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A multivariate evaluation of German output growth and inflation forecasts

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Abstract

Abstract We examine the joint efficiency of German output growth and inflation forecasts using a multivariate loss function which allows for loss asymmetry and different degrees of curvature. Efficiency is evaluated with respect to financial market variables as stock market returns and interest spreads. Thereby we find evidence that the loss function is approximately linear with a considerable degree of asymmetry. Compared to the situation where the two forecasted variables are considered univariately, forecast efficiency is also rejected more frequently. Adding a forward-looking survey-based expectations indicator leads to even stronger rejections of forecast efficiency.

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1 Introduction

Economic forecasts are usually evaluated using symmetric loss functions leading to the usual (root) mean square error or mean absolute error metrics. In reality, however, the loss of underpredicting a variable usually differs from the loss of overpredicting this variable. Granger (1969) provides an early account of the problem and further papers appeared especially since the 1990s.[1] For applied research the approach by Elliott, Komunjer and Timmermann (2005, 2008), EKT henceforth, is particularly appealing. In this approach, the parameters of a flexible loss function allowing for asymmetry and curvature are estimated jointly with a test of forecast efficiency against a set of instrumental variables. The idea is to determine the shape of an univariate loss function which is consistent with forecast rationality. Further applications of the EKT approach include evaluations of US inflation forecasts (Capistrán (2008)), German business cycle forecasts (Döpke et al. (2010)), forecasts of output growth and inflation rates in Germany (Krüger and Hoss (2012)) and US state revenue forecasts (Krol (2013)).

In the EKT approach, however, an unreasonably large degree of asymmetry often is required for forecast rationality to hold, which implies unreasonable differences in the costs of overpredictions and underpredictions. Recently, Komunjer and Owyang (2012), KO henceforth, pointed out that one deficiency of the EKT approach is that the loss function is estimated separately for each of the forecasted series. When the forecasts of multiple variables from a forecaster (or a group of forecasters) are evaluated, such univariate forecast evaluations implicitly assume that the loss of mispredicting one variable is independent of mispredictions of other jointly forecasted variables. This would hold when the forecasters have an additively separable loss function where the marginal loss of each variable is independent of the other variables.

Therefore, KO propose a generalization of the EKT loss function to the joint evaluation of multiple forecast error series where the assumption of independence of the forecast errors and the requirement of additive separability are no longer necessary. This more flexible loss function can be used to evaluate the rationality of a vector of forecasts pertaining to different variables jointly with an assessment of the functional form of the loss function (i.e. asymmetry) in the same way as proposed by EKT. KO claim that the independence assumption affects rationality tests and leads to a bias towards asymmetry of the loss function. Using the proposed multivariate loss function may thus lead to finding a lower degree of asymmetry.

In this paper we use the multivariate approach of KO to assess the efficient use of financial and survey-based expectations indicators in the output growth and inflation forecasts of the Council of Economic Experts[2], the most important group of forecasters in Germany. The study extends the univariate analysis of Krüger and Hoss (2012) to this multivariate approach. In Krüger and Hoss (2012) we applied the EKT loss function to these data finding the loss function of output growth forecasts to be approximately symmetric while there is asymmetry in the loss function of the inflation forecasts. The information of financial variables seems to be adequately incorporated in the output growth forecasts, but to a lesser extent in the inflation forecasts. The main objective here is to explore whether these conclusion stay robust when both variables are considered jointly and when in addition a forward-looking survey-based expectations indicator is added to the information set. Thereby, we also want to contribute experience with the recently developed multivariate KO loss function and a direct comparison to the univariate EKT approach.

The plan of this paper firstly is to outline the loss function and estimation method in section 2. This is followed by a discussion of the data in section 3 and the results in section 4 together with a comparison to the previous results of Krüger and Hoss (2012). A brief conclusion is provided in section 5.

2 Multivariate Loss

The loss function proposed by KO depends on the forecast errors of n forecasts collected in the $n \times 1$ vector $\boldsymbol{e}_{t+1} = (e_{1t+1}, ..., e_{nt+1})'$. Each forecast error is defined as realization y_{it+1} minus the forecast $f_{it+1|t}$ based on the information up to the previous period t, i.e. $e_{it+1} = y_{it+1} - f_{it+1|t}$ $(i = 1, ..., n)$. Formally, the loss function is defined by

[1] See e.g. Christoffersen and Diebold (1997), Batchelor and Peel (1998), Granger and Pesaran (2000), Elliott, Komunjer and Timmermann (2005, 2008) and Patton and Timmermann (2007).

[2] In German language: Sachverständigenrat zur Begutachtung der gesamtwirtschaftlichen Aktivität.

$$L_p(\boldsymbol{\tau}, \boldsymbol{e}_{t+1}) = (\|\boldsymbol{e}_{t+1}\|_p + \boldsymbol{\tau}'\boldsymbol{e}_{t+1}) \cdot \|\boldsymbol{e}_{t+1}\|_p^{p-1}, \tag{1}$$

with $\|\boldsymbol{e}_{t+1}\|_p = (|e_{1t+1}|^p + ... + |e_{nt+1}|^p)^{1/p}$ as vector norm. The loss function depends on the curvature parameter $p \geq 1$ as well as the asymmetry parameters collected in the $n \times 1$ vector $\boldsymbol{\tau} = (\tau_1, ..., \tau_n)'$ with $-1 < \tau_i < 1$ for all $i = 1, ..., n$ ($\tau_i = 0$ implies symmetric loss in that variable).

The EKT loss function is contained as a special case for $n = 1$. Further special cases (here stated for $n = 2$ forecasts) are linear asymmetric loss ($p = 1$) $L_1(\boldsymbol{\tau}, \boldsymbol{e}_{t+1}) = |e_{1t+1}| + |e_{2t+1}| + \tau_1 e_{1t+1} + \tau_2 e_{2t+1}$ and quadratic asymmetric loss ($p = 2$) $L_2(\boldsymbol{\tau}, \boldsymbol{e}_{t+1}) = e_{1t+1}^2 + e_{2t+1}^2 + (\tau_1 e_{1t+1} + \tau_2 e_{2t+1}) \cdot (e_{1t+1}^2 + e_{2t+1}^2)^{1/2}$. Additive separability is covered as a special case for either $p = 1$ or $\tau_i = 0$ for all $i = 1, ..., n$ (independent of p). These examples are particularly useful for spotting the role of τ_1 and τ_2. Positive values of the asymmetry parameters are associated with a larger loss of positive forecast errors (underprediction of the target variable) compared to negative forecast errors (overprediction) of the same size. The relation of the loss of positive and negative forecast errors is reverse for negative values of the asymmetry parameters.

The first-order optimality conditions are given by the conditional expectation of

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$$\frac{\partial L_p(\boldsymbol{\tau}, \boldsymbol{e}_{t+1})}{\partial \boldsymbol{e}_{t+1}} = p\boldsymbol{v}_p(\boldsymbol{e}_{t+1}) + \boldsymbol{\tau}\|\boldsymbol{e}_{t+1}\|_p^{p-1} + (p-1)\boldsymbol{\tau}'\boldsymbol{e}_{t+1}\|\boldsymbol{e}_{t+1}\|_p^{-1}\boldsymbol{v}_p(\boldsymbol{e}_{t+1}), \tag{2}$$

with respect to the information available in period t. Here, we define the $n \times 1$ vector $\boldsymbol{v}_p(\boldsymbol{e}_{t+1}) = (\text{sgn}(e_{1t+1})\,|e_{1t+1}|^{p-1}, ..., \text{sgn}(e_{nt+1})\,|e_{nt+1}|^{p-1})'$ with $\text{sgn}(\cdot)$ denoting the sign function.[3]

These first-order conditions should be orthogonal to any variables from the information set of period t collected in the vector $\boldsymbol{w}_t$ and generate the moment conditions

$$\boldsymbol{g}_p(\boldsymbol{\tau}, \boldsymbol{e}_{t+1}, \boldsymbol{w}_t) = \frac{1}{T}\sum_{t=1}^{T-1}\left[p\boldsymbol{v}_p(\boldsymbol{e}_{t+1}) + \boldsymbol{\tau}\|\boldsymbol{e}_{t+1}\|_p^{p-1} + (p-1)\boldsymbol{\tau}'\boldsymbol{e}_{t+1}\|\boldsymbol{e}_{t+1}\|_p^{-1}\boldsymbol{v}_p(\boldsymbol{e}_{t+1})\right] \otimes \boldsymbol{w}_t \tag{3}$$

for the GMM estimation (Hansen (1982)) of the parameters p and $\boldsymbol{\tau}$ jointly with testing the validity of the orthogonality with $\boldsymbol{w}_t$ by the J-test.[4] The orthogonality conditions for information efficiency imply that the objective function of the GMM estimation should be zero at the optimum which is tested by the J-test. The procedure is designed to estimate the parameters of the loss function which are consistent with multivariate forecast optimality. By doing so the shape of the loss function is backed out jointly with the assessment of forecast optimality. We use the derivative-free Nelder-Mead algorithm (Nelder and Mead (1965)) for minimization which is a robust method superior to quasi-Newton methods in the present case of an asymmetric loss function.[5] Like the univariate approach of EKT the multivariate procedure proposed by KO takes into account the forecast estimation uncertainty and leads to consistent and asymptotically normal distributed estimates of the loss function parameters.

3 Data

To preserve the direct comparability with the univariate approach the data used here are the same as in the assessment of Krüger and Hoss (2012). The forecasts of the German Council of Economic Experts are basically judgmental forecasts of a group of five experts supported by a staff of assistants who are preparing the forecasts also using econometric models. We focus on the out-of-sample evaluation of the forecasts of annual output growth and inflation rates. The forecasts are published in November of each year (period t) and refer to the following year (period $t+1$). The data for the output growth and inflation forecasts are assembled from the annual reports where they are consistently published since 1970 for the

[3]With $\text{sgn}(x) = -1$ for $x < 0$, $\text{sgn}(x) = 1$ for $x > 0$ and $\text{sgn}(0) = 0$.

[4]See Hoffman and Pagan (1989) for an early application of GMM to forecast evaluation.

[5]GMM estimation is performed using the continuously updating estimator of Hansen, Heaton and Yaron (1996) with a Bartlett kernel implemented in the R package "gmm" and described in Chaussé (2010). The lag length is selected according to Newey and West (1994). Here we also estimate p while KO optimize only over $\boldsymbol{\tau}$ keeping p fixed in the expectation of numerical problems. In the case of the simultaneous optimization over p and $\boldsymbol{\tau}$ we found that Newton and quasi Newton methods were frequently subject to convergence problems.

growth rate of real GDP and since 1969 for the inflation rate of the consumer price index.[6] We use real-time realizations which are taken from Döpke et al. (2010). The sample period for the analysis in this paper extends to 2010.

Financial variables as interest term spreads and stock market returns are considered to have predictive power for output growth and inflation. In surveying this literature, Stock and Watson (2003) document the predictive power of these variables as well as pointing to the potential instability of these relations. Key advantages of these variables for forecast efficiency evaluation are that they are readily observed with negligible measurement error and that they are not subject to data revisions. Moreover, theoretical relations to the target variables can be established. In that respect, interest spreads are indicating tighter monetary policy which is associated with rising short-term interest rates but has a smaller effect on long-term rates. Accordingly, if spreads are reduced (the yield curve flattens) and we can expect slower real growth in the near future. Stock market returns reflect changes in expected future earnings of firms and thus directly refer to future economic activity. See Estrella and Mishkin (1998), Estrella and Trubin (2006) and Adrian and Estrella (2008) for more elaborate expositions of the argument. Here, we use interest term spreads of 9-10 year and three month interest rates as well as returns of the leading German stock market index DAX to construct instrumental variables.

Let rs_t denote the average interest term spread during the first six months of period t. The spread is simply the difference of monthly average yields on debt securities outstanding issued by residents with a mean residual maturity of more than 9 and up to 10 years and the monthly averages of the money market rates reported by banks hosted in Frankfurt for three-month funds.[7] Furthermore, let rs_{t-1} denote the average term spread of the previous year $t-1$. This timing convention ensures that rs_t and rs_{t-1} are definitely contained in the set of information available to the forecasters when they are preparing their report for November. Analogously, let dax_t and dax_{t-1} denote the average monthly returns of the DAX during the first six months of period t and the average monthly returns during the previous year, respectively.[8] These time series are evidently stationary. We consider the following sets of instrumental variables A to I:

$$\boldsymbol{w}_{\mathrm{A}t} = (1,\, dax_t,\, dax_t^2)' \qquad \boldsymbol{w}_{\mathrm{F}t} = (1,\, dax_t,\, rs_t,\, dax_t \cdot rs_t)'$$
$$\boldsymbol{w}_{\mathrm{B}t} = (1,\, rs_t,\, rs_t^2)' \qquad \boldsymbol{w}_{\mathrm{G}t} = (1,\, dax_t,\, rs_t,\, dax_{t-1},\, rs_{t-1})'$$
$$\boldsymbol{w}_{\mathrm{C}t} = (1,\, dax_t,\, dax_{t-1})' \qquad \boldsymbol{w}_{\mathrm{H}t} = (1,\, dax_t,\, rs_t,\, dax_{t-1},\, rs_{t-1},\, dax_t \cdot rs_t,\, dax_{t-1} \cdot rs_{t-1})'$$
$$\boldsymbol{w}_{\mathrm{D}t} = (1,\, rs_t,\, rs_{t-1})' \qquad \boldsymbol{w}_{\mathrm{I}t} = (1,\, dax_t,\, rs_t,\, dax_t^2,\, rs_t^2,\, dax_t \cdot rs_t)'$$
$$\boldsymbol{w}_{\mathrm{E}t} = (1,\, dax_t,\, rs_t)'$$

These IV sets comprise one or two lags as defined above, together with squares and interactions of the term spreads and DAX returns. These IV sets are exactly those used in Krüger and Hoss (2012) with the corresponding results reported in table I below.

In the second part of the results section we add two modifications of the analysis.[9] First, we extend the information of the variables used for period t to the first nine (instead of six) months of the respective year. This brings the instrumental variables closer to the forecast origin while still preserving their validity. Second, we use survey-based expectations from the Ifo Institute, which is the most prominent institute in Germany asking a sample of firms in manufacturing, construction, wholesaling and retailing each month about their business expectations for the next six months. The series ifo_t and ifo_{t-1} are constructed in the same way as the series above from the monthly changes of the business expectations index.[10] Table II below reports the results with these two modifications and the additional instrument sets J to P:

$$\boldsymbol{w}_{\mathrm{J}t} = (1,\, ifo_t,\, ifo_t^2)' \qquad \boldsymbol{w}_{\mathrm{N}t} = (1,\, dax_t,\, ifo_t,\, dax_{t-1},\, ifo_{t-1})'$$
$$\boldsymbol{w}_{\mathrm{K}t} = (1,\, ifo_t,\, ifo_{t-1})' \qquad \boldsymbol{w}_{\mathrm{O}t} = (1,\, dax_t,\, ifo_t,\, dax_{t-1},\, ifo_{t-1},\, dax_t \cdot ifo_t,\, dax_{t-1} \cdot ifo_{t-1})'$$
$$\boldsymbol{w}_{\mathrm{L}t} = (1,\, dax_t,\, ifo_t)' \qquad \boldsymbol{w}_{\mathrm{P}t} = (1,\, dax_t,\, ifo_t,\, dax_t^2,\, ifo_t^2,\, dax_t \cdot ifo_t)'$$
$$\boldsymbol{w}_{\mathrm{M}t} = (1,\, dax_t,\, ifo_t,\, dax_t \cdot ifo_t)'$$

[6] The reports are in German language and can be downloaded from the homepage http://www.sachverstaendigenrat-wirtschaft.de/gutachten.html?&L=1.

[7] These are the time series SU0107 and WU8608 from the time series database of the German central bank. The former series is available since December 1959 whereas the latter is available since April 1973 which restricts the sample period accordingly.

[8] This is the time series WU3141 (end of month DAX performance index, normalized to 100 at the end of 1987) also taken from the time series database of the German central bank.

[9] Both modifications have been suggested by an anonymous referee and I am grateful for these ideas.

[10] These data series can be directly retrieved from the homepage of the Ifo Institute and documentation can be found at http://www.ifo.de/w/45YCTv5Bp.

4 Results

Table I shows the estimation results. Reported are GMM parameter estimates $\hat{\tau}_1$, $\hat{\tau}_2$ and $\hat{p}$ together with standard errors in parentheses as well as the J-test statistics with their p-values in parentheses. For each IV set the estimates $\hat{\tau}_1$ and $\hat{\tau}_2$ are first computed with fixed $p = 1$ and $p = 2$ and afterwards $\hat{\tau}_1$, $\hat{\tau}_2$ and $\hat{p}$ are estimated simultaneously. Without instruments we have just two moment conditions so that τ_1 and τ_2 can only be estimated with fixed p and the J-statistic is identically zero. We also report the norms $\|\hat{\boldsymbol{\tau}}\|_p$ as suggested by KO to have a summary measure of the overall degree of asymmetry.[11]

We observe predominantly positive $\hat{\tau}_1$ for the output growth forecasts implying a larger loss of positive forecast errors. Hence loss appears to be larger when underpredicting output growth compared to over-predicting by the same magnitude. This holds consistently whenever $\hat{\tau}_1$ differs significantly from zero (as is quickly tested by comparing the estimate with two times its standard error) and holds for the IV sets B and C irrespective of the value of p. Likewise $\hat{\tau}_2$, indicating the degree of asymmetry of the inflation forecasts, is also mostly positive and is significantly so in case of the IV sets F, G, H, and I for all p. Thus, underpredicting the inflation rate appears to be more costly than predicting too large values of this variable. The estimates of τ_1 and τ_2 are quite diverse and there is no clear pattern across the IV sets. Like the individual asymmetry parameters, their norm $\|\hat{\boldsymbol{\tau}}\|_p$ varies considerably and indicates a non-negligible overall degree of asymmetry.

The estimates of the curvature parameter p are all between 1 and 2 and are quite precise. On several occasions the estimate almost hits the lower bound of unity. This is quite interesting and is not caused by the configuration of initial values since robustness has been checked by widely varying the initial values (the estimates are actually not exactly equal to unity but differ in the rear decimal places). Thus, in these cases the loss function appears close to piece-wise linear which implies additive separability or at least approximate additive separability. Rejections of the J-test are observed for the IV sets C (containing past DAX returns), E, G (containing both past DAX returns and interest spreads) and H (which in addition contains interaction terms) at least on a 10 percent level of significance. Thus, both stock market returns and interest rate spreads provide information suited to improve the forecasts even when asymmetry of the loss function is permitted and should be considered more thoroughly by the forecasters.

Comparing the real-time results with the corresponding findings in table 2 of Krüger and Hoss (2012) which follows the univariate approach we reach three main conclusions. First, we find that asymmetry is equally pronounced in the multivariate approach. For this comparison we have to convert the asymmetry parameter α in the EKT loss function which assumes values in the interval $[0, 1]$ to τ equivalents by $2\alpha - 1$. Based on that we actually find $2\alpha - 1$ either smaller or larger than τ in about half of the cases for both output growth and inflation rate forecasts. Second, the estimates of p obtained with the multivariate approach are much smaller and more reasonable than the corresponding estimates from the univariate approach. This indicates a lower degree of curvature of the loss function. Many estimates of p from the multivariate approach are indeed close to unity which implies additive separability of the loss function. Third, rejection of rationality and thus the detection of forecast inefficiency occurs more frequently when using the multivariate approach. Here it should be noticed that the univariate approach produces twice as much J-test statistics for two forecasted variables. This is the consequence of having one J-test statistic for each variable and IV set in the univariate approach whereas in the multivariate approach there is only one J-test statistic for all variables together and each IV set.

The results with the two modifications announced above are shown in table II. Now we find more rejections of forecast optimality in the case of the IV sets A to I which can be attributed to bringing the instruments of period t closer to the forecast origin (our first modification). We also find more rejections of optimality for the new IV sets J to P including the changes of the Ifo business expectations index (our second modification). Thereby we find consistent rejections for $p = 1$, $p = 2$ and $\hat{p}$ in case of the IV sets K, N and O where the changes of the Ifo index appear for periods t and $t - 1$ either exclusively or jointly with the DAX returns. Except for set J where no rejection occurs we have rejections for single values of p also for the IV sets L, M, and P. This is strong evidence in favor of neglected information contained in the survey expectations which could be used to improve the forecasts of the Council of Economic Experts for the German economy.

Regarding the estimates of the τ and p parameters we get similar conclusions to the previous results. One remarkable exception is that the estimates of the asymmetry parameters τ_1 and τ_2 significantly negative

[11] It should be noted that all estimates respect the norm requirement $\|\hat{\boldsymbol{\tau}}\|_q < 1$ established by KO with q such that $1/p + 1/q = 1$ and sup-norm in the case of $p = 1$.

in the case of IV set O where both DAX returns and the Ifo index together with their interactions are included and therefore the number of instruments gets rather large. However, this assertion is limited to this case.

5 Conclusion

The multivariate forecast evaluation conducted in this paper provides further results on the power of financial variables like interest term spreads and stock market returns for business cycle forecasting, i.e. forecasting output growth and inflation. We find a moderate degree of asymmetry of the loss function and also moderate curvature, which is permitted by the used functional form. Mainly, loss is larger in the case of positive forecast errors associated with unterpredictions of the target variables. This holds for both output growth and inflation. Nevertheless we also find rejections of forecast rationality with respect to some of the instrument sets constructed from the financial variables.

A further interesting finding is that bringing the information in the instrumental variables closer to the forecast origin increases the frequency of rejections of forecast optimality. Finally, including a survey-based business expectations indicator like the Ifo index leads to much more rejections of forecast optimality. This suggests that the forecasters of the German Council of Economic Experts seem not to pay enough attention to this information. However, this is rather surprising since the publication of the Ifo index receives broad media coverage each month. Thus, the results in this paper not only reinforce the conclusions of Krüger and Hoss (2012) with the multivariate approach, but also show that the forecasters systematically neglect the information comprised in financial variables and survey expectations even when the forecast errors are evaluated with a flexible loss function also allowing for asymmetry. More focus on these variables could improve their forecast accuracy.

In the light of these findings, the users of such forecasts are advised to be skeptical when a business cycle forecast is not consistent with the signals of financial variables and survey expectations. If such an inconsistency is found, the forecast tends to be overly optimistic as concerns output growth and overly pessimistic as concerns the inflation rate avoiding the higher cost of underpredictions in both cases.

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Table I: GMM Estimates of the Loss Function (1)

	$\hat{\tau}_1$	$\hat{\tau}_2$	$\hat{p}$	J	$\|\hat{\boldsymbol{\tau}}\|_p$
without IV	0.282 (0.146)	0.026 (0.175)	1	0	0.282
	0.232 (0.185)	-0.143 (0.199)	2	0	0.273
IV set A	0.243 (0.155)	0.108 (0.181)	1	4.571 (0.334)	0.243
	0.111 (0.179)	-0.044 (0.208)	2	4.277 (0.370)	0.119
	0.273 (0.178)	-0.012 (0.243)	1.462 (0.857)	2.828 (0.419)	0.273
IV set B	0.342 (0.137)	0.235 (0.182)	1	4.916 (0.296)	0.342
	0.358 (0.149)	0.296 (0.178)	2	4.085 (0.395)	0.465
	0.342 (0.138)	0.237 (0.183)	1.000 (0.340)	4.917 (0.178)	0.342
IV set C	0.358 (0.135)	0.267 (0.176)	1	9.946 (0.041)	0.358
	0.486 (0.166)	-0.515 (0.145)	2	17.364 (0.002)	0.708
	0.362 (0.144)	0.278 (0.187)	1.000 (0.342)	9.952 (0.019)	0.362
IV set D	0.353 (0.104)	0.249 (0.179)	1	3.468 (0.483)	0.353
	0.234 (0.197)	0.228 (0.139)	2	3.360 (0.500)	0.327
	0.353 (0.104)	0.250 (0.179)	1.000 (0.310)	3.469 (0.325)	0.353
IV set E	0.205 (0.100)	0.376 (0.165)	1	8.021 (0.091)	0.376
	0.230 (0.210)	0.298 (0.169)	2	6.561 (0.161)	0.377
	0.216 (0.180)	0.390 (0.176)	1.614 (0.386)	6.316 (0.097)	0.420
IV set F	0.221 (0.097)	0.429 (0.158)	1	7.988 (0.239)	0.429
	-0.029 (0.198)	0.388 (0.143)	2	6.775 (0.342)	0.389
	0.164 (0.143)	0.456 (0.140)	1.435 (0.310)	6.411 (0.268)	0.461
IV set G	0.203 (0.090)	0.503 (0.139)	1	14.421 (0.071)	0.503
	0.102 (0.173)	0.648 (0.112)	2	10.999 (0.202)	0.656
	0.121 (0.120)	0.621 (0.113)	1.550 (0.261)	9.631 (0.210)	0.623
IV set H	0.148 (0.066)	0.681 (0.113)	1	23.295 (0.025)	0.681
	-0.223 (0.149)	0.569 (0.109)	2	15.377 (0.221)	0.611
	-0.046 (0.131)	0.696 (0.110)	1.901 (0.182)	14.266 (0.219)	0.697
IV set I	0.238 (0.124)	0.479 (0.171)	1	13.672 (0.188)	0.479
	0.072 (0.168)	0.468 (0.133)	2	8.847 (0.547)	0.474
	0.239 (0.127)	0.479 (0.171)	1.000 (0.282)	13.672 (0.134)	0.479

Note: Shown in parentheses are standard errors for $(\hat{\tau}_1, \hat{\tau}_2, \hat{p})$ and p-values for the J-test statistics.

Table II: GMM Results with the Modifications

	$\hat{\tau}_1$	$\hat{\tau}_2$	$\hat{p}$	J	$\lVert\hat{\boldsymbol{\tau}}\rVert_p$
IV set A	0.254 (0.126)	0.126 (0.173)	1	5.480 (0.242)	0.254
	-0.031 (0.155)	-0.355 (0.143)	2	6.992 (0.136)	0.357
	0.254 (0.139)	0.126 (0.178)	1.000 (0.399)	5.480 (0.140)	0.254
IV set B	0.336 (0.136)	0.279 (0.185)	1	5.100 (0.277)	0.336
	0.422 (0.164)	0.345 (0.155)	2	6.365 (0.174)	0.545
	0.336 (0.136)	0.279 (0.186)	1.000 (0.318)	5.100 (0.165)	0.336
IV set C	0.321 (0.133)	0.227 (0.174)	1	8.761 (0.067)	0.321
	-0.223 (0.186)	0.533 (0.189)	2	9.838 (0.043)	0.578
	0.321 (0.137)	0.227 (0.184)	1.000 (0.370)	8.761 (0.033)	0.321
IV set D	0.393 (0.104)	0.274 (0.177)	1	3.717 (0.446)	0.393
	0.235 (0.196)	0.278 (0.133)	2	4.104 (0.392)	0.365
	0.393 (0.104)	0.274 (0.177)	1.000 (0.290)	3.717 (0.294)	0.393
IV set E	0.219 (0.107)	0.222 (0.168)	1	7.734 (0.102)	0.222
	0.233 (0.207)	0.332 (0.168)	2	5.662 (0.226)	0.406
	0.256 (0.181)	0.318 (0.174)	1.636 (0.415)	5.481 (0.140)	0.379
IV set F	0.219 (0.117)	0.138 (0.172)	1	10.595 (0.102)	0.219
	-0.064 (0.200)	0.485 (0.130)	2	6.469 (0.373)	0.489
	0.144 (0.161)	0.522 (0.137)	1.611 (0.291)	7.319 (0.198)	0.529
IV set G	0.113 (0.127)	0.149 (0.153)	1	15.619 (0.048)	0.149
	0.137 (0.163)	0.651 (0.116)	2	10.777 (0.215)	0.665
	0.119 (0.120)	0.623 (0.115)	1.604 (0.275)	9.436 (0.223)	0.626
IV set H	0.022 (0.113)	0.263 (0.143)	1	25.062 (0.015)	0.263
	-0.195 (0.134)	0.654 (0.102)	2	16.372 (0.175)	0.683
	0.019 (0.131)	0.299 (0.142)	1.090 (0.114)	24.791 (0.010)	0.299
IV set I	0.132 (0.111)	0.401 (0.161)	1	17.370 (0.067)	0.401
	0.219 (0.192)	0.386 (0.125)	2	10.743 (0.378)	0.444
	0.132 (0.135)	0.400 (0.163)	1.000 (0.263)	17.370 (0.043)	0.400
IV set J	0.345 (0.125)	0.248 (0.178)	1	3.561 (0.469)	0.345
	0.432 (0.097)	0.041 (0.125)	2	6.100 (0.192)	0.433
	0.271 (0.158)	0.014 (0.195)	1.417 (0.498)	1.997 (0.573)	0.271
IV set K	0.515 (0.105)	-0.239 (0.162)	1	47.319 (0.000)	0.515
	-0.173 (0.097)	0.158 (0.094)	2	29.537 (0.000)	0.234
	0.335 (0.105)	-0.009 (0.141)	1.287 (0.224)	44.513 (0.000)	0.335
IV set L	0.222 (0.136)	-0.046 (0.177)	1	4.819 (0.306)	0.222
	0.036 (0.111)	-0.002 (0.145)	2	11.207 (0.024)	0.036
	0.253 (0.136)	-0.063 (0.195)	1.000 (0.654)	4.883 (0.181)	0.253
IV set M	0.247 (0.138)	0.052 (0.166)	1	4.990 (0.545)	0.247
	0.066 (0.100)	0.078 (0.109)	2	14.803 (0.022)	0.102
	0.247 (0.138)	0.052 (0.178)	1.000 (0.424)	4.990 (0.417)	0.247
IV set N	-0.111 (0.115)	-0.353 (0.165)	1	45.267 (0.000)	-0.111
	-0.358 (0.077)	0.134 (0.091)	2	36.877 (0.000)	0.382
	0.018 (0.068)	0.384 (0.099)	1.520 (0.192)	34.128 (0.000)	0.384
IV set O	-0.467 (0.126)	-0.617 (0.127)	1	57.603 (0.000)	-0.467
	-0.566 (0.103)	-0.348 (0.080)	2	50.023 (0.000)	0.664
	-0.403 (0.064)	-0.114 (0.095)	1.367 (0.169)	48.641 (0.000)	0.404
IV set P	0.145 (0.097)	0.051 (0.109)	1	9.379 (0.497)	0.145
	0.153 (0.064)	-0.034 (0.040)	2	27.972 (0.002)	0.157
	0.180 (0.155)	-0.059 (0.110)	1.392 (0.373)	5.734 (0.766)	0.181

Note: Shown in parentheses are standard errors for $(\hat{\tau}_1, \hat{\tau}_2, \hat{p})$ and p-values for the J-test statistics.