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Penalized indirect inference[☆]

Francisco Blasques[a,b,*], Artem Duplinskiy[a,c]

[a] VU University Amsterdam, Netherlands
[b] Tinbergen Institute, Netherlands
[c] Coders Co, Netherlands

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We dedicate this article to the memory of our dear friend Jean-Pierre Urbain

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ABSTRACT

Parameter estimates of structural economic models are often difficult to interpret at the light of the underlying economic theory. Bayesian methods have become increasingly popular as a tool for conducting inference on structural models since priors offer a way to exert control over the estimation results. Similarly to Bayesian estimation, this paper proposes a penalized indirect inference estimator that allows researchers to obtain economically meaningful parameter estimates in a frequentist setting. The asymptotic properties of the estimator are established for both correctly and incorrectly specified models, as well as under strong and weak parameter identification. A Monte Carlo study reveals the role of the penalty function in shaping the finite sample distribution of the estimator. The advantages of using this estimator are highlighted in the empirical study of a state-of-the-art dynamic stochastic general equilibrium model.

1. Introduction

In economics, it is often difficult to reconcile the estimates obtained for parameters of structural models with the underlying economic theory. This problem is especially evident when employing frequentist estimation techniques that leave the researcher unable to exert some control over the estimator, at least within the parameter space bounds. Such problems are well known in the dynamic stochastic general equilibrium (DSGE) literature. Canova and Sala (2009) show that identification problems are pervasive in New Keynesian DSGE models; see also Ma (2002), Beyer and Farmer (2004), Nason and Smith (2008). Model misspecification also leads to difficulties since parameter estimates are biased and multiple pseudo-true parameters may exist.

Full information maximum likelihood estimation of DSGE models is difficult because these models are often nonlinear and contain unobserved state variables. Typically, DSGE models contain fewer shocks than observed state variables. In order to avoid stochastic singularities, researchers add measurement errors, but this leads to a loss in estimation precision; see, amongst others, An and Schorfheide (2007), Fernandez-Villaverde (2010), and Gorodnichenko and Ng (2010) for recent discussions. Indirect inference estimation allows the researcher to avoid many of these issues. Ruge-Murcia (2012) proposes the use of simulated method of moments to estimate the parameters of DSGE models. Creel and Kristensen (2013) propose an indirect likelihood estimation method that maximizes the likelihood of the auxiliary statistics. Calzolari et al. (2004) propose

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* Correspondence to: VU University Amsterdam, FEWEB/EOR, de Boelelaan 1105, 1081 HV Amsterdam, Netherlands.
E-mail address: f.blasques@vu.nl (F. Blasques).

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an extension of Indirect Inference that allows for the imposition of equality or inequality restrictions on the parameters of the auxiliary model. This delivers a way of enhancing the information used to estimate the parameters of the structural model. Dridi et al. (2007) provide an insightful discussion concerning the calibration of DSGE models that highlights how some parts of the model may be misspecified. They then introduce a Partial II estimator that focuses only on the part of the model that is deemed correctly specified.

In the case of DSGE models, the problem of model misspecification and the challenge posed by parameters that are unidentified, or only weakly identified, has lead to the widespread adoption of Bayesian methods. The introduction of priors in Bayesian estimation allows the researcher to exert control over the estimation procedure, in the effort to obtain economically meaningful parameter estimates, by including information that is not contained in the data sample.

For example, An and Schorfheide (2007) point out that *"Any estimation and evaluation method is confronted with the following challenges: potential model misspecification and possible lack of identification of parameters of interest"*. and that Bayesian methods become useful since *"prior distributions can be used to incorporate additional information into the parameter estimation"*. Similarly, Fernandez-Villaverde (2010) defends the use of additional structure in estimation since *"Pre-sample information is often amazingly rich and considerably useful and not taking advantage of it is an unforgivable omission"*. He further concludes that *"Yes, our inference would have depended heavily on the prior, but why is this situation any worse than not being able to say anything of consequence?"*.

This paper proposes a tool for incorporating pre-sample information in an indirect inference estimation setting. The added structure is provided by a penalty function that plays a role that is similar to that played by the prior in Bayesian estimation. The penalty function is allowed to be data dependent. This is similar in spirit to the empirical Bayes method; see e.g. Morris (1983).

Penalized estimation is not new in the frequentist literature. On the contrary, the basic idea of adding penalties to estimation criterion functions such as least squares, maximum likelihood or the method of moments is present in many statistical applications.[1] This paper 'brings' the use of penalties to a simulation-based estimation setting, which allows us to estimate complex, high-dimensional, nonlinear dynamic models with unobserved variables, like DSGE models. In particular, we introduce a penalty in the criterion function of the indirect inference (II) estimator proposed by Gourieroux et al. (1993) and Smith (1993). The penalized indirect inference (PenII) estimator possesses a number of features, similar to those of Bayesian methods, that may be valuable for the estimation of complex structural economic models such as DSGE models.

First, the PenII estimator allows for a wide range of criterion functions. Specifically, the PenII estimator encompasses both limited information estimation methods, such as the simulated method of moments of Duffie and Singleton (1990) and Lee and Ingram (1991), as well as likelihood-based full information estimation methods, such as the efficient method of Gallant and Tauchen (1996). Popular indirect inference criteria include moment matching, matching VAR parameters, and matching impulse response functions at certain periods, or maximizing the likelihood of the selected auxiliary statistics; see e.g. Christiano et al. (2005), Ruge-Murcia (2007), and Dupor et al. (2009), and Creel and Kristensen (2013) for examples of these different approaches. PenII is similar to Bayesian estimation in this respect as the latter can also be performed with different criteria; see e.g. Gallant and Tauchen (2015) for Bayesian estimation with GMM type objective functions.

The ability to choose among different criteria is important for estimation of potentially misspecified models. Indeed, Fukac and Pagan (2010) argue for the use of limited information estimation techniques in DSGE models since the maximum likelihood (ML) estimator requires the entire probabilistic structure of the model to be well specified, rather than just a few features of interest. Furthermore, ML estimators may have poor robustness properties; see e.g. the seminal work of Huber (1967, 1974).

Second, the penalty function can take a wide range of forms. It is thus easy to incorporate various forms of pre-sample information in a flexible way. Strong parameter restrictions can be imposed by letting the penalty diverge to infinity. Areas of indifference in the parameter space can characterized by plateaus in the penalty function. Intervals where the penalty is strictly concave can be used to identify a unique preferred parameter value. As we shall see, the asymptotic properties of the PenII estimator can be established under very mild regularity conditions on the nature of the penalty function.

Third, the influence of the penalty is allowed to vanish asymptotically at any pre-specified rate. Depending on this rate, the penalty may or may not influence the asymptotic distribution of the estimator. Different rates may reflect the extent to which the researcher wishes the pre-sample information to influence the asymptotic behavior of the PenII estimator as the sample size diverges to infinity. In practice, the choice regarding the influence of the penalty can be made based on a second criterion. In this paper we explore both in-sample and out-of-sample criteria for setting the penalty strength through the use of a validation sample. The PenII estimator is also similar to a Bayesian estimator is this respect as the selection of the prior may take the sample size into account and depend on the data.

The remainder of the article is organized as follows. Section 2 introduces the PenII estimator. Section 3 establishes its asymptotic properties. Section 4 analyses finite-sample properties by means of a Monte Carlo exercise and discusses how to choose the influence of the penalty in practice. Section 5 applies the new PenII estimator to a state-of-the-art DSGE model. Section 6 concludes.

[1] Examples include the lasso penalties used e.g. in Zou (2006) and Liao (2013), as well as the penalties used in non-parametric and semi-nonparametric estimation; see e.g. Chen (2007), Dalalyan et al. (2006) and Green (1996).