Doing Lifeworld Economics: an Example from Slovenia

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Abstract: The discipline of economics is undergoing a critical re-evaluation of its methods. The mainstream has tried to become a 'hard science' by attempting to adopt the mathematical formalism and quantitative methods of physics. However there are two stages in comparing models to what happens in the world: first the production of data from real world phenomena, then the comparison of that data to models. Just as experimental particle physicists pay close attention to the physics of particle detection, economists as social scientists must pay attention to the social science of the production of data from the social world. Lifeworld economics thus places emphasis on the first stage – producing data that gives access to people's lifeworlds. This paper justifies the use of the Biographic-Narrative-Interpretive Method in studying the economic development of Slovenia. The method uses the uninterrupted narratives of key informants, comparing the telling of their life stories to the actual courses of their lives. This approach is being used in the ongoing research project *Habitus of the Slovene Entrepreneur*, where we have interviewed several of the key managers in the development of the Slovene industrial system during socialism. In terms of Margaret Archer's realist social theory, we are accessing their evolving 'internal conversations' as they navigated the courses of their own biographies, tied to the management of their companies, leading to industrial development under the very complex and opaque Yugoslav socio-economic system. The reason that the Slovene case is so interesting is that Slovenia developed fairly rapidly under socialism and took a very gradualist approach to transition upon independence. It is therefore instructive to see how that system was made to work, and is largely still functioning, under a very peculiar 'heterodox' economic system. We are now in the process of analysing the narratives of the managers in our attempt to put economic pluralism into action.

1. Introduction

This paper provides the theoretical underpinning of the project *Habitus of the Slovene Entrepreneur*, which is an ongoing research project on *lifeworld economics*. Note that while I have recently (Turk 2007) used the term *interpretive* economics to describe the method used in the *Habitus* research project, in this paper I have switched to using the term *lifeworld* economics to refer to the subject matter to which the proposed method of interpretive economics is well tuned. This is because I take the subject matter as prior to the method used for its study. The term lifeworld economics is thus used to make it clear that the subject matter of the research is not some abstract economy providing generic data from which we can fathom general economic laws, but is rather a historically situated economic reality that was *lived* in one particular socio-historical case.

This paper thus provides an underpinning for the switch from a mathematically based approach to economics to an interpretive method better suited to the subject matter of lifeworld economics. The interpretive method used is only summarized, since it is available elsewhere (Turk 2007). So this is mostly a *why* paper with a brief review of *how* and some hints at outcomes.

The reason I will put forth for *why* we should favour interpretive methods to mathematical ones is due to the impossibility of the treatment of systematic uncertainty as it is done in the physical sciences, which precludes a similar usefulness of abstract mathematical models in the social sciences as compared to physics. In anticipation of a more detailed discussion below, I just note here that measurement uncertainties in experimental physics are divided into two components: statistical uncertainty, which is associated with precision; and systematic uncertainty, which is associated with accuracy. Both are quoted together (not combined) for any measurement of a physical quantity. Estimation of systematic uncertainty is crucial for an experiment, since it sets a limit on the total uncertainty that cannot be improved by increased statistical precision.

The paper fits within the growing literature questioning the practice of 'orthodox' or 'mainstream' economics, where economics is defined as much by its methods as by the object

of its study. Lawson, for instance, recounts (Lawson 2003, 3) "four theses on the state of modern economics":

- Academic economics is currently dominated to a very significant degree by a mainstream tradition or orthodoxy, the essence of which is an insistence on methods of mathematical-deductivist modelling.
- This mainstream project is not in too healthy a condition.
- A major reason why the mainstream project performs so poorly is that mathematical-deductivist methods are being applied in conditions for which they are not appropriate.
- Despite ambitions to the contrary, the modern mainstream project mostly serves to constrain economics from realising its (nevertheless real) potential to be not only explanatorily powerful, but scientific in the sense of natural science.

There are numerous good critiques of the use of mathematics in economics (e.g. Lawson 1997 and 2003; Fullbrook 2004). One of the major issues in this literature is that of methodological monism/dualism. Critics of the mainstream project argue for pluralism in economics, whereas proponents of the mainstream project, such as Mark Blaug argue 'the case for methodological monism' (Blaug 1980: 46-52). This paper argues that because of the non-treatment of systematic uncertainty, there is already *de facto* methodological dualism between economics and experimental physics, so that the mainstream argument for monism does not actually reflect the current state of economics. But furthermore, I argue that because of the nature of the data available in economics, which precludes a similar treatment of systematic uncertainty, methodological monism between economics and experimental physics is not even tenable.

This paper in particular builds upon an argument by Gillies (2004), who asks: 'Can mathematics be used successfully in economics?' To which he answers (ibid.: 197): 'The application of mathematics to economics has proved largely unsuccessful because it is based on a misleading analogy between economics and physics.' Gillies suggests that (ibid.: 197): 'Economics would do much better to model itself on another very successful area, namely medicine, and, like much of medicine, to adopt a qualitative causal methodology.' Although I do not necessarily support using a borrowed model from medicine, his reasons for rejecting the physics analogy are sound and the purpose of this paper is to strengthen that argument. So to begin with, let us recall his argument:

> [T]here is a fundamental difference between physics and economics which could be put like this. The physical world appears on the surface to be qualitative, and yet underneath it obeys precise quantitative laws. That is why mathematics works in physics. Conversely economics appears to be mathematical on the

> surface, but underneath it is really qualitative. This is why attempts to create a successful mathematical economics have failed. (ibid.: 190)

He suggests that the reason that economic phenomena appear to be well suited to mathematical treatment is that the relevant quantities all come with numbers attached (ibid.: 191): 'Thus goods have prices, firms have a market value, and each item in a firm's accounts is given an exact monetary value.' Gillies' main contribution is his argument that

> …this appearance is misleading because the numbers attached to economic phenomena are what [he] propose[s] to call *operational numbers*. Whereas numbers in physics are estimates, which may be more or less accurate, of exact quantities which exist in reality, operational numbers do not correspond to any real quantities. They are a convenient, but sometimes misleading, way of summing up a complicated, qualitative situation. Moreover their values depend to a large extent on conventional decisions and procedures and are therefore arbitrary to a degree. Operational numbers are the numerical surface form of an underlying reality which is qualitative in character. (ibid.: 191; emphasis in the original)

Another treatment of economic quantities and their measurement is given in Reiss (2001). Reiss discusses the difference between 'natural' and 'ficticious' quantities in economics, where 'natural quantities are those whose behaviour is described by our causal laws and which can be measured in a non-ambiguous way' (Reiss 2001: 1-2). However this still differs from the (critical) realist stance that the underlying quantities in physics are unambiguously ontologically real (at least at the point at which they are measured, taking quantum complications into account) independently of epistemological considerations of whether or not our causal laws describe their behaviour or we have an unambiguous measurement procedure. Describing the quantities of economics as operational numbers is therefore arguably more appropriate.

Gillies (2004: 193-5) examines the use of operational numbers in the economics. He first gives as example the calculation of the goodwill value of a firm, and then discusses GDP as an 'excellent example of an operational number' (Gillies 2004: 195). Thus GDP is the end result of a calculation procedure and there is no connection between the computed GDP and a really existing quantity somehow out there. Since Gillies provides his own examples, what I do in this paper instead is to go into further depth in examining some of the standard practices from physics in order to explain why the techniques of physics are incompatible with the use of operational numbers.

We should first note that not all science is physics, nor are the methods used in experimental elementary particle physics the appropriate tools for all of the physical sciences. However my focus is on economics, which tends to use (see Gillies' analysis above) abstract physics as its model; therefore the counterexample of physics with emphasis on the use of data in

experimental physics is useful for comparison. Likewise not all social science is done like economics, which I criticise in order to help clear the way for more suitable approaches to the study of economic issues.

My focus in this paper is restricted to consideration of how data is actually used in the experimental physical sciences in determining how well a given abstract model, for instance the Standard Model of particle physics, represents what happens in the real world. I do not explicitly consider the development of the model, nor how it has come to supplant other possible models. Instead I only consider the comparison of measured data against the abstract model. I then address the problem of using (or indeed not using) similar techniques with the data available in the social sciences.

So let me first set out the main points to be made in this paper before I outline its structure:

1. The techniques of physics cannot be used with the kinds of data available in the social sciences, which mostly consists of operational numbers.
2. This is because the relation between the operational number and the real physical quantity to which it should refer is not well defined, which precludes an adequate treatment of systematic uncertainty.
3. Since the level of systematic uncertainty sets a lower bound on the total uncertainty in a physical measurement, statistical analysis of data in the physical sciences is limited according to the level of systematic uncertainty.
4. What this means is that whereas in the physical sciences the project (which is achieved to a remarkable degree) is to use measured data to probe whether and how well the models we have created fit what actually happens in the physical world, the best that can be done in the social sciences is to find how well a given model fits the available data, not fully treating the relationship between the data and the real world phenomena giving rise to the data.
5. In order to go from probing how well the model fits the data to how well the model accords with what happens in the physical world, an adequate treatment of systematic uncertainty is required.
6. This treatment is not possible with operational numbers.

Having set out the main points, I will also set out a few other topics that will be addressed in order to support them. I will sketch out a conceptual picture to help illustrate the physical and social realms and where systematic uncertainty comes into play. I will also address the use of various forms of friction in the physical sciences and why these forms of friction are not invoked as explanation of discrepancies between model and observation in the physical

sciences. Note that I am not addressing analogies of friction as explicit parts of economic models, such as Williamson's transaction costs or Tobin's tax. What I address here is the common use of an analogy to friction in playing down residual discrepancies in the data that are not explicitly accounted for by the model used, as if it were common for such discrepancies to arise in physics because of frictional effects. The treatment of frictional effects is instead part of the treatment of systematic uncertainty and the effects are normally quite well understood.

Let me also note that concept of uncertainty is fairly well developed in economics, usually in terms of market uncertainties, probabilities, imperfect information and risk. Indeed *fundamental uncertainty* is a key element of post-Keynesian economics (e.g. Dequech 2000). Again, I am not addressing these kinds of concepts explicitly written into models or used as part of our understanding of economic behaviour; I am instead specifically addressing the very technical issue of the uncertainty involved in connecting the models (which may or may not have some conceptualisation of friction or uncertainty explicitly incorporated within them) to the real world through data. Even more directly, the issue is not at all the match between the model/theory/school of thought (however it does or does not conceptualise friction or uncertainty) and the data, but rather the uncertainty in the relationship between the data and quantities in the real world. This is a crucial part of linking model/theory to real world. In other words, there are two issues involved here: the first is real world to data, and the second is data to model/theory. It is the first issue I address here.

Thus in more detail: In the first part of this paper I sketch out a simple schematic picture of the emergence of social reality within the physical world. I then consider how the sciences have developed as different subsystems within the human cultural system. The purpose of introducing this picture is to provide a tentative but plausible tool for easier explanation of the role of systematic uncertainty in experimental physics. This framework will only be used as an aid in illustrating how data is used differently in economics and physics. It is those differences that I wish to emphasize and not a detailed derivation of the picture I propose for their illustration. What I try to get across is that systematic uncertainty is a very well developed, institutionalised and indispensable concept in experimental physics. My schematic framework is thus only introduced to help explain why it is so important and what the implications are of neglecting it.

Mainstream economics involves the construction of abstract mathematical models for social phenomena. These models can be fit to data with varying degrees of agreement, but not perfectly. Since the residual misfit between data and model is often brushed off with reference

to the effects of friction in physics, I devote a section in this paper to explaining that rather than acting as some kind of nuisance to physicists, causing unavoidable discrepancies between the observed universe and the underlying physical laws, the various forms of friction are studied in detail, very well understood and used as essential tools in experimental physics. In fact, a thorough understanding of different aspects of friction (processes involved in the passage of particles through matter) is necessary in order even to design measuring equipment for the purpose of studying the underlying processes in elementary particle physics, for example, since the use of various forms of friction is essential for data acquisition. Of course there are subtleties involved in the interaction of the phenomena studied and the experimental set-up used for their study, but all sources of uncertainty deriving from friction or any other source are usually quite predictable and are carefully studied for their effects. Such uncertainties are captured and quantified within the estimate of the systematic uncertainty of the measured quantity, which is carefully controlled so as not to dominate the total uncertainty of the measurement.

I will therefore discuss the paramount importance of the treatment of systematic uncertainty in experimental physics. In light of its centrality in experimental physics and its relative absence in economics, I consider the consequences. I argue that the use of abstract mathematical models in the social sciences is not as useful as in the physical sciences, and indeed can be misleading, due to these inherent and insurmountable systematic uncertainties.

I should also note that in this paper I do not delve deeply into the very broad literature on the philosophy of natural and social science, although the paper seems quite compatible with the framework of critical realism, with its insistence on ontological realism and epistemological fallibility. I should mention that while critical realists tend to (rightly) note the difficulty of experimentation in the open systems characteristic of social phenomena, the language used in experimental physics for describing the importance of controlled experimentation is again in controlling for systematics or systematic uncertainty. Experiments are thus designed as closed systems specifically to reduce the effects of what is discussed in this paper. This is why the vocabulary of systematic uncertainty might be quite useful to critical realists in discussions of the importance of the lack of closure in human social systems.

The Centre for Philosophy of Natural and Social Science at the London School of Economics also has a set of discussion papers devoted to Measurement in Physics and Economics (e.g. Reiss 2001; Frigg 2002). However I have not found anywhere in this literature any mention of how the central concept of systematic uncertainty is dealt with in experimental physics, let alone of its absence in the social sciences.

I should also mention the related topic of validity in the social sciences. An introductory text on *Social Research Methods* (Bryman 2001, 72; emphasis in the original) explains: '*Validity* refers to the issue of whether an indicator (or set of indicators) that is devised to gauge a concept really measures that concept'. Although this addresses an issue vaguely similar to systematic uncertainty in physics, it is not quite the same. Systematic uncertainty deals directly with the accuracy of a measured value compared to the true value of a real physical quantity. Validity is more of an indirect concept that (rightly) questions whether that real value is even out there. Kvale (1996: 229-52) in fact discusses in detail the social construction of validity in the social sciences. He notes that the term is 'often unfamiliar to natural scientists' (ibid. 230). Indeed it is not part of the everyday discourse of experimental physics, while systematic uncertainty is essential.

So instead of trying to bridge the gap between the physical and social sciences by going through a higher level philosophy of science/economics, I focus on how experimental physicists specifically rely on the key concept of systematic uncertainty, and starting from that perspective try to understand the implications of its absence in the social sciences. My purpose is not to defend or reject science in general, but is limited to pointing out the problem of trying to make social science appear equivalent to physics. I therefore launch my critique of mainstream economics directly from the methods developed and used in experimental physics.

Incidentally, it is worth noting that the problem of anchoring models to real world phenomena is not at all absent even in theoretical physics. Insider Lee Smolin (2006) has recently written a thought-provoking book on the emergence of string theory as the dominant research programme in theoretical physics despite its apparent lack of connection to the real world. He notes in a remarkable parallel to the mainstream of economics: 'Despite the absence of experimental support and precise formulation, the theory is believed by some of its adherents with a certainty that seems emotional rather than rational' (Smolin 2006: XX). Thus while I do use physics as an ideal, I especially stress its experimental aspects.

In summary, I do not here address the construction or change of theories and models: I address the testing of a particular model to see whether or not it is in complete agreement with what we are able to observe in our own world. Experimental physics is not particularly interested in how well a model fits the data, but how well the model describes what actually happens in the real world to the greatest extent it can be measured using data; and for this an accounting of systematic uncertainty is required.

2. Social reality and the physical and social sciences

In this part of the paper I sketch a simple picture of the emergence of social reality in the physical world. This simple picture is introduced only to help illustrate the concept of systematic uncertainty in the next sections. I must note here that systematic uncertainty is a very important concept in physics even without reference to this framework, which again is only introduced for illustrative purposes. The sketch is therefore kept simple and only loosely grounded in the literature.

I will present a very simple picture of reality where groups of physical and social scientists form separate disciplines and develop different procedures for studying their different subject matters. I will highlight the importance of the treatment of systematic uncertainty in the sub-discipline of experimental particle physics. I consider what the absence of a similar treatment of systematic uncertainty in other disciplines, particularly in the social sciences, means for the connection between the physical world and the formal mathematical models often used in those disciplines.

According to Klein & Edgar (2002) the modern human mind probably emerged about 40,000 years ago at the *Dawn of Human Culture*. At around that time modern humans apparently crossed a threshold of self-awareness coupled with cognitive abilities that allowed culture to flourish far beyond anything that had come before. There are now two levels of reality – one that does not depend on human cognition – the physical world, and a new level of social reality (see for instance Searle, 1995), which comprises an inter-subjective understanding of the world, both social and physical mixed together. (This is also in line with the critical realist insistence on the stratification of reality.)

Figure 1 is a conceptual diagram of the physical world, the projected image of that world we acquired through the course of human interaction with it, and the social world built through the social interaction of human actors with each other. The diagram is used to illustrate the development of the separate disciplines of the social and physical sciences. First we start with the assumption that there is a physical universe into which the human species evolved. This physical universe along with physical human beings is depicted in the figure as area A. (No dimensionality is implied by the word ‘area’, which is actually depicted as a volume in the figure.) The image of that physical world by an observer is depicted as area B. However in the case of humans, this picture of a duality of an external reality and a perceived image of that reality is not quite sufficient. Humans are a highly social species. Very quickly infants become socialised into their joint physical and social world with the help of their caretakers.

They pick up the social meaning of physical objects through interactions with the objects and their caretakers. (See e.g. Hala 1997 for a good reference on the development of social cognition in children.) The social significances of objects are thus perpetuated through the socialisation of children. The regions of area B that are separated by depth indicate that different cultures or groups may have differing conceptualisations, images or social meanings of the same physical object.

>> Figure 1 around here <<

Of course, once the capability of assigning different social meanings to physical objects has developed, the ability to create social/conceptual objects without direct reference to a physical object is an easy next step. We can call this social reality and depict it as area C in the figure. The explosion of human culture over the past tens of millennia is then depicted as the rapid growth and development of (culturally specific, although not necessarily isolated) social reality in the figure. Historically recent developments are the expanding areas of mathematics and the social and physical sciences. (A good reference on how mathematics is brought into being is Lakoff and Nuñez 2000.)

Although developments of mathematics and the sciences are essentially parts of area C without necessarily implying any difference from any other parts of area C, I have hived off and moved areas D, the social sciences, and E, the physical sciences, down to the right for easier exposition in the discussion to follow. We note that the models constructed by physical scientists in area E refer to processes out in the physical realm of area A, even though the data used for comparison with the models consist of measurements of assumed real physical quantities, where the measured values (in area B) are accessible to and understandable by people. In contrast, the data used in the social sciences in area D typically consist of operational numbers or textual information referring to abstract quantities, socially acquired answers to questionnaires, interview materials or data entered by people into tables or tax forms. We will come back to this in a later section.

This simple conceptual diagram will provide a framework for better explanation of the very real and important differences between the practices of experimental physics and those of mainstream economics. Note that the diagram is also largely consistent with the ontological realism and epistemological constructivism of critical realism.

How does economics differ from physics?

In this section I further consider approaches to social science that use abstract mathematical models in an attempt to make social science appear similar to physics. Lawson's (2002: 247-282) Chapter 10 'An explanation of the mathematising tendency in modern economics' presents a good treatment of the problem for the field of economics, from whence the tendency has spread to other branches of the social sciences. The main difference between the economic approach to science and that of experimental physics derives from the fact that physics deals with things that, to the greatest extent it can be measured, are actually out there as real features of the physical world. This is in opposition to the use of the operational numbers, which are all that is available in much of the social sciences. Thus what is typically sought in economics (with arguably little success) is an abstract mathematical model that is consistent with or at least partially explains patterns in the available data set of operational numbers. If there is good consistency between the model and this data, then it is thought that we have gained a better understanding of what happens in the world.

Having a good match between model and data is insufficient for experimental physics. We are instead interested in how well the model fits with what actually happens out there in the physical world. This entails understanding the relationship between the data and the physical world; and this is where systematic uncertainty comes in, as will be discussed in the next section.

One last key and pertinent difference I will discuss is how economics conceptualises frictional effects. Experimental conditions that give rise to what might be loosely considered 'friction' are not some unavoidable complication that must simply be accepted and played down, but are essential for understanding the relation between the measured values and the physical quantities that produce them. Indeed, in experimental particle physics, there are no data without taking advantage of one of many well-studied and understood forms of friction to produce measurements of the underlying physical processes. In other words, friction is not used as a term for inconvenient effects to be ignored in physics, which seems to be how it is often understood in the social sciences when effects that are not well understood are said to be analogous to the effects of friction in physics. This will be discussed further below.

Operational numbers, measurements and systematic uncertainty

Now we turn our attention to the difference between operational numbers and measurements of physical quantities. The difference is that systematic uncertainty between the measurement

and the physical quantity estimated is a well-defined (although perhaps often difficult to estimate) quantity. On the other hand, an operational number is an ascribed indicator of a conceptual quantity; and thus the uncertainty between the indicator and the true quantity indicated need not be defined at all. This is because the quantity indicated is conceptual in nature, requiring a (possibly composite) indicator to be defined as its proxy – in order to operationalise the conceptual quantity.

This part of the paper takes a closer look at the concepts and techniques used for the measurement of physical parameters including estimates of uncertainties in their measurement in experimental elementary particle physics. Systematic uncertainty is an essential and core consideration in experimental design, measurement and data analysis in the physical sciences. First I discuss what systematic uncertainty is and how it is treated in the physical sciences, and then I consider the implications of its non-treatment.

Although measurements in physics may not always be particularly accurate, the relationship and associated uncertainties between the measurement (which may be a composite measurement calculated on the basis of various bits of measured data), and the underlying physical quantity estimated are always explicitly quantified as part of the measurement. Thus when dealing with data in terms of a given abstract mathematical-theoretical model, the model is always conceptualised as having relevance at the level of what is really out there, whereas the experimenter only has measurements of those physical quantities at her disposal. It is therefore of crucial importance to be able to quantify how well the measurement approximates the underlying physical parameter. Again, the experimenter is not interested in possible relations between the measured quantities, but in the relations between the real physical quantities that give rise to them.

In the physical sciences, uncertainty is always broken down into two types: statistical and systematic, where the total uncertainty is the quadratic sum of the two. Here I will refer to the standard textbook for data reduction most commonly used in the first undergraduate physics laboratory course: Bevington (Bevington and Robinson 1992). The first chapter description of systematic and statistical uncertainties is perfectly adequate for interpreting the meaning of the published result of any measured parameter in experimental elementary particle physics. (Setting limits on parameters is somewhat more complicated, but considerations of systematic and statistical uncertainty are also of great importance in setting limits on physical parameters.)

Very briefly, statistical uncertainty is associated with precision, while systematic uncertainty deals with accuracy:

> The *accuracy* of an experiment is a measure of how close the result of the experiment is to the true value. Therefore it is a measure of the correctness of the result. The precision of an experiment is a measure of how well the result has been determined, without reference to its agreement with the true value. (Bevington and Robnison 1992: 2; emphasis in the original)

Statistical uncertainty arises from random errors; and is fairly well understood and treated using similar statistical techniques in both the physical and social sciences. The main difference comes in the (non-)treatment of systematic uncertainty:

> The *accuracy* of an experiment, as we have defined it, is generally dependent on how well we can control or compensate for *systematic errors*, errors that will make our results different from the "true" values with reproducible discrepancies. Errors of this type are not easy to detect and not easily studied by statistical analysis. They may result from faulty calibration of equipment or from bias on the part of the observer. They must be estimated from an analysis of the experimental conditions and techniques. A major part of the planning of an experiment should be devoted to understanding and reducing sources of systematic errors. (ibid.: 3; emphasis in the original. Note that the terms 'error' and 'uncertainty' are nearly synonymous here – uncertainty being an estimate of the expected error.)

We should note here that the standard picture associated with differentiating between systematic and statistical errors for a series of measurements is that the individual measurements form a distribution around the true value. If there is no systematic bias then the measured values are distributed randomly around the true value with standard deviation from the true value equal to the statistical uncertainty. Systematic errors lead to a systematic shift away from the true value, so that the measured values have the same distribution, but the mean is shifted away from the true value by the amount of the systematic error. The systematic uncertainty is thus an estimate of the size of that shift from all possible sources. As illustration of the centrality of these simple concepts in experimental physics, we note that every publication in experimental particle physics in which a parameter is measured presents the estimated parameter together with separate estimates of both the statistical and systematic uncertainties associated with the measurement. There are several conventions for doing so, typically something similar to this:

$$\mathbf{P} = \mathbf{E} \pm \mathbf{U}_{\mathbf{stat}} \pm \mathbf{U}_{\mathbf{sys}}$$

Here, **P** is the estimated parameter, **E** is the numerical estimate of the parameter, $\mathbf{U}_{\mathbf{stat}}$ is the estimated statistical uncertainty of **E** (usually from the fitting program used in the parameter estimate), and $\mathbf{U}_{\mathbf{sys}}$ is the expected systematic uncertainty of the parameter, which cannot come directly from the fitting program. The systematic uncertainty has to be estimated according to how the measured parameter might be affected by external factors perhaps not accurately taken into account in the fitting program. These sources would arise from not

exactly knowing the relationship between the measured quantities and the physical quantities they are supposed to represent, since this could lead to a systematic bias in the measurement. In principle, the reported systematic uncertainty is never significantly larger than the statistical uncertainty, unless a single dominant source of systematic uncertainty is identified and isolated. A measurement is said to have become *systematics limited* when the systematic uncertainty begins to impinge on the total uncertainty of the measurement (as statistical uncertainty is reduced by increasing statistics from measurement, for instance).

The only time that the reported systematic uncertainty significantly exceeds the statistical uncertainty is where there is a single dominant source of systematic uncertainty that can be separated from other smaller sources of systematic uncertainty. In this case the measurement will be reported in a form such as:

$$\mathbf{P = E \pm U_{stat} \pm U_{dom} \pm U_{other}}$$

Here $\mathbf{U_{stat}}$ stands for statistical uncertainty, $\mathbf{U_{dom}}$ stands for the single dominant systematic uncertainty and $\mathbf{U_{other}}$ stands for the total of all other sources of systematic uncertainty. The other sources of systematic uncertainty will again be smaller than (or at least not much larger than) the statistical uncertainty. This format is used in cases where the single dominant source of systematic uncertainty might be reduced in the future, perhaps by a different measurement, so that the parameter can be estimated again in light of the reduction in that dominant source of systematic uncertainty.

Uncertainties may also be asymmetric where the uncertainties involving possible positive bias may be larger or smaller than those involving negative bias. This can be signified with a slightly more complex notation; however this additional complication is not essential for our discussion.

With this brief presentation of the centrality of the treatment of systematic uncertainty in the experimental physical sciences, we can consider the implications of the absence of such treatment. This would amount to producing high precision measurements with no accounting for accuracy.

Locating systematic uncertainty in our diagram

Let us return to our conceptual diagram (see Figure 2). We can see where the treatment of systematic uncertainty comes in. It is the uncertainty in going from our measured quantities (in area B) to what is really out there (in area A) in the physical world. This piece is necessarily absent in much of the social sciences, where socially generated quantities are

considered (in area C). This is especially true for indicators, which are not explicitly connected to any specific underlying physical quantity.

>> Figure 2 around here <<

To be fair, systematic biases are certainly not unknown to statistical analysis in the social sciences. However, the approach to systematic bias in the social sciences is to determine the size of the bias and to correct for it, removing the bias and leaving only statistical sources of uncertainty. The problem comes from not knowing all sources of bias, not estimating the expected uncertainties due to them and not reporting those uncertainties in addition to estimates of systematic uncertainty.

The problem is fundamental. As discussed earlier, much of the data in the social sciences consist of operational numbers. What this means is that the data are not measured in such a way that the relationship between the measured value and the true value has meaning. For instance, operational numbers are often defined as proxies for conceptual quantities, such as well-being, human capital or wealth, where there need not be any real physical quantity behind the concept. Even the value of money must be socially defined, so there is no direct relation between amounts denominated in a currency and some existing true physical quantity. Therefore the relationship between the indicated and true quantity is not well defined, since there need not even be a true quantity. So while there may be a statistical distribution in the indicator allowing for estimation of statistical uncertainty, systematic uncertainty is not even conceptualised, let alone empirically identified.

Thus from the perspective of experimental physics, the lack and apparent impossibility of a rigorous treatment of systematic uncertainty for the phenomena of the social world makes it difficult to anchor an abstract model to the real world through analysis of accessible data. The fact that the dynamics of social phenomena can change through time and across populations without any direct connection to underlying natural laws makes it impossible to demonstrate that a given abstract model does, in fact, describe what is really happening in some kind of an underlying real world.

Open systems and systematic uncertainty

A very important point I would like to make here is the connection between systematic uncertainty and open or closed systems in experimental physics. The issue is important because of the critical realist critique on the use of mathematical methods in the open systems

of economics (for a recent discussion see Mearman 2006). The point that I would like to make here is that the issue of openness or closure in experimental physics is subsumed within the concept of systematic uncertainty. As noted in the discussion on systematic uncertainty above, all possible effects on the measurement from external sources have to be examined and accounted for in the systematic uncertainty. Thus where a measurement is not dominated by systematic uncertainty, we can take this to mean there is sufficient closure in the experimental design for the measurement. There thus need not be absolute closure in a physical experiment, just sufficient closure, which is accounted for in the systematic uncertainty.

3. The use of friction in physics

In this section I try to dispel some common misconceptions about the role of friction in physics, updating the concept to the 21st century and proposing a fitting counterpart in the social sciences. First, let us note that using an analogy of friction in physics to describe processes secondary to the main processes under consideration has a long history in economics. Indeed John Stuart Mill used the very words '[l]ike *friction* in mechanics, to which they have been often compared
' (Mill 1967: 330; quoted with emphasis by Blaug 1980: 64) as early as 1844 to describe how 'disturbing causes' modify the more general laws of interest. This discourse is still prevalent today and implies that there is no need to account for all of the effects involved in a given process, just the main ones, with the less important effects left aside analogously to how physicists are perhaps (wrongly) presumed to treat friction.

Rather than acting mainly as a source of difficult, non-essential and unwanted complications, friction is well understood and utilised in particle physics. Friction (the processes involved in the passage of particles through matter) is the set of precision tools used for producing data in modern experimental physics. As I will discuss, for a modern particle physics experiment, no friction means no data.

To back up this assertion, we make use of a general textbook by Dan Green (2005) of Fermilab, *The Physics of Particle Detectors.* His first sentence in the Introduction of the book is: 'The subject of particle detectors covers those devices by which the existence and attributes of particles in a detecting medium are made manifest to us' (ibid.: 1). And how are those particles in a detecting medium made manifest to us?

> The role of detectors can be visualized by assuming that an interesting interaction occurs at a point in space and time. From that point several secondary particles of different masses are emitted with various angles

> and momenta... It is the job of the detector designer to measure the time of interaction, t, and the vector momenta, $\mathbf{p}_i$, and masses, M_i, of those emitted particles. The text is organized so as to show the ensemble of tools available to the designer. (ibid.: 1)

The bulk of Green's book is separated into two parts – the first of which covers 'non-destructive' measurements, or 'those which do not appreciably change the measured particle's position or momentum' (ibid.: 1), and the second covers 'destructive' measurements, where 'the particle to be measured loses a significant fraction of its energy or is fully absorbed in the detector' (ibid.: 2). All of the detection techniques discussed in the book make use of the way that charged and neutral particles characteristically lose energy in traversing a detector medium, and the many different (frictional) processes involved are then ingeniously exploited in order to produce data for the study of the whatever underlying other physical processes may be of interest. The only particles that do not lose energy in a detector are the neutrinos. Neutrinos are perhaps the best way to stress the importance of friction in physics. The fact that these are nearly 'frictionless' particles severely complicates their measurement. Again equating friction with energy loss in the detector medium, Green describes neutrino detection: "The neutrinos carry off energy without interacting, and therefore their existence and energy can be inferred by measuring the total final state energy in comparison to that of the well prepared initial state' (ibid.: 295). This means that instead of frictional effects interfering with the underlying true quantities, the lack of frictional effects really complicates the determination of those quantities. In a particle detector, the least well-measured particles are the neutrinos whose existence and kinetic properties have to be determined by calculating what is missing from the measured properties of the particles that fortunately do undergo frictional energy loss in the detector. So this is what should come to mind when we think of friction in physics: multiple well understood processes used strategically for the production of data – making the study of other underlying physical properties possible.

For additional information, a condensed overview entitled 'Passage of Particles through Matter', complete with tables, formulae and a lengthy list of references for further information, is made available yearly by the Particle Data Group (Yao *et al.* 2006: 258-270) and is accessible online (http://pdg.lbl.gov/2006/reviews/passagerpp.pdf). A further condensed overview of particle detection methods made available by the same group (ibid.: 270-292) details how the signals thus produced through the passage of particles through matter (friction) are exploited for the production of experimental data (http://pdg.lbl.gov/2006/reviews/pardetrpp.pdf).

Although the physics associated with these processes is quite complicated, the specific details are perhaps not as important as the fact that these numerous different processes involved in producing and recording signals from the passage of particles through matter are very well understood. Furthermore, even the uncertainties involved in unwanted random (Molière) particle scattering and missed signals are thoroughly studies and accounted for in the estimates of the systematic uncertainties of the final measurements, as discussed in the previous section. Thus all effects of friction have to be carefully studied in order to understand the relationship between the data in area B of figure 2 and the underlying physical quantities in area A.

The bottom line of this section is that there is no counterpart in experimental physics to the deliberate non-consideration of complicating effects not deemed as central processes of interest in economics, which indeed are often quite inappropriately disregarded and dismissed by reference to the effects of friction in physics.

Data production in social science – like friction in physics

Similar to the physics of particle detectors, which is the study of the use of the *physical* processes (friction) used in producing data from the underlying real quantities of interest, we have to study and properly account for the *social* processes involved in the production of data in the social sciences, which are used to probe underlying socio-economic processes. If we take the role of friction in physics as the clever way of using particle interactions in a detector medium, then the counterpart of friction in the social sciences is social interaction with an appropriately designed research method. Thus similarly to how there is no data without the clever use of frictional particle interactions in the detector medium, the social sciences should arguably best use social interactions in a social medium (participant observation or oral or written accounts using language as the quintessential social medium) to produce data for the study of the social phenomena of interest. Just as particles are induced to deposit the information they carry away from the underlying physical processes we wish to study into the detector medium, we aim to induce participants to socio-economic phenomena to deposit the information they carry into the socio-linguistic medium so that those underlying phenomena can be made accessible for study. This is the general approach we take in lifeworld economics.

Of course there are obvious differences between data production in the social and physical sciences: informants on social phenomena carry far richer information than can be carried by and measured from elementary particles. Furthermore, information from the lifeworld does

not arise from the external physical world, but from another localised part of the social world from the collective social world of the social scientists (refer back to figure 2). This means that while the concept of systematic uncertainty is not well defined and is not useful in the social sciences (whereas it is essential in particle physics), it is also not necessary, since the social scientist has direct access to the lifeworlds of informants through normal human social interaction. The main difference in outcomes is that physical science needs to produce more abstract mathematical descriptions of the underlying phenomena than is necessary or useful in the social sciences.

4. Interpretive economics

In this section I summarise the interpretive method we have chosen as an appropriate approach to the study of lifeworld economics in the ongoing research project *Habitus of the Slovene Entrepreneur between 1960 and 1990*. A more detailed account of the method and its use is available elsewhere (Turk 2007). We follow the Biographical-Narrative Interpretive Method (BNIM) as described by Wengraf (2001). Chamberlayne et al. (2000) provide a good case for and review of the biographical turn in social science. We use this approach for data production and analysis on the realist social framework of Archer (1995), specifically using her account of the internal conversation (Archer 2003) as the key to linking structure and agency. The BNIM approach thus separates the two tracks of the telling of the personal story from the actual course of the lived life, and we analyse the internal conversations of key managers – made external as they freely recount their stories in an impromptu fashion – using the internal conversation as a way of linking the two tracks.

5. Summary and prospects

The purpose of this paper was to argue the case for using an interpretive approach to the study of lifeworld economics in the specific case of a research project on Slovene managers under socialism. In doing so, I have discussed the difficulty of properly accounting for systematic uncertainty in mainstream approaches to economics. I presented a sketch of how the social and physical sciences fit into our socially enacted world. I pointed out the difficulty in using abstract mathematical models for human social systems due to the problem of properly accounting for systematic uncertainty when dealing with operational numbers. I argued that because of the nature of the type of data available for the study of human social reality, it is not possible to reduce systematic uncertainty to the level that a model can be demonstrated to explain phenomena in the real world in the way that it is done in physics. Furthermore,

perhaps contrary to common misconception, friction is not invoked in physics as a simple explanation or a catchall for discrepancies between model and what is observed in the real world. Sources of uncertainty deriving from friction or experimental set-up are carefully accounted for in the estimate of systematic uncertainty, which is explicitly noted and generally smaller than the statistical uncertainty reported for the measurement. The lack of a comparable treatment of systematic uncertainty in economics deprives the mathematical models of the levels of demonstrability achievable in the physical sciences.

The reason I have devoted so much attention to this issue is to provide a sound justification to the interpretive alternative I have suggested (Turk 2007), where we use such an approach in a research project on Slovene managers under socialism. In that project we have so far conducted interviews with eight influential managers from among the most important companies involved in the rapid development of Slovenia during the socialist period. We are now preparing the panel analysis work on the line-by-line textual analysis of the interview transcripts and will soon have results to present.

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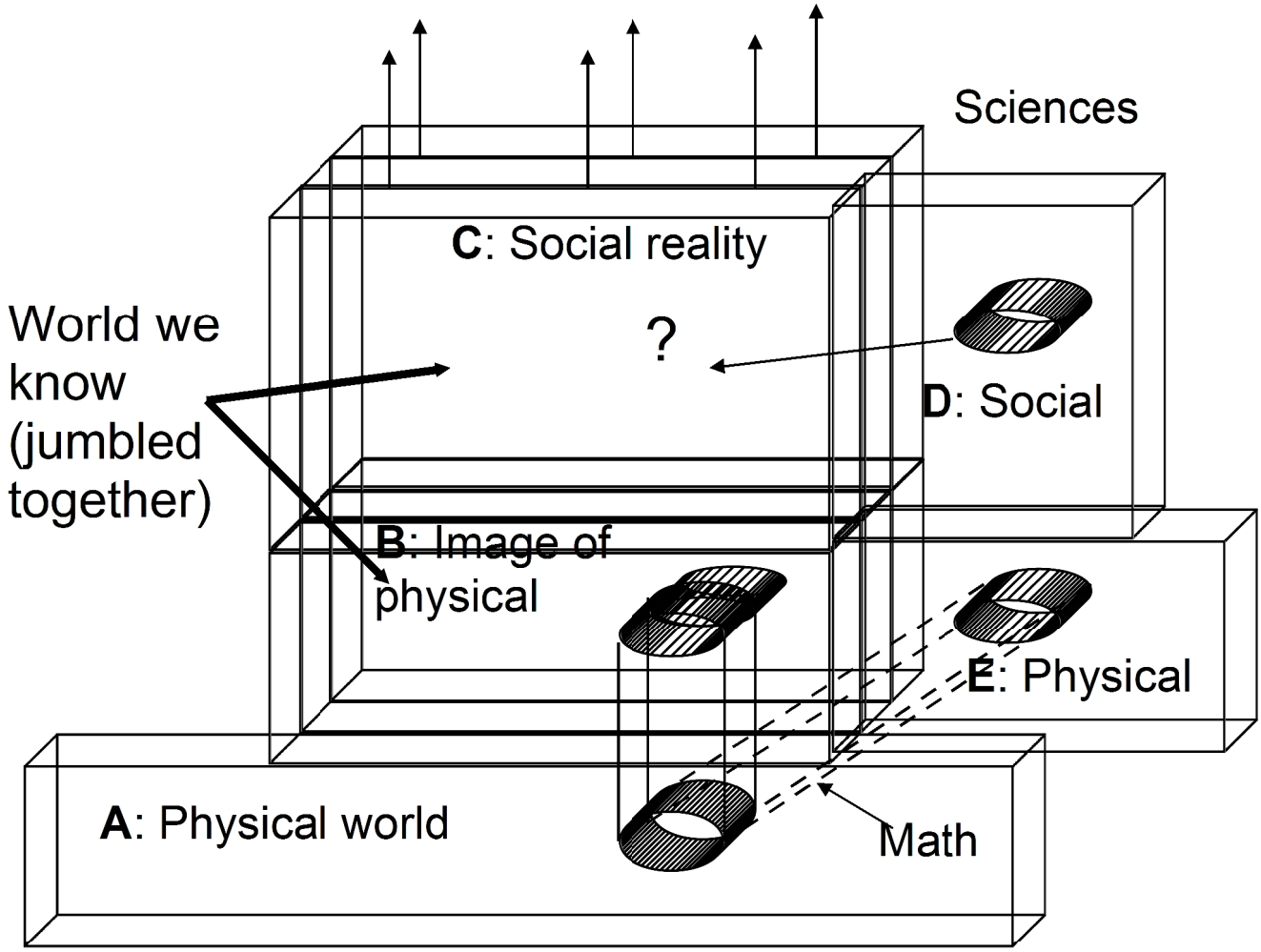
Captions and figures:

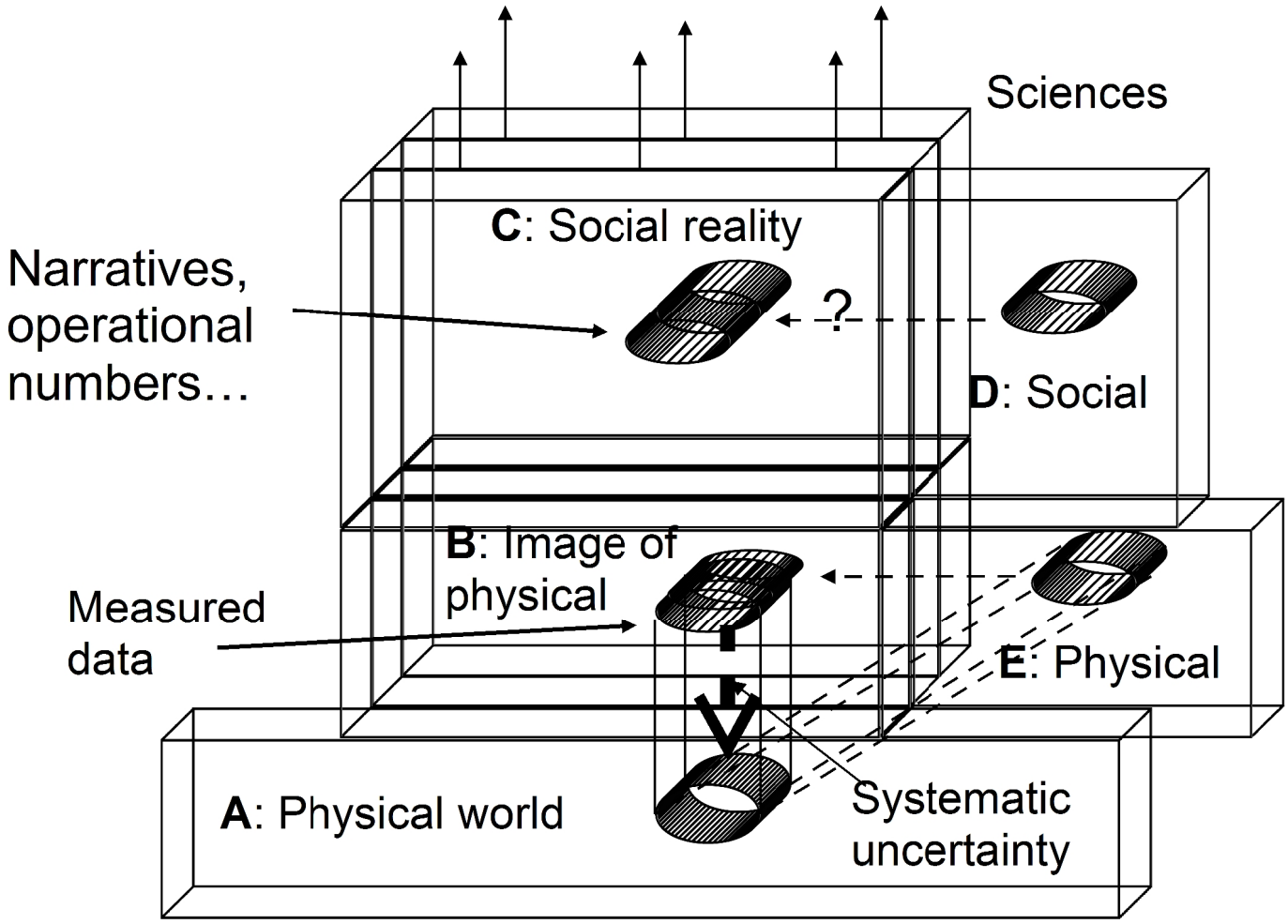
Figure 1. The sciences add to the world we know.

Figure 2. Systematic uncertainty in the physical sciences.

(Figure 1)


Sciences
C: Social reality
?
World we know (jumbled together)
D: Social
B: Image of physical
E: Physical
A: Physical world
Math

(Figure 2)


Sciences
C: Social reality
Narratives, operational numbers…
?
D: Social
B: Image of physical
Measured data
E: Physical
A: Physical world
Systematic uncertainty