271

Gali J, Rabanal P (2005) Technology shocks and aggregate fluctuations: How well does the RBC model fit postwar U.S. data? IMF Working Papers 04/234
Gallegati M (2008) Wavelet analysis of stock returns and aggregate economic activity. Comput Stat Data Anal 52:3061–3074
Gallegati M, Ramsey JB (2013) Structural change and phase variation: A re-examination of the q-model using wavelet exploratory analysis. Struct Change Econ Dyn 25:60–73
Gallegati M, Gallegati M, Ramsey JB, Semmler W (2011) The US wage Phillips curve across frequencies and over time. Oxf Bull Econ Stat 73:489–508
Gençay R, Selçuk F, Whitcher B (2001) An Introduction to Wavelets and Other Filtering Methods in Finance and Economics. San Diego Academic Press, San Diego
Gençay R, Selçuk F, Whitcher B (2005) Multiscale systematic risk. J Int Money Financ 24:55–70
Gençay R, Gradojevic N, Selçuk F, Whitcher B (2010) Asymmetry of information flow between volatilities across time scales. Quant Financ 10:895–915
Gordon RJ (1997) Is there a trade-off between unemployment and productivity growth? In Snower D, de la Dehesa G (ed) Unemployment policy: government options for the labor market. Cambridge University Press, Cambridge, pp 433–463
Gong G, Semmler W (2006) Stochastic dynamic macroeconomics: theory and empirical evidence. Oxford University Press, New York
Grinsted A, Moore JC, Jevrejeva S (2004) Application of the cross wavelet transform and wavelet coherence to geophysical time series. Nonlinear Processes Geophys 11:561–566
Hannan EJ (1963) Regression for time series with errors of measurement. Biometrika 50:293–302
Hudgins L, Friehe CA, Mayer ME (1993) Wavelet transforms and atmospheric turbulence. Phys Rev Lett 71:3279–3282
Keim MJ, Percival DB (2010) Assessing Characteristic Scales Using Wavelets. arXiv:1007.4169
Kim S, In FH (2005) The relationship between stock returns and inflation: new evidence from wavelet analysis. J Empir Financ 12:435–444
Landes DS (1969) The unbound Prometheus: technological change and industrial development in Western Europe from 1750 to the present. Cambridge University Press, London
Landmann O (2004) Employment, productivity and output growth. In: World Employment Report 2004 International Labour Organization, Geneva
Liu Y, Liang XS, Weisberg RH (2007) Rectification of the bias in the wavelet power spectrum. J Atmos Oceanic Technol 24:2093–2102
Miyamoto H, Takahashi Y (2011) Productivity growth, on-the-job search, and unemployment. Economics & Management Series 2011–06, IUJ Research Institute
Mortensen DT, Pissarides C (1998) Technological progress, job creation and job destruction. Rev Econ Dyn 1:733–753
Muscatelli VA, Tirelli P (2001) Unemployment and growth: some empirical evidence from structural time series models. Appl Econ 33:1083–1088
OECD (2001) Measuring productivity OECD manual. OECD, Paris
Okun A (1962) Potential GNP: Its measurement and significance. In: Proceedings of the business and economic statistics section, American Statistical Association
Percival DB, Walden AT (2000) Wavelet methods for time series analysis. Cambridge University Press, Cambridge
Pissarides C (1990) Equilibrium unemployment theory. Blackwell, Oxford
Pissarides C (2000) Equilibrium unemployment theory, 2nd edn. MIT Press, Cambridge
Pissarides CA, Vallanti G (2007) The impact of TFP growth on steady-state unemployment. Int Econ Rev 48:607–640
Postel-Vinay F (2002) The dynamic of technological unemployment. Int Econ Rev 43:737–60
Ramsey JB (2002) Wavelets in economics and finance: Past and future. Stud Nonlinear Dyn Econ 6:1–29.
Ramsey JB (2010) Wavelets. In: Durlauf SN, Blume LE (ed) The new Palgrave dictionary of economics. Palgrave Macmillan, Basingstoke, pp 391–398
Ramsey JB, Zhang Z (1995) The analysis of foreign exchange data using waveform dictionaries. J Empir Financ 4:341–372

Ramsey JB, Zhang Z (1996) The application of waveform dictionaries to stock market index data. In: Kravtsov YA, Kadtke J (ed) Predictability of complex dynamical systems. Springer, New York, pp 189–208

Ramsey JB, Lampart C (1998a) The decomposition of economic relationship by time scale using wavelets: money and income. Macroecon Dyn Econ 2:49–71

Ramsey JB, Lampart C (1998b) The decomposition of economic relationship by time scale using wavelets: expenditure and income. Stud Nonlinear Dyn Econ 3:23–42

Ramsey JB, Uskinov D, Zaslavsky GM (1995) An analysis of U.S. stock price behavior using wavelets. Fractals 3:377–389

Ramsey JB, Gallegati M, Gallegati M, Semmler W (2010) Instrumental variables and wavelet decomposition. Econ Model 27:1498–1513

Schreiber S (2009) Explaining shifts in the unemployment rate with productivity slowdowns and accelerations: a co-breaking approach. Kiel Working Papers 1505, Kiel Institute for the World Economy

Silverman B (1999) Wavelets in statistics: beyond the standard assumptions. Phil Trans R Soc Lond A 357:2459–2473

Solow RM (2000) Towards a macroeconomics of the medium run. J Econ Perspect 14:151–158

Staiger D, Stock JH, Watson MW (2001) Prices, wages and the U.S. NAIRU in the 1990s. NBER Working Papers no. 8320

Steindel C, Stiroh KJ (2001) Productivity: What Is It, and Why Do We Care About It? Federal Reserve Bank of New York Working Paper

Stock JH, Watson MW (1999) Business cycle fluctuations in US macroeconomic time series. In: Taylor JB, Woodford M (ed) Handbook of macroeconomics. North-Holland, Amsterdam

Torrence C, Compo GP (1998) A practical guide to wavelet analysis. Bull Am Meteorol Soc 79:61–78

Tripier F (2006) Sticky prices, fair wages, and the co-movements of unemployment and labor productivity growth. J Econ Dyn Control 30:2749–2774

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