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A model-based measurement device in European fiscal policy-making: The ontology and epistemology of potential output

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A model-based measurement device in European fiscal policy-making: The ontology and epistemology of potential output

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Abstract

While the development of scientific theories and measurement concepts has always been strongly intertwined, model-based measurements, specified as parameters in a statistical model, have been receiving increasing attention over the last decades. In this paper, we analyze the ontological and epistemological characteristics of such a model-based measurement device in an economics context. Specifically, our analysis focuses on the European Commission's model for estimating 'potential output' and 'natural unemployment', which is employed to facilitate the coordination of fiscal policies across the European Union. We find that the model's estimates strongly reflect the ontological and epistemological preconceptions underlying its design. Thereby, we point to a series of decisive differences in the realms of engineering and economics when it comes to the actual implementation of measurement techniques as well as the application and interpretation of measurement outcomes.

Keywords: measurement theory, model-based measurement, economic models, economic policy, Kalman filter, European Union.

1 Introduction

Although science clearly goes beyond pure measurement, it is quite evident that the history of science is closely intertwined with the development of measurement systems and devices dedicated to assessing empirical objects as well as to mediating between theory and the properties of these objects (Bunge, 1967, 207). In particular, the evolution of the natural sciences has been closely associated with the development of ever more precise and varied devices of measurement, which provide a series of examples for the mutual enrichment of theory and observation. The clearest and most-thoroughly researched case is probably that of temperature, which was a prime example for an immeasurable "quality" in the works of Aristotle (2009, Part 10) and has successively been quantitatively "invented" in the course of centuries of research (Chang, 2004). While the invention and design of most measurement devices is guided by theoretical conjectures of very different degrees of sophistication, they are typically associated with some practical dimension in the form of an intended application. Generally speaking, measurement devices serve to map some properties of objects onto numerical scales. They can do so in different ways, e.g. by directly measuring properties (the length of a rod), by indirectly calculating some value based on given conceptual definitions (miles/hour), or by exploiting some theoretical mechanism (quicksilver in a thermometer) or statistical correlation (test for personality characteristics in

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psychology) to derive numerical data. Over the last few decades, these more classical routines have been complemented by model-based approaches to measuring, where the measured quantities are parameters in a theoretical or statistical model (e.g. Tal, 2015; Hoover, 2015; Tal, 2016). In this view, models serve as a mode for translating 'instrument indications' in the sense of raw data points into 'measurement outcomes', i.e. actual knowledge claims. Thereby, proponents of such a model-based perspective on measurement emphasize that "inferences from instrument indications to measurement outcomes are non-trivial and depend on a host of theoretical and statistical assumptions about the object being measured, the instrument, the environment and the calibration process" (Tal, 2015, 13).

Given this context, this paper is concerned with a specific and prominent variant of such a model-based measurement device, namely the in-house model of the European Commission (EC) for estimating 'potential output' (Havik *et al.*, 2014; Planas and Rossi, 2015). This model is employed on a pan-European level to facilitate the coordination of national fiscal policies in accordance with the EU's fiscal regulation framework. Thereby, it contributes to the development of economic policy as well as public discourse within and beyond Europe. As this model is guided by current economic theory, incorporates state-of-the-art technical concepts and is constructed for a specific – and essential – practical purpose in the field of European politics, it constitutes a prime case for assessing and understanding the role of model-based measurement in a social science context.

In this paper, we show that the core idea of the model under study is one of model-based measurement aiming for an empirical differentiation between 'structural' and 'cyclical' components in economic development to obtain a measure for the theoretically postulated concept of 'potential output'. As theory provides only implicit guidance, statistical technique – ordinarily used for aggregating and not for acquiring observations – eventually gains a prime role when obtaining quasi-observational data on the interrelated concepts of 'natural unemployment', 'potential output' and 'structural deficits'. Hence, this paper is dedicated to exploring the basic idea and actual implementation of the potential output model as well as the "host of theoretical and statistical assumptions" surrounding this implementation.

This study proceeds as follows: in section 2, we provide a short introduction to the inner workings and the political implementation of the potential output model to explain the necessary economic foundations and its context. In turn, section 3 inspects the model's implicit assumptions on the nature and ontology of business cycles and contextualizes basic, but contested, preconceptions on macroeconomic issues inherent in this measurement device. Section 4 takes a look at the heart of the EC's potential output model by discussing the role of Kalman Filter techniques in the provision of quasi-observational data on business cycles. In doing so, it employs a comparative approach by contrasting the use of the Kalman Filter in the potential output model with its intended and established applications in engineering to allow for a better assessment of the adequacy and suitability of this intellectual transfer into a macroeconomic model. Drawing on this assessment, section 5 turns to showing how the explanation of 'structural' factors within the potential output model fundamentally differs from the political recipes drawn from the very same model, thereby pointing to a severe gap between theoretical explanation and technological advice. Section 7 concludes the paper.

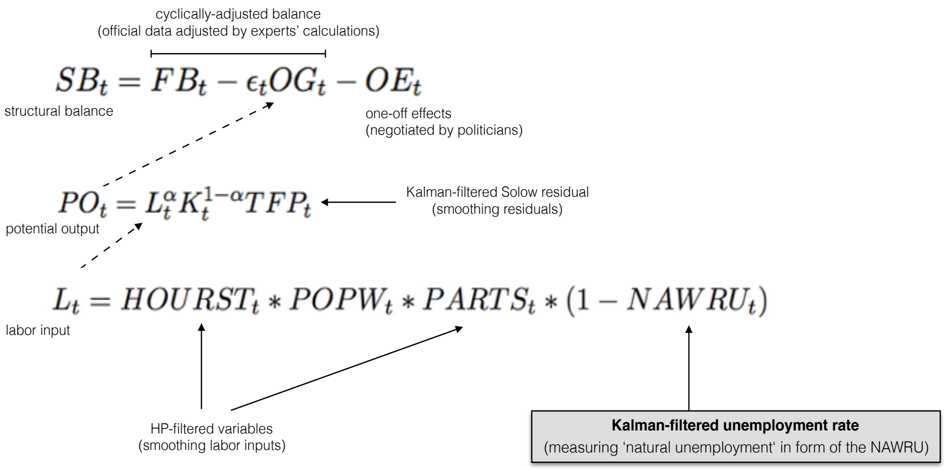
2 The potential output model: basic structure and political implementation in the EU

In assessing the sustainability of public finances in EU member countries, the EU's fiscal regulation framework relies heavily on measures of the so-called 'structural budget balance'. Since its reforms in 2005 and 2011, the Stability and Growth Pact (SGP) has made use of the structural balance as the most important control indicator for medium-term fiscal conduct. Furthermore, rules in the Fiscal Compact set deficit limits in terms of the structural balance (ECFIN, 2013).

The size of the structural balance directly depends on estimations derived from the EC's potential output model (e.g. Klär, 2013; Tereanu *et al.*, 2014; Heimberger and Kapeller, 2016), which is used as a scientific measurement device for computing the position of an economy in the business cycle. In this context, potential output is understood as the maximal level of output and employment at which inflation remains constant; hence, if an economy actually attained its potential output, it would exhibit a neutral position vis--vis the business cycle – neither overheated nor underutilized –, where 'neutrality' is defined with respect to inflation.

The structural balance translates the estimates obtained from the potential output model into the political sphere, as it is used to correct the headline fiscal balance for the effects of the business cycle on government revenues and spending to arrive at the so-called cyclically-adjusted budget balance. The economic reasoning for this adjustment is that cyclical fluctuations automatically have an effect on the fiscal balance as government revenues typically decline during a recession, while unemployment-related government spending increases. Hence, the fiscal balance deteriorates automatically during an economic downswing. Vice versa, the headline balance improves during an upswing, as revenues increase and unemployment-related spending falls. The cyclically-adjusted budget balance is supposed to exclude such automatic stabilization effects on the budget balance (e.g. Carnot and deCastro, 2015). In a second calculation step, the EC subtracts politically-negotiated budgetary one-off effects (e.g. costs related to bailing-out financial institutions) from the cyclically-adjusted balance.

Figure 1: The basic components of the potential output model

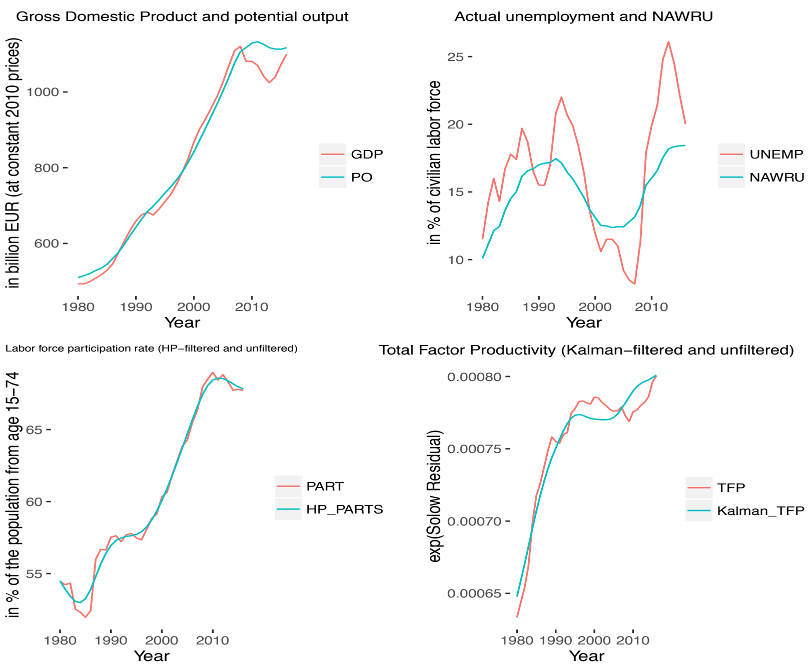


The first equation from Figure 1 summarizes the computations that need to be made to arrive at the structural balance. In this formula, SB_t denotes the structural balance, FB_t is the headline fiscal balance of individual EU countries, ϵ_t ('semi-elasticity parameter') captures how strongly the fiscal balance reacts to the output gap, and OG_t is the output gap, given by the difference between Gross Domestic Product (GDP, at constant prices) and potential output expressed in percent of potential output. Finally, OE_t are one-off and temporary effects on the fiscal balance (Mourre et al., 2014). The cyclically-adjusted budget balance results from subtracting the term ϵ_t OG_t from FB_t.

Hence, the potential output model comes into play to estimate the output gap OG_t (see Figure 1), i.e. to assess whether an economy is overheated (resulting in a positive output gap), underutilized (negative output gap) or running at potential output (output gap of zero). To calculate estimates for potential output according to the second formula in Figure 1, the EC employs a Cobb-Douglas production function, the reference model in the neoclassical growth literature (Cobb and Douglas, 1928; Solow, 1957; Barro and Sala-i Martin, 2003), to obtain estimates of the theoretically postulated concept of unobservable potential output PO_t (Havik *et al.*, 2014). The upper-left panel in Figure 2 illustrates model-based potential output measurement for the case of Spain. It can be seen that in the run-up to the financial crisis of 2008/2009, actual GDP is estimated to have stood above potential output, implying a positive output gap and an overheating Spanish economy. Since the start of the crisis, however, actual GDP has been measured to stand below the EC's potential output estimates, where the resulting negative output gap indicates underutilization of economic resources.

The model is best understood as a calculatory vehicle for processing empirical data, where the factor inputs labor (L_t) and capital (K_t) are transformed into output, and where total factor productivity TFP_t is a residual[1] interpreted as a proxy for technological progress.[2] Estimates for the capital stock K_t are taken from the EC's AMECO database. TFP_t is first calculated as average output per hours worked, then corrected for 'cyclical' deviations by a Kalman-Filter and then again put into the model as a measure for cyclically-adjusted technical progress. (See the lower-right panel in Figure 2 for a visualization of the EC's TFP estimates in the case of Spain.) The calculation of the production factor labor is more involved, as it tries to express the hypothetical number of total hours worked in the absence of any cyclical influence. As shown by the third equation in Figure 1, labor is operationalized as a filtered trend of total working hours ($HOURST_t$) offered by the active trend labor force ($POPW_t$*$PARTS_t$)[3] in a case where a 'natural rate' of unemployment ($NAWRU_t$) prevails.

Figure 2: The case of Spain



Data: European Commission (Spring 2016)

The EC defines 'natural unemployment' as the unobservable non-accelerating wage inflation

[1]Residual in this context means: the part of potential output growth that cannot be explained by labor and capital.

[2]In the interpretation of Havik *et al.* (2014), α and (1 - α) are understood as the constant output elasticities of labor and capital, respectively – which represents by how many percentage points output changes when the respective input is increased by one percentage point (Havik *et al.*, 2014, 10).

[3]Both the labor force participation rate ($PARTS_t$) and the trend of total working hours ($HOURST_t$) are detrended by employing a Hodrick-Prescott filter, which is a mechanical, univariate approach to separating the cyclical component of a time series from the trend (Hodrick and Prescott, 1997). See Kaiser and Maravall (2001) for a discussion on the basic limitations of the HP filter. See the lower-left panel of Figure 2 for HP-filtered values of PARTS in the case of Spain.

rate of unemployment (NAWRU) – a measure of 'structural unemployment'; i.e., unemployment caused by market rigidities rather than cyclical fluctuations (Friedman, 1968; Phelps, 1967).[4] In the rest of this paper, we follow this definition and analyze the ontology, epistemology and application of the NAWRU model on which measurements of 'natural unemployment' are based. There are three main reasons for this focus. First, the EC explicitly defines potential output as the level of output consistent with non-accelerating inflation, so that the NAWRU is central to the whole conceptual measurement framework (Havik *et al.*, 2014; European Commission, 2014). Second, the EC uses estimates of the NAWRU as indicators of 'structural unemployment', which serve as an empirical basis for policy suggestions on how to lower 'natural unemployment' and how to increase potential output (Orlandi, 2012; see section 5). Third, as can be seen from the upper-right panel in Figure 2 for the case of Spain, the EC's model-based NAWRU measurements exhibit a falling trend when the unemployment rate decreases, while they are estimated to increase as unemployment shoots up (which has been the case after the financial crisis of 2008/2009; see Klär (2013) and Heimberger and Kapeller (2016)). These first takeaways on the EC's official measurements for Spain raise the question on how the model's theoretical foundations interact with the estimation approach chosen by the EC to smooth the actual unemployment rate and arrive at the final model estimates.

In the EC's NAWRU model, unemployment is split into two components: 'cycle' and 'trend', where the trend component is equal to the NAWRU (Planas and Rossi, 2015). The model is cast into state space form, which is basically a model representation in matrix notation (e.g. Harvey, 1990; Grewal and Andrews, 2015). The state space variant of the EC's NAWRU model is shown in equations 1 and 2, whose single equations will be analyzed in sections 3 and 4. Crucially, finding an answer to the question "Which part of the unemployment rate is 'cyclical' and which part 'structural'?" is passed to the statistical de-trending of the respective time-series. In this context, the de-trending process is based on a Kalman-filter approach (Kalman, 1960; Durbin and Koopman, 2012). The Kalman-Filter builds on a recursive procedure, which updates its predictions whenever new empirical information on unemployment (and labor cost inflation) becomes available (see section 4).

$$\begin{bmatrix} u_t \\ \Delta rulc_t \end{bmatrix} = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 0 & \beta_1 & \beta_2 \end{bmatrix} \begin{bmatrix} N_t \\ \eta_t \\ G_t \\ G_{t-1} \end{bmatrix} + \begin{bmatrix} 0 \\ V_t^{rulc} \end{bmatrix} \tag{1}$$

$$\begin{bmatrix} N_{t+1} \\ \eta_{t+1} \\ G_{t+1} \\ G_t \end{bmatrix} = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & \phi_1 & \phi_2 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} N_t \\ \eta_t \\ G_t \\ G_{t-1} \end{bmatrix} + \begin{bmatrix} V_t^N \\ V_t^\eta \\ V_t^G \\ 0 \end{bmatrix} \tag{2}$$

While the specific matrix notation of the NAWRU model depicted in equations 1 and 2 is ready-made for the processing of the Kalman-filter recursions that are employed to de-trend the unemployment rate (Planas and Rossi, 2015), this state space form has the additional advantage of providing a concise explication of the most important theoretical and statistical assumptions inherent in the measurement of 'natural unemployment'.[5] In the subsequent chapter, we will

[4]Stockhammer (2008) shows that the Friedman-type (Monetarist) interpretation for the existence of an unemployment rate at which inflation does not accelerate (NAIRU) can be substituted by Post-Keynesian or Marxist arguments. The formal models that result from varying Monetarist, Post-Keynesian and Marxian rationales for the NAIRU differ only slightly.

[5]The state space form in equations 1 and 2 depicts what the Commission calls the 'New Keynesian' NAIRU model, which – as of November 2015 – has been in use for all EU countries but Austria, Belgium, Germany,

detail our arguments by pointing to essential parts of the NAWRU model setup and explore their meaning and purpose in greater detail. In addition, section 4 will then turn to the epistemological foundations of using a Kalman filter approach to de-trending empirical data inputs into a model by comparing the filter technique's usual field of application (engineering) with the usage in case of the EC's NAWRU model.

3 The ontology of potential output: Cycle vs. trend

As already emphasized, a closer inspection of equations 1 and 2 allows for assessing the underlying assumptions of the potential output model. In a first step, we want to illuminate the model's ontology by discussing the representation of its core variable – unemployment – and the conceptual commitments underlying its decomposition. The three relevant equations, which can be obtained by applying the rules of matrix multiplication to equations 1 and 2, are reproduced below.

$$u_t = N_t + G_t \tag{3}$$

$$\Delta N_t = \eta_{t-2} + V_t^{\eta} + V_t^{N} = \eta_{t-1} + V_t^{N} \tag{4}$$

$$G_t = \phi_1 G_{t-1} + \phi_2 G_{t-2} + V_t^{G} \tag{5}$$

Equation 3 summarizes the core assumption on unemployment (u_t), namely that the latter is composed out of a 'natural' (N_t) or 'structural' part as well as some kind of cyclical 'gap' (G_t). Equation 4 and equation 5, in turn, tell us how these two components are conceptualized in the model. Specifically, natural unemployment (N_t) is understood as the main force of economic development as it is mainly characterized by a trend-component (η_t), which represents the basic trajectory of a given economy in terms of employment (both, N_t and η_t, are also subject to white noise terms, V_t^N and V_t^{η}). Cyclical unemployment, on the other hand, is explicitly understood as a conceptual 'gap' between theoretically predicted and actually observed values. This interpretation is especially evident as the first equation actually equates empirically given data (u_t) with natural unemployment and the cyclical gap, without the addition of further error terms. Keeping in mind that in economic practice "residuals could be a composite of shocks (omitted causes + fundamental indeterminism) and (measurement + specification) error" (Hoover, 2015, 3521), the cyclical 'gap' G_t could also be interpreted as a more inclusive catch-all variable covering all types of theoretical and statistical errors.

However, even in this more flexible view, cyclical unemployment is treated in analogy to statistical noise, as a possibly complex, but eventually analytically unimportant collection of details, which is technically rationalized in equation 5 as a second-order autoregressive process. The basic setup of core variables, therefore, incorporates an ontological commitment: namely that 'natural' or 'structural' unemployment is the real driving force in the economy and, hence, theoretically more autonomous than cyclical unemployment – pointing to an ontological priority of the trend over the cycle. Although such reasoning is well in line with the standard readings of the 'natural rate of unemployment' or the NAWRU in the economic literature (e.g. Friedman, 1968; Ball and Mankiw, 2002), it is notable that the exact specification of natural unemployment in the model under study is only based on a heuristic. It is roughly inspired by the underlying theory, but does nowhere make explicit reference to the actual theoretical determinants of unemployment – the structural features or 'rigidity' of labor markets (e.g. European Commission, 2014) – but rather posits a parameter to statistically measure the outcome of the

Italy, Luxembourg, Malta, Netherlands. For these 7 countries, the Commission is still using the 'Traditional Keynesian' NAIRU model (European Commission, 2014, 22).

postulated mechanism.

Eventually, this arrangement asserts that the business cycle is not a systematic economic phenomenon, but rather a form of statistical noise surrounding the 'true development path' of the economy, which is to be captured by the trend-component as modeled according equation 4. This separation follows the standard economic "ontology that partitions economic processes into a deterministic structure and indeterministic shocks" (Hoover, 2015, 3532). Heuristically, it is given by the conjoined ideas of (a) a basic and undiminishing growth rate driven by technological progress (rationalized via the Kalman-filtered TFP_t), (b) a 'natural level' of (un)employment largely determined by labor market regulations (N_t and its trend component η_t) and (c) periodical fluctuations of employment (the cyclical gap G_t), which are best understood as statistical noise of a specific type. Thereby, the parts (a) and (b) form the "deterministic structure", while (c) collects the "indeterministic shocks" mentioned.

While the focus on the estimation of the NAWRU as a measure of natural unemployment is useful for analyzing the ontological presumptions regarding the basic features of economic development, it has also been made clear that the estimates for potential output are best understood as 'composite measures'. They are based on a series of statistical treatments applied to the relevant raw data to finally obtain a measure for potential output. In the model under study, a Cobb-Douglas production function (second equation in Figure 1) is used to tie together these different composites, which either stem directly from raw data or come in the form of Hodrick-Prescott- or Kalman-filtered time-series.

Following the usual practices (see Bunge (1996, 363-364) and Sugden (2000, 13)), this specific production function is mostly chosen for reasons of computational convenience (Havik *et al.*, 2014, 10). Nonetheless, it does come with a set of ontological presumptions: it not only defines labor, capital and technology as relevant inputs for determining aggregate output, but also assumes that the former two factors are mutually dependent, symmetric factors of production. This arrangement stands in contrast to the more classical position of viewing labor as autonomous and capital as solely labor-augmenting (Clark, 1899). Finally, the empirical application of the Cobb-Douglas production function requires an estimate for the parameter α. It can be shown that estimates for α and (1-α) do not represent the constant output elasticities of labor and capital, respectively. Instead, they typically measure the wage and profit share, i.e. the share of national income received by the corresponding factors of production (e.g. Felipe and McCombie, 2014). By using these estimates for computing the contribution of the production factors to final output, one effectively posits an environment of fully competitive markets to assure equivalence between cost and contribution of production factors. This aspect complements the ontology of the model, which is based on the idea that constant technological growth embedded in highly competitive markets implies steady economic progress, which is sometimes constrained by regulation (natural unemployment) and random deviations (the cyclical gap).

As a further remark, our discussion of the ontology of the potential output model has also made clear that the model does not build on a methodological individualism as typically espoused in economics textbooks. This observation is true for many macroeconomic models and is sometimes rationalized by viewing macroeconomics as supervening on microeconomics (e.g. Hoover, 2001, Chapter 5), while in other contexts it is criticized as not following the state-of-the-art of economic thought, i.e. 'micro-foundations' of macroeconomic relationships (Lucas, 1976). As a response, many aggregate models posit an underlying representative household (a single household representing all households in an economy) to provide their macroeconomic account with an individualist appealing (Kirman, 1992). This feature also holds true for the model under study: while the official description does not explicitly introduce individual behavior, it is argued that the Phillips-curve relationship employed for modeling the NAWRU can, in principle, be derived from a representative household setup (Havik *et al.*, 2014, 16).

While the EC's approach to measuring NAWRU and potential output builds on the notions a) that trend and cycle are distinct phenomena, b) that both components can be neatly separated by means of statistical technique, and c) that the 'trend' captures the essence of an economy's equilibrium development path, the economic literature includes challenges to all three aspects. Regarding notion a), Richard Goodwin has prominently argued that cycle and trend are indissolubly fused (Goodwin, 1967, 1982), i.e. they cannot be regarded as separate phenomena, because the factors bringing them about are not independent from each other (Harcourt, 2015). Regarding notion b), the relevant statistical filtering literature raises doubts about whether trend and cycle can be accurately separated by means of statistical filtering. In the recursive Kalman-filtering process for estimating the NAWRU (see section 4), the model's predictions are updated whenever a new data point is made available. Hence, the most recent observations play a crucial role in determining the trend. In fact, the last data points of the time series that are to be filtered typically have a disproportionate impact on measures of the trend. This phenomenon – called the 'end-point bias' (e.g. Kaiser and Maravall, 2001; Ekinci *et al.*, 2013) – implies marked revisions in de-trended estimates when new data is brought into the model-based measurement process, especially when the new data points derive from times of macroeconomic distress (Havik *et al.*, 2014; Palumbo, 2015).[6] Finally, regarding notion c), the theoretical work of prominent economists suggests that the business cycle is not only to be studied as a systematic economic phenomenon instead of as mere statistical noise. Rather, a profound theoretical understanding of a cycle is of the essence for determining the evolution of output and employment. In this view, relevant 'trends' are always of a genuine cyclical character and driven by the boom-bust-promoting behavior of actors in financial markets (Minsky, 1982) or by the innovation-based 'creative destruction' within existing economic structures (Schumpeter, 1942).

According to the EC's ontology of potential output, the trend is governed by the economy's drive towards macroeconomic equilibrium, as the unemployment gap represents a mere temporary deviation from this equilibrium. In the model framework, the assumption that the unemployment gap follows an autoregressive process ensures that, eventually, the unemployment rate will always converge to the natural rate of unemployment. Thereby, "specifying the unemployment gap as a process that reverts to a zero mean [...] seems to capture Friedman's (1968) view that the unemployment rate cannot be kept away indefinitely from the natural rate [of unemployment]" (Laubach, 2001, 221). From a critical macroeconomic perspective, however, the notion of a leveling-out of the noise around the steady trend path is rejected on the grounds that neither does the trend have a life separate from the cycle (e.g. Goodwin, 1982; Minsky, 1982; Schumpeter, 1942) nor do highly competitive, unregulated markets automatically make the economy convergence to 'equilibrium unemployment', i.e. to the NAWRU (e.g. Galbraith, 1997; Sawyer, 2001). Instead, one has to account for short- and medium-term fluctuations, which may create endogenous instability – a view that is implicitly denied by the EC's ontology of potential output, which builds on the notion of a stable, long-term growth trend, surrounded by temporary cyclical fluctuations, where the gap is modeled as noise and always reverts to a zero mean, thereby ensuring convergence towards 'equilibrium'.

A final crucial ontological aspect is that the EC models potential output as being determined by the supply side of an economy (Havik *et al.*, 2014). While demand may affect the level of economic activity both in the short-run and in the long-run so that the course of demand impacts on the path of supply (Sawyer, 2011), the EC models potential output in a way so that changes in investment and consumption (i.e., on the demand side) are deemed non-essential to understanding the trend evolution of output and employment. Hence, the possibility that inadequate aggregate demand might cause persistent underutilization of economic resources in the aftermath of a severe crisis such as the Great Depression (Keynes, 1936) or the financial crisis of 2008/2009 (e.g. Krugman, 2012) is simply not part of the EC's ontological framework.

[6]The end-point problem results in a pro-cyclical measurement bias: NAWRU estimates tend to be revised downwards during an economic upswing and to be revised upwards in a downswing (Klär, 2013; Heimberger and Kapeller, 2016).

4 The epistemology of potential output: The role of the Kalman Filter in engineering and macroeconomics

Until this point, it has become clear that the NAWRU – as a specific, model-based measurement of 'natural unemployment' – serves as a central pillar of the EC's potential output model. Thereby, the underlying separation of actual unemployment into a trend-part (the NAWRU) and a purely cyclical part (the gap) is based on a statistical procedure – a Kalman-Filter –, but is nonetheless given a theoretical embedding as NAWRU estimates are interpreted as indicators for 'natural' or 'structural unemployment' (Orlandi, 2012; European Commission, 2014). Hence, the underlying idea is to measure a theoretically postulated, but practically non-observable variable – 'natural unemployment' as determined by structural labor market characteristics – by means of a statistical filtering technique. Taking this basic setup into account, it becomes obvious that the epistemological adequacy of the EC's model strongly depends on the accuracy and suitability of the Kalman-Filter as a measurement device for 'natural unemployment'. Hence, this section provides a short overview on the origins, usage and practical properties of Kalman-Filtering. In this context, we pose the question whether the underlying conceptual transfer from control theory to macroeconomics is convincing and epistemologically adequate.

The Kalman-Filter is a recursive statistical technique originally developed for purposes in engineering (Kalman, 1960), with particular importance for fields like navigation, (automated) guidance and spacecraft engineering. It has become "a standard approach in signal processing and control theory" (Eichstädt *et al.*, 2016, 2), aiming for the fusion of different streams of signals or data to arrive at a single, more precise metric for measuring the position or properties of some object. Against this background, it comes as no surprise that the discipline of data-fusion in general and the Kalman Filter in particular "owes much to people working in defence, particularly in target tracking and identification" (Girao *et al.*, 2009, 220). The basic purpose of using the Kalman-Filter in its typical engineering contexts can be summarized as the refinement of noisy empirical measurements (delivered, e.g., by optical sensors or a GPS-signal) and slightly inexact theoretical predictions to arrive at more precise and exact estimates of the true values of interest. To provide such a refinement, the Kalman Filter makes use of a state-space model describing the dynamics of a given system based on known control inputs (e.g. driving speed), established law-like relationships (e.g. Newton's laws of motion) and empirical observations taken from some inaccurate measurement device (e.g. a car's GPS-tracker). Kalman filters can be found in satellite navigation devices, in smart phones, computer games etc. (e.g. Grewal and Andrews, 2010; Girao *et al.*, 2009). The filter always builds on a recursive algorithm to incorporate new data points and provides real-time updates of estimates about a system's state as new data enters the recursive processing.

To the best of our knowledge, economics is the only discipline outside the natural and technical sciences, which has adopted the Kalman Filter, by integrating it into its technical portfolio as a technique for the de-trending of time-series (Harvey, 1990; Durbin and Koopman, 2012). Having said that, we may notice a first conceptual difference between the use of the Kalman Filter in its original context and its use in economics. In engineering, the Kalman Filter is mainly understood as a rather practical tool employed to increase the precision and reliability of technical applications designed on the basis of already well-corroborated theories by aggregating different measures. In economics, on the other hand, the very same technique is used as a genuine measurement device to make sense of existing theories by providing estimates for a hitherto unobservable variable: 'natural' or 'structural' unemployment.

In what follows, we further analyze the tacit assumptions and implications of this conceptual framework. In doing so, we start by providing a short explanation of the Kalman Filter's basics, continue with illustrating the filter's workings with an example from classical mechanics, and then exlore the Kalman Filter model as advanced by the EC to provide a more accurate comparison of the use of Kalman Filtering across the two different disciplinary contexts.

4.1 Basics of state space models and the Kalman Filter

In state space modeling, the development of the system that is to be modeled is determined by an observation equation and a state equation, where the latter describes the core system dynamics, while the former maps these dynamics onto the level of measurements. A system composed of these two equations already "exhibits the basic characteristic structure of state space models in which there is a series of unobserved values α_1, ..., α_m which represents the development over time of the system under study, together with a set of observations y_1, ..., y_n which are related to the α_t's by the state space model" (Durbin and Koopman, 2012, 12). Hence, the state equation, explicated below in a general form, is the conceptual heart of a state space model as it contains the model's fundamental theoretical and/or statistical assumptions.

$$\begin{aligned} \alpha_{t+1} = T_t\alpha_t + B_t u_t + R_t\eta_t \\ \eta_t \sim \ (0, Q_t) \\ t = 1, ..., n \end{aligned} \tag{6}$$

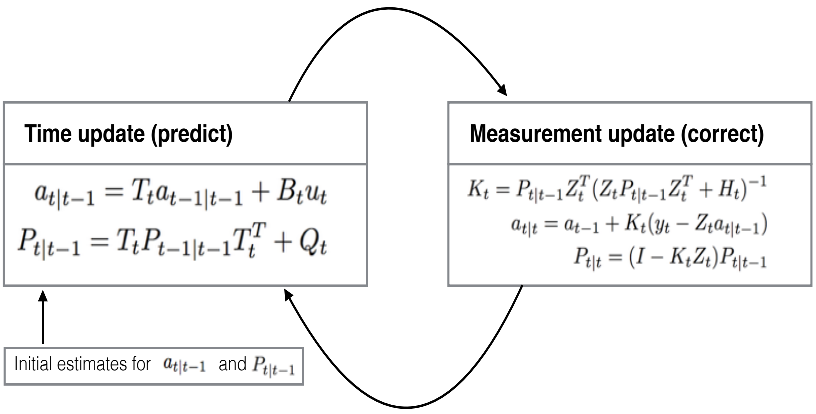
Here, α_t is an unobserved state vector, which contains "unobserved values" for describing the "development" of a given system (e.g. the position of an object and its velocity in the case of GPS tracking; or the 'natural rate of unemployment' in the case of the EC's NAWRU model). The unobserved state in this model is affected by three components, where T_t is the 'transition matrix', which relates the state α_t at the previous time step (t-1) to the state at the current step (t), B_t is the 'control input matrix', which maps known exogenous control inputs u_t (like gravitational force in case of a falling object) on the state vector α_t, and R_t is a vector of white noise shocks with covariance matrix Q_t, called the 'process noise covariance matrix ' (see Durbin and Koopman (2012, 43)). Intuitively, the process noise captures the idea that in practical applications theoretical predictions are often slightly inexact as the underlying models do not incorporate all relevant variables, but mostly ignore those with minor influence (e.g. the impact of weather conditions on the exact trajectory of a car). As the elements of the state vector t are sometimes unobservable in the sense that they cannot be directly confronted with empirical data, the state equation is complemented by an observation equation, which relates the postulated system's dynamics (α_t) to some series of observations collected in the observation vector y_t.

$$\begin{aligned} y_t = Z_t\alpha_t + \epsilon_t \\ \epsilon_t \sim \ (0, H_t) \end{aligned} \tag{7}$$

Here, Z_t is a matrix, which relates the state t to the observation y_t , i.e. it maps the parameters of the state vector into the observation domain, while $\epsilon\ _t$ is a vector of shocks with covariance matrix H_t, called the 'measurement covariance matrix'. Basically, the measurement noise indicates that the empirical data brought into the filtering process is inaccurate and noisy. The process noise from the state equation and the measurement noise from the observation equation are both assumed to follow normal probability distributions (i.e. zero mean Gaussian white noise) and to be independent of each other. They can be interpreted as separate statements on the imprecision of theory (process noise) and measurement device (measurement noise).

The Kalman Filter is now a recursive application of a state space model as described here, which is designed "to update our knowledge of the system each time a new observation y_t is brought in" (Durbin and Koopman, 2012, 11). While the primary aim of the Kalman recursions is to find the "best estimate" of the state variable(s) of interest given noisy measurement feedback, its main routine is to assess the relative performance of the underlying theoretical or statistical model vis-a-vis past empirical measurements when predicting the next set of data points. This relative importance is expressed in a separate variable – the Kalman gain K_t – which assigns weights to model and past data, based on the amount of error they introduce into the actual predictions. Specifically, the Kalman-Filter assumes that the state α is distributed according to N(a, P), where the mean a represents the 'filtered estimator' of the state α and P its variance (Durbin and Koopman, 2012, 11). Intuitively, if the state variance of α (P) is high relative to the measurement error, the underlying model is less trustworthy than the measurements, and vice versa. More formally, this intuition is explicated in the Kalman filter recursions depicted in Figure 3.

Figure 3: Kalman filter recursions



Subscripts: $_{t|t}$, current time period; $_{t-1|t-1}$, previous time period, $_{t|t-1}$, intermediate step.

As shown by the time update equations in Figure 3, the filter recursions start with projecting estimates for the next time step of the dynamic process ("time update"). These predicted measurements are then compared to the data that is brought in ("measurement update"), and the resulting difference between predicted and observed measurement is adjusted in accordance with the Kalman Gain (K_t) to deliver improved a posteriori estimates of the system's state ($a_{t|t}$) and error covariance ($P_{t|t}$) as well as predictions for the next time step.

Generally, if the assumption that all noise is Gaussian were true, the Kalman filter would be an optimal estimator as it minimizes the mean square error of the parameters that are inferred from the noisy observations. The noise modeling is an essential part of the Kalman filter design, as the performance of the system – made up by state equation and measurement equation – is largely determined by setting the noise terms (e.g. Harvey, 1990). In many applications, especially in econometrics, error variances and parameter values in the transition matrix and observation matrix are typically unknown, but rather have to be estimated by numerical Maximum-Likelihood-procedures (Durbin and Koopman, 2012, 170–189). Other complications can arise in the context of calibrating and initializing the filter, i.e. finding appropriate initial values for a and P.

4.2 The example of a falling object

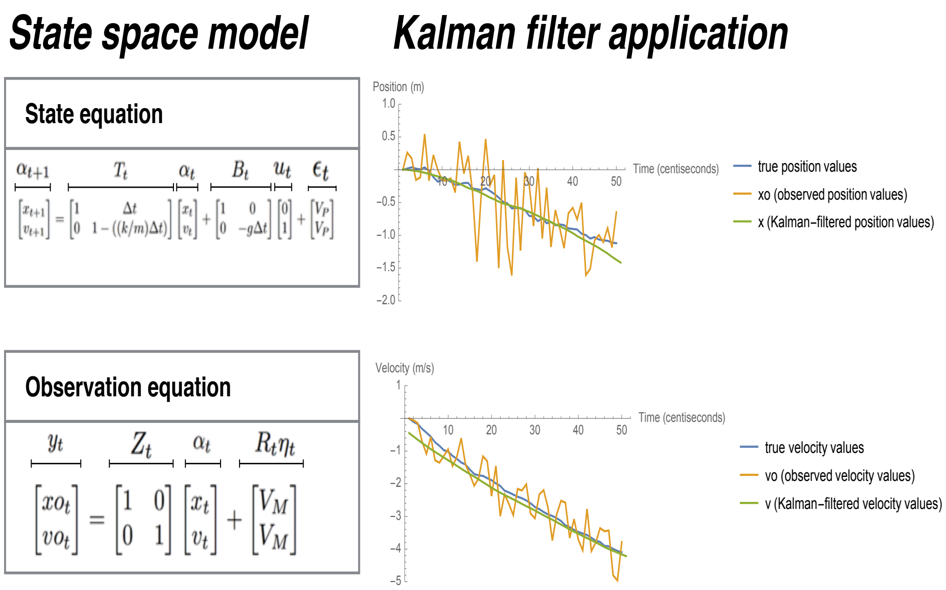
In this subsection, we provide a short introduction to the application of the Kalman filter in Newtonian mechanics to illustrate the typical properties of said Filter as used in engineering. In this example, we investigate the case of a falling object and we are interested in the object's position and velocity. These two variables make up the state vector, which cannot be observed directly but only by means of imprecise measurement. The employed theoretical model is guided by Newtonian physics and has the following basic form, describing the change in position (x) and speed (v) of our falling object, where the latter is influenced by gravity (g) as well as frictional force (k/m):

$$\begin{aligned} x_{t+1} &= x_t + v_t \Delta t \\ v_{t+1} &= v_t(1 - ((k/m)\Delta t) - g\Delta t \end{aligned} \tag{8}$$

The basic goal of the filtering process is to provide a more accurate description of the object's properties than theory or measurements in isolation could provide. Theoretical predictions may be imprecise or even erroneous due to unconsidered forces (drift), while measurements are noisy by definition in this example.

The left panel of Figure 4 collects the relevant elements of such an application: the state equation, which is given by the matrix form of our theoretical model, as well as the observation equation, which simply maps theoretically predicted values onto measured position (xo$_t$) and velocity (vo$_t$). The right panel of Figure 4 shows the results of such an application in a simulated setup and with known error variances – both measurement noise variance (V$_M$) and process noise variance (V$_P$) are assumed to be zero mean Gaussian white noise –, which illustrates how the Kalman Filter transforms noisy measurements into filtered measurements serving as estimates for the true position and speed of the falling object. As our simulation provides us with the 'true' values of interest, we can therefore show how the Kalman Filter succeeds in reducing error and noise as compared to empirical measurements.

Figure 4: Object falling in air



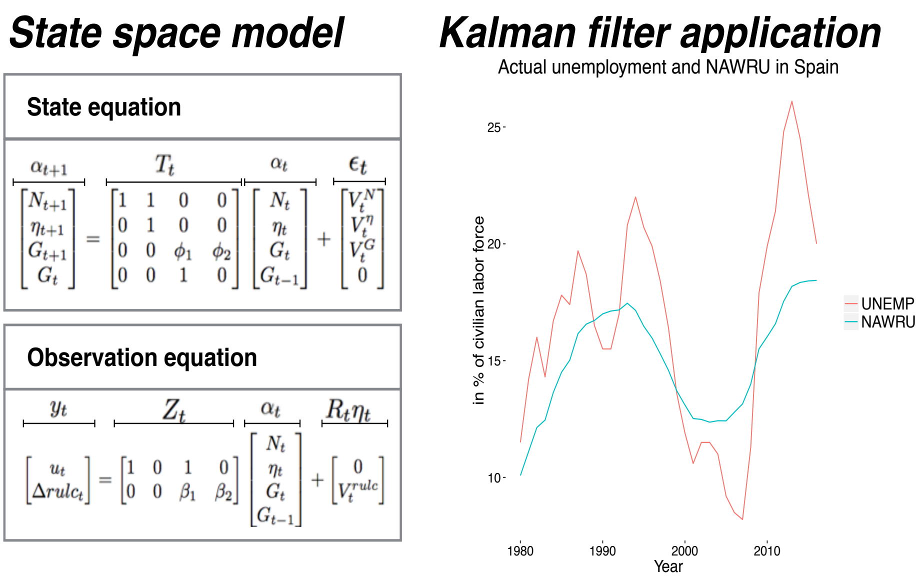
In the case of the falling object, the application of the Kalman filter rests on established, law-like relationships from Newtonian physics. The Kalman filter mediates between the theoretically predicted values for position and velocity and the noisy data obtained from the GPS measurement device in order to find the "best estimate" for the state variables. In doing so, the filtering process aids the application of already well-established theoretical and empirical tools – it does not resolve conceptual questions, but merely aligns the application of these tools. Additionally, the Kalman Filter tracks true values that are guaranteed to exist: a falling object can be said to always have some 'true' position and speed, even though the measurement of these values might be imprecise. Finally, from the perspective of measurement theory, the

Kalman Filter is a tool for aggregating knowledge from diverse sources into a more precise and smooth final output.

4.3 The European Commission's Kalman filter model for inventing NAWRU estimates

To better understand the peculiarities of the underlying conceptual transfer from engineering to macroeconomics, we now again turn to a closer inspection of the use of the Kalman Filter within the EC's NAWRU model. Figure 5 provides a representation of the basic characteristics of the EC's NAWRU model in analogy to Figure 4, containing the main equations of the state space model under study (left panel; see also equations 1 and 2) and an actual example of its application (right panel). In the case of the falling object, the state equation included a well-corroborated theoretical model based on classical mechanics; in contrast, the NAWRU model's state equation is based on a set of assumptions regarding the statistical properties of the cyclical component (G_t) and trend component (N_t) of the unemployment rate, largely devoid of theoretical arguments. Conversely, in the case of the falling object the observation equation was simply used to map theoretical results onto the level of empirical measurement, while theoretical arguments play a key role for the NAWRU model: the observation equation does not only include the crucial definition of unemployment as the sum of 'natural' and 'cyclical' unemployment, but, additionally, conceptualizes a relation between unemployment and (wage) inflation. It does so by means of introducing a so-called Phillips-curve, which "links cyclical unemployment (i.e. the unemployment gap) to labour cost developments [real unit labor costs, rulc], while non-cyclical unemployment is assumed not to be affected by labour cost developments. In this setting, non-cyclical unemployment estimates are commonly referred to as the non-accelerating wage rate of unemployment (NAWRU)" (European Commission, 2014, 22).

Figure 5: Kalman-filtering of the unemployment rate



Data: European Commission (Spring 2016)

Hence, the state equation conceptualizes the key theoretical components, natural and cyclical unemployment, as purely statistical relations based on the relative fit of different autoregressive models. This is indeed remarkable, as the theoretical construct of a 'natural rate of unemployment' posits that the structure of labor markets – such as employment protection legislation, unemployment benefits, the organization of wage negotiations etc. – determines labor market performance (Friedman, 1968; Orlandi, 2012), an argument that does not appear in the equations given in Figure 5 (see also the subsequent argument developed in section 5).

Conversely, the observation equation employs two very basic theoretical rationales of the NAWRU concept, namely that a natural rate of unemployment exists and that deviations from this natural rate will manifest in changes in inflation. This asymmetry in the basic setup of the Kalman Filter's design points to the interesting fact that the underlying statistical model is not formulated in terms that are actually observable (although it is a statistical model), so that the observation equations need to introduce additional arguments on the relation of these unobservables to the relevant empirical data. Although the EC is keen to emphasize "the preference for an economic, as opposed to a statistical, approach" (Havik *et al.*, 2014, 5), this setup also implies that one of the two main theoretical assumptions – the Phillips curve relation between the unemployment gap and labor cost inflation – is not meant to actually explain the variable of interest (unemployment); instead, it is introduced to aid in calibrating the Filter, i.e. providing additional information for calculating the Kalman gain. Overall, theoretical and empirical discussions on a trade-off between unemployment and inflation do not only feature prominently in widely used macroeconomic textbooks (e.g. Blanchard and Johnson, 2012; Mankiw, 2016); Phillips-curve type relations also provide the dominant framework for macroeconomic policy evaluation and formulation, especially in the field of monetary policy (e.g Blanchard, 2016). The non-accelerating inflation rate of unemployment (NAIRU) is a major concept in modern macroeconomics – with its core proposition that, for any economy and at any point in time, there exists some (unobserved) rate of unemployment at which inflation remains constant (e.g. Ball and Mankiw, 2002). From this perspective, the EC's emphasis that its NAWRU model is connected to 'natural rate' theory pays tribute to the dominant prevailing canon in macroeconomics. Nonetheless, the NAWRU as an approach to explaining the unemployment-inflation trade-off has repeatedly been criticized for its conceptual foundations (e.g Galbraith, 1997; Davidson, 1998; Sawyer, 2001) and its empirical track record, which is characterized by large uncertainties around estimated NAWRU values (e.g. Staiger *et al.*, 1997; Estrella and Mishkin, 2007) and by severe difficulties in matching 'natural rate' theory with empirical observations on the evolution of unemployment and inflation (e.g. Farmer, 2013). Similarly, the Phillips curve has been subject to intense academic debate about whether a stable unemployment-inflation relation actually exists over time (e.g. Lucas, 1976; Hall and Hart, 2012).

In practical Kalman filter applications, the engineers' goal is to get as close as possible to current true values of the unobservable variable(s) of interest, such as the position of a falling object (see Figure 4). Hence, the so-called end-point bias in statistical filtering – which has been discussed in section 3 and assigns a disproportionate impact to the last observations (e.g. Kaiser and Maravall, 2001; Ekinci *et al.*, 2013; Havik *et al.*, 2014) – can be considered as a feature in the realm of engineering. With regard to the EC's NAWRU model, however, the very same end-point bias is much more of a bug: as 'natural rate theory' assumes that the evolution of structural unemployment is determined by long-term structural properties related to the institutional characteristics of the labor markets (Friedman, 1968), the cyclical influences of the ups and downs of the business cycle should not have much impact on NAWRU estimates (Heimberger and Kapeller, 2016). However, as illustrated in the right-upper panel of Figure 2 for the case of Spain, the crisis that started in 2008/2009 has led to drastic upward movements in the NAWRU: estimates of 'natural unemployment' have followed actual unemployment, without any significant changes in labor market regulation. While these upward revisions are cyclically induced as they are translated into estimates via the end-point bias, they are hard to challenge in practice, as they gain an authoritative stance when it comes to judging a nation's economic development, as there is no benchmark for true values of 'natural unemployment'.

Introducing a Phillips curve-type relation into the state space model is instrumental for making the Kalman filter calibrate the model's parameters (e.g. Staiger *et al.*, 1997; Franz, 2005; Watson, 2014). As long as the Kalman filter produces estimates on the extent of 'structural unemployment' in rough accordance with the concept of the 'natural rate of unemployment' (e.g. Laubach, 2001), existing theories that postulate the existence of an unemployment rate at which inflation remains stable are rationalized. From this perspective, applying the Kalman filter in order to separate the trend from the cycle serves to resolve a core conceptual issue by providing quasi-observational data on a hitherto unobservable, but theoretically postulated variable. In our example from classical mechanics, the Kalman filter provided 'best estimates' for the 'true' values regarding a falling object's position and velocity, thereby operating as a tool for refining the noisy GPS measurements in mediation with law-like theoretical predictions based on Newtonian physics. In contrast, the NAWRU Kalman filter does not work as a practical tool for finding the best filtered estimates for variables that are guaranteed to exist; rather, it plays a prime role by generating novel and authoritative knowledge claims,[7] which serve to 'invent' natural unemployment in the sense of Chang (2004).

In sum, three related aspects are crucial for characterizing the epistemological differences between the two applications of the Kalman filter compared here. First, the theoretical arguments used by the EC are not based on well-corroborated theory, but rather come with a long history of doubt fostered by their speculative nature (natural unemployment) as well as empirical uncertainties (the Phillips curve). Hence, the Kalman Filter is not employed as a means for the practical refinement of the application of well-established theories, but used to provide an empirical representation of the rather speculative model of natural unemployment, which can be applied in the context of political decision-making. Second, it follows that the Kalman Filter in the EC's model does not necessarily measure something that actually exists. Even if there was no such thing as a 'natural rate of unemployment' – and this is what critical economists have been arguing all the way – the Kalman Filter model as depicted in Figure 5 would still provide point-estimates in form of specific numbers; and these model-based estimates are employed to coordinate fiscal policies in Europe (Heimberger and Kapeller, 2016). Third, we conclude that in the economics context studied in this paper, the Kalman Filter is not used in accordance with its basic intention from the field of engineering – to provide an aggregation of different estimates of uncertain or known quality in order to refine noisy empirical data – but rather to invent a novel way of seeing and assessing the world by generating estimates for a theoretically postulated, but hitherto 'unseen' and crucial variable.

5 The technological features of the EC's NAWRU model: the obvious gap between explanation and design

Econometric models often serve purposes in the design of economic and public policy aiming to inform decision-makers on the potential consequences of different choices (e.g Klein, 1947; Sims, 2004). Employed as technological rules (Bunge, 1967)), they are regularly interpreted as guides for navigating through the complexity characterizing the social realm. In this context, econometric models can be said to be useful as a navigation device for reality insofar as they employ or signify the (most) relevant causal relationships governing the phenomenon of interest (Hoover, 2015). This crucial point is recognized by economists at the European Commission working on the potential output model:

"[W]ith an economics based method, one gains the possibility of examining the underlying economic factors which are driving any observed changes in the potential output indicator and consequently the opportunity of establishing a meaningful link." (Havik *et al.*, 2014, 5)

As has been emphasized throughout this paper, the 'natural rate theory' underlying the

[7] NAWRU estimates are authoritative because they are readily available from the European Commissions AMECO database, so that they are widely used by economists as a proxy for structural unemployment.

EC's framework postulates a causal relationship running from 'rigid labor market institutions' to higher structural unemployment: labor market regulations such as employment protection legislation, minimum wages, centralized bargaining by labor unions etc. supposedly hinder the workings of free market forces and constrain the economy, which, in turn, cannot reach full employment. While this underlying 'natural rate theory' roughly inspires the greater part of the policy implications drawn from the model, these very same labor market institutions do nowhere actually enter the NAWRU model to explain natural unemployment in the first place. Moreover, as shown elsewhere (Heimberger *et al.*, 2016), indicators for labor market regulation are largely unsuitable for explaining differences across NAWRU estimates (see also sections 3 and 4). Instead of turning to actual labor market indicators – a series of such indicators would be readily available[8] – the EC's approach posits a parameter to statistically measure the outcome of the postulated mechanism (see section 4).

After obtaining point-estimates on the NAWRU by means of model-based measurement, these estimates are reinterpreted in the policy arena as a proxy for 'structural unemployment', employed by the European Commission as an authoritative guide for policy-making: by means of advocating 'structural reforms', member countries that face an increasing NAWRU are urged to lower structural unemployment by 'supply side reform' (Canton *et al.*, 2014), i.e. they are supposed to deregulate their labor markets by cutting unemployment benefits and minimum wages, dismantling employment protection law etc. Additionally, NAWRU estimates serve as a crucial variable for assessing the budgetary situation in EU member countries (Klär, 2013; Heimberger and Kapeller, 2016): as the NAWRU increases, a larger part of a country's budget deficit is automatically interpreted to be of a 'structural nature', i.e. not caused by a downswing in the business cycle. Hence, deficits are considered as more problematic for the long-run sustainability of public finances, so that the demand for fiscal consolidation imposed by European authorities increases (ECFIN (2013); see also section 2).

Hence, the imperative of inventing NAWRU estimates as authoritative knowledge on the extent of 'natural unemployment' constrains EU countries' policy leeway when it comes to finding democratically legitimate and socially sustainable configurations for fiscal policy and labor market regulation. In sum, it can be acknowledged that there is at least a conceptual transmission belt between the NAWRU model's estimates and the political suggestions derived from these estimates. However, assuming that the asserted relationship between labor market institutions and unemployment is indeed reliable, one has to ask why it does not enter the model in the very first place. Certainly, the gap between the model's design and its political explanation by European policymakers is unusual and striking.

6 Conclusions

In this paper, we have analyzed the conceptual foundations of a macroeconomic model carrying major implications for the political management of the European Union in general and the Eurozone in particular. We argue that the model under study can be best understood as a form of model-based measurement device. We have focused on how the model is employed to invent empirical representations of a traditional concept in economic thought, namely the idea of a 'natural rate of unemployment'. These representations are in large part derived from purely statistical consideration, but then re-applied to the material at hand on the basis of a very different conceptual apparatus: to achieve the aim of measuring an unobservable, theoretically postulated value (the 'natural rate of unemployment'), the model not only imposes a series of pivotal theoretical and ontological commitments, but also relies on a statistical modeling and filtering technique – the Kalman Filter –, which represents a core element of the measurement

[8]For example, the OECD operates a regularly updated database on many institutional labor market variables, sich as trade union density, active labor market policies, minimum wages, tax wedges, employment protection legislation etc.

approach. The usage of the Kalman Filter in the European Commission's potential output model differs remarkably from the filter's traditional applications in engineering; and this raises further research questions, not only regarding the validity of the obtained estimates, but also with respect to the more general problem of how to sensibly and accurately import and adapt formal or statistical techniques developed in the natural sciences to social and economic issues.

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