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Aggregation bias in macro models:
does it matter for the euro area?

by Libero Monteforte

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AGGREGATION BIAS IN MACRO MODELS:
DOES IT MATTER FOR THE EURO AREA?

by Libero Monteforte*

Abstract

The euro area represents a case-study of great institutional relevance for the econometric problem of aggregation bias. The available data can be used to analyze the area either with aggregate or with country-specific models. The choice should be the result of a statistical comparison between the two options, with respect to the specific model. In this paper we suggest a representation of the aggregation error based on unobservable components and explicitly conceived for aggregations over a small number of economies.

In the empirical application two alternative models are estimated: the first specifies the main euro countries while the other refers to the whole area. We then evaluate the aggregation error either from the viewpoint of a comparison of the two models with standard methods, or looking at the components of the representation suggested here. Both categories of results indicate non-negligible aggregation errors for the euro area.

JEL classification: C52, F47.

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* Bank of Italy, Economic Research Department.
1. Introduction

The adoption of the euro by twelve countries created a new economic object of interest for institutions, market operators, and researchers aiming to study the whole zone using the same currency. Since the late 1990’s many works have analyzed the macroeconomic properties of the area with regard to not just the financial relationships, but also the markets for labor, goods and services, and public finances. These works include Dornbusch, Favero and Giavazzi (1998), Ramaswamy and Sloek (1997), Giovannetti and Marimon (1998), Guiso, Kashyap, Panetta and Terlizzese (1999), Dedola and Lippi (2000), De Bandt and Mongelli (2000), Clements, Kontolemis and Levy (2001), Ciccarelli and Rebucci (2001), van Els, Locarno, Morgan and Villetelle (2001), Angeloni, Kashyap, Mojon and Terlizzese (2002), Hughes Hallett and Piscitelli (2002), Clausen and Hayo (2002), Gali and Perotti (2003) and Honohan and Lane (2003).

In macroeconometric studies there are two different strategies to represent the euro area: one is to use models with aggregate data (which we call AEAM-Aggregate Euro Area Model); the alternative is to adopt models specified for each country and to pool the results (we call this class of model DEAM-Disaggregate Euro Area Model). Most of the macro empirical literature on the euro area has conducted the study either at the country or at the area level, but only some work considered explicitly the possibility that AEAM could be affected by aggregation bias. In addition, only a few papers have performed a preliminary analysis to decide which one of the two approaches would be the best.

The choice between an aggregate and a disaggregate strategy is a more general issue than our specific problem, which arises in the context of the euro area. In practice, the choice turns out to be “imposed” by practical issues, in particular the availability and quality of the data. In this paper we skip these practical issues, as irrelevant for our focus on the euro countries, and we assess the best modeling approach for the EMU on the basis of the statistical properties of

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2 The euro-wide data are computed from the national figures and the techniques are under debate (See Beyer, Doornik and Hendry, 2000, and Labhard, Weeken and Westaway, 2001, and Bull, 2004).
the estimated models. In particular, we look at the representation and the empirical relevance for the EMU of the aggregation error, being a measure of the difference between AEAM and DEAM residuals.

It is fairly intuitive that when comparing correctly specified models the use of disaggregate data expands the information set from which the parameters are extracted and therefore improves the efficiency of the estimates. The aggregate model parameters are the result of minimization over a smaller number of degrees of freedom than the disaggregate (aggregate coefficient can be seen as a restricted version of the disaggregate), then estimates turns to be inefficient. However, the disaggregate specification may imply greater specification errors, as suggested for the first time by Grunfeld and Griliches (1960, in the following GG), because in several cases aggregate variables have explanatory power in representing micro behavior.

For these reasons it is now acknowledged by the literature that the choice between the two classes of models (AEAM versus DEAM in this paper) does not have a unique theoretical solution but should be empirically investigated case by case, on the base of the goals and the objects of the study (see Pesaran Pierse and Kumar, 1989).

In this paper we assess the existence and the characteristics of the aggregation error in estimated macroeconometric models for the euro area. Together with the standard diagnostics we compute alternative measures of the potential bias, consistently with the formal representation of the aggregation bias suggested here. This representation allows us to identify the sources of non-perfect aggregation, and can thus complement the standard statistical analysis of the aggregation error. In addition, the representation proposed here is particularly useful when the number of aggregated units is small and the units are countries.

Section 2 gives an overview of the literature; in section 3 we present an alternative representation of the aggregation error and the related approach to detect the bias. In the empirical application we estimate an AEAM and a DEAM (section 4) and we assess the aggregation error, comparing the models with standard criteria and with the procedure suggested here (section 5). We therefore provide an assessment of AEAM versus DEAM properties, based on both approaches.
2. Aggregation bias in structural models

The first seminal work on aggregation bias is Theil (1954), where a formal analysis of the choice between aggregate and disaggregate structural models is performed in a simple framework.

Given $n$ time series observations on a set of variables $(y, x)$ available for $m$ micro units (i.e. agents, sectors, countries), Theil assumes that each micro unit $y_{it}$, is generated by the following linear model:

\[
y_{it} = x_{it} \beta_i + e_{it}, \quad i = 1, 2, ..., m; \quad t = 1, 2, ..., n
\]  

where $y_{it}$ is the endogenous variable of unit $i$ at time $t$. $x_{it} = (x_{1it}, x_{2it}, ..., x_{Kit})$ is the $(1 \times K)$ regressor vector of the $x_{it}$ exogenous variables, $\beta_i$ is the constant coefficient vector for the $i$-th unit and $e_{it}$ is the stochastic disturbance (with zero mean and variance $\sigma_i^2$) for the $i$-th unit. Define by linear aggregation the aggregated variables $y_{at} = \sum_{i=1}^{m} y_{it}$, $x_{kat} = \sum_{i=1}^{m} x_{kit}$ and $x_{at} = (x_{1at}, x_{2at}, ..., x_{Kat})$. Consistently with the micro equation specification the aggregate equation would be $y_{at} = x_{at} \beta_a + e_{at}$.

To derive the relationship linking the estimated aggregate disturbance $\hat{e}_{at}$ to the micro disturbances $\hat{e}_{it}$, Theil introduced a set of auxiliary regressions (the projections of the micro exogenous variables on the aggregate ones), corresponding to the following multivariate OLS:

\[
x'_{it} = X_{rt} \beta_i + v_{it}
\]

with $X_{rt} = \text{diag}(x_{1at}, x_{2at}, ..., x_{Kat})$ and $v_{it} = (v_{1it}, v_{2it}, ..., v_{Kit})'$. 

Substituting these expressions into equation (1) above and summing across the micro equations, the aggregate equation error can be written as:

\[
\hat{e}_{at} = \sum_{i=1}^{m} (v'_{it} \hat{\beta}_i + \hat{e}_{it})
\]

The auxiliary regression error is uncorrelated with the structural model disturbance, therefore the aggregate error variance can be represented as follows:
\[ \hat{\sigma}_a^2 = \sum_{i=1}^{m} \hat{\sigma}_i^2 + \sum_{i \neq j}^{m} \hat{\sigma}_{i,j} + \hat{\omega}_i^2 \]

where \( \hat{\omega}_i^2 = 1/n \sum_{t=1}^{n} (v_{it}^t \hat{\beta}_i)^2 \) is the variance of the product between the auxiliary regression residual times the correspondent parameter in the structural equation.

Given the auxiliary regression errors and coefficient properties\(^3\), equation (3) could be written alternatively as:

\[ \hat{\sigma}_a^2 = \sum_{i=1}^{m} \hat{\sigma}_i^2 + \sum_{i \neq j}^{m} \hat{\sigma}_{i,j} + \sum_{i=2}^{m} \sum_{k=1}^{K} (\hat{\beta}_{ki} - \hat{\beta}_{k1})^2 \hat{\sigma}_{vki}^2 \]

where \( \hat{\sigma}_a^2 \) is the variance of the estimated aggregate error \( \hat{e}_{at} \), \( \hat{\sigma}_i^2 \) is the variance of the structural micro residual error \( \hat{e}_{it} \), \( \hat{\sigma}_{i,j} \) is the covariance of i-th and j-th micro residual error and \( \hat{\sigma}_{vki}^2 = 1/n \sum_{t=1}^{n} (v_{Kit})^2 \) is the variance of the auxiliary regression residual \( v_{Kit} \).

From equation (2) we can see that the aggregate equation error is the sum of two components, the micro equation residuals and the aggregation bias (or aggregation error). Given the assumed exogeneity of independent variables in the structural equation, there are no cross correlations among micro structural errors and auxiliary regressions errors, and representation in equation (3) and equation (4) results. The aggregation error variance can then be seen as an average of auxiliary regression error variances, weighted with the micro coefficient squares. Theil shows two special cases of interest for the perfect aggregation: the micro homogeneity and the compositional stability. Micro homogeneity is the equality of the parameters in each micro equation; compositional stability means that the ratio of the micro exogenous variables over the aggregate series is constant over time. In both cases we can see from equation (4) that the aggregation bias vanishes.

Theil’s study was based on strong assumptions, specifically that the aggregate and the disaggregate models are correctly specified. With these hypotheses aggregation is “necessarily bad”. GG significantly widen the perspective, by considering the case of possibly misspecified models. GG stress that a joint analysis of the aggregation and specification

\(^3\) In particular, the sum across i of the \( v_{it}^t \) is a \( K \times 1 \) vector of time series of zeros and the sum across i of the \( b_i \) is a \( K \times 1 \) vector of ones.
error is needed and they conjecture that in practice misspecification is likely to be a more serious issue in disaggregate models; if that is the case, then a trade-off may arise between specification and aggregation errors. The reason for this conjecture is related to the fact that often microeconomic relationships should include aggregate explanatory variables.

The presumption of worst specification in disaggregate models was initially proved to be unreasonable in simulation experiments by Orcutt, Watts and Edwards (1968). Later, Pesaran, Pierse and Kumar (1989, in the following PPK) analytically showed that the GG conjecture corresponded to a special case that applies, for example, when the macro variables are not included in the micro specifications or when there is a greater statistical noise in the micro data than in the aggregate figures.

The criterion of choice proposed in GG is simply the sum of square residuals:

$$\sum_{t=1}^{n} \hat{e}_{dt}^2 \leq \sum_{t=1}^{n} \hat{e}_{at}^2$$

(5)

where $\hat{e}_{dt} = \sum_{i=1}^{m} \hat{e}_{it}$.

PPK correct the GG criterion small sample bias and obtain a correct and consistent estimator of the structural error standard deviations. Assuming the structural model is specified as in equation (1), the criterion for the aggregate errors corresponds to the square of the standard error of the regression:

$$s_a^2 = \sum_{t=1}^{n} \hat{e}_{at}^2/(n - m),$$

(6)

while with micro regression residuals PPK show that the correct estimate assumes the following form:

$$s_d^2 = \sum_{t=1}^{n} \sum_{i=1}^{m} \sum_{j=1}^{m} \left[ n - 2K + tr(P_iP_j) \right]^{-1} \hat{e}_{at} \hat{e}_{jt}$$

(7)

$$s_d \leq s_a$$

(8)

where $P_i = R_i(R_iR_i)^{-1}R_i'$ with $R_i$ the reshaped $(n \times k)$ matrix of regressor observations $x_{it}$.
In correctly specified models by construction $s_d \leq s_a$, therefore, the criterion prescribes that aggregate models could be used only in case of equality. On the contrary, the case of $s_d$ greater than $s_a$ is possible only in the event of misspecification and, if that is the case, then it will represent a measure of (greater) specification error for the disaggregate model.

PPK also propose a formal statistical test of the equality of the two residuals.\(^4\) The test is designed considering the possibility of different micro specification. A drawback is that it is feasible only when the number of units is large relative to the degrees of freedom.\(^5\)

Lippi and Forni (1990, in the following LF), propose a more general representation that emphasizes the dynamics as a possible source of aggregation bias. They use ARMAX models and find complete correspondence with the aggregability conditions indicated above, but with a different approach. Their analysis separates the $m$ units into subsets for which the parameters are homogeneous, and examines the sub systems of heterogeneous units. They recover sufficient conditions for perfect aggregation, and remark that for dynamic models the perfect aggregation is no longer limited to Theil’s two special cases, since it can also derive from the different structures of the dynamic polynomials in the specifications. We can then summarize that aggregation error may depend on coefficients, variables and dynamics.

In conclusion, the literature on aggregation error recalled above presents two different analytical representations of the aggregation error: one is the static framework of Theil and the other, more general one, is that of LF which focuses on the dynamic structure as an additional source of non-perfect aggregation. In terms of application, Theil’s representation leads to criteria and tests that are useful for comparing the two classes of models. In the following pages Theil’s framework, criteria and tests are denoted as SAE (standing for Standard Applied analysis on aggregation Error).

3. A factor representation of the aggregation error

The LF approach is designed to derive theoretically macro functional forms from a large number of heterogeneous micro units. The analytical formulation of the aggregation error is

\(^4\) A necessary condition for the feasibility of the test is that $K_a(m + 1) \geq n$ with $K_a\text{rank}(P_a)$; the test is then only feasible when $m$ is large relative to the number of observations.

\(^5\) For instrumental variable estimates Pesaran, Pierse and Lee (1994) recommend the use of the same criterion, as in equation (8), but they do not have a formal test.
obtained by means of the moving average representation of the structural model. We retain LF’s idea of grouping the units on the base of homogeneity and we show that the aggregation bias can be decomposed by means of a factor analysis of the micro variables.

Assuming the structural micro equations are specified as in eq (1) and the vector of all the micro exogenous variables shares a common component \((x_{ct})\), we can write the following factor model:

\[
X_t = A x_{ct} + \xi_t
\]

(9)

with

\(X_t = (x_{1t}, x_{2t}, \cdots, x_{mt})\),

\(A = (A_1, A_2, \cdots, A_m)'\),

\(A_i = \text{diag}(a_{1i}, a_{2i}, \cdots, a_{Ki})\) where \(a_{Ki}\) is the \(K\)-th factor loading on the \(i\)-th regressors,

\(\xi_t = (\xi_{1t}, \xi_{2t}, \cdots, \xi_{mt})'\),

\(\xi_{it}\) is the \((K \times 1)\) vector of idiosyncratic components and

\(x_{ct} = (x_{ct}, x_{ct}, \cdots, x_{ct})'\) is the \((K \times 1)\) vector of common factors series \(x_{tc}\).

Equation (9) represents a standard factor model, on a vector of time series, across a number of units that, in our case, are countries. The endogenous variability is explained by unit-specific coefficients (loadings) on a component shared by all the units (common component) plus a term that is specific to the single units (idiosyncratic error).

The individual micro model can then be written as:

\[
y_{it} = (A_i x_{ct} + \xi_{it})' \hat{\beta}_i + \hat{e}_{it}.
\]

(10)

Summing across the \(i\) relationship we obtain an expression for the aggregate variables:

\[
y_{at} = \sum_{i=1}^{m} y_{ti} = \sum_{i=1}^{m} (A_i x_{ct})' + \sum_{i=1}^{m} \xi_{it}' \hat{\beta}_i + \sum_{i=1}^{m} \hat{e}_{it}.
\]

(11)

The factor decomposition in equation (9) is the analogue of Theil’s auxiliary regressions. There are evident similarities also in terms of the aggregate error variance:

\[
\hat{\sigma}_{a}^2 = \sum_{i=1}^{m} \hat{\sigma}_i^2 + \sum_{i \neq j} \hat{\sigma}_{ij} + \sum_{i=1}^{m} \hat{\omega}_i^2
\]

(12)
and \( \hat{\sigma}^2_i = 1/n \sum_{t=1}^{n} (\xi_{it}' \hat{\beta}_i)^2 \).

The aggregate variance formulation in equation (12) is the analogue of equation (3). The only difference is that in this context the common factor is non-observable and should be estimated, while in the auxiliary regressions the micro exogenous series are projected over the (observable) aggregate exogenous variable.

Expressing the \( x_{ct} \) in terms of the micro variables in equation (9) and substituting in equation (11), we have the following formulation for the aggregate error and the error variance:

\[
\hat{e}_{at} = \sum_{i=1}^{m} \xi_{it}' (\hat{\beta}_i - (A_i (\sum_{i=1}^{m} A_i)^{-1})' \hat{\beta}_i) + \sum_{i=1}^{m} \hat{e}_{it},
\]

\[
\sigma^2_a = \sum_{i=1}^{m} \hat{\sigma}^{(2)}_{\xi_i} m + \sum_{i=1}^{m} \sum_{j=1}^{m} \hat{\sigma}_{i,j},
\]

with \( \hat{\sigma}^{(2)}_{\xi_i} = (\hat{\sigma}^2_{\xi_{i1}}, \hat{\sigma}^2_{\xi_{i2}}, ..., \hat{\sigma}^2_{\xi_{iK_i}}) \) the \((1 \times K)\) vector of the i-th idiosyncratic component variances and \( m = \text{diag}((\hat{\beta}_i - (A_i (\sum_{i=1}^{m} A_i)^{-1})' \hat{\beta}_i)') (\hat{\beta}_i - (A_i (\sum_{i=1}^{m} A_i)^{-1})' \hat{\beta}_i)). \]

From equation (14) we see that taking into account the residual cross-correlations of micro equations, the aggregation error variance is an average of the idiosyncratic component variances weighted with squared functions of the heterogeneity in structural parameters. Assuming the correct specification of the disaggregate model, we see that even in this context the variance of the disaggregate error would be no greater than that of the aggregate.

We deduce that the aggregation error can be expressed as a function of the micro homogeneity and the idiosyncratic component of the structural model regressors; thus, in empirical research, it is possible to detect the conditions of existence of the aggregation bias by looking at these two elements. In the following we call this approach FAE (standing for Factor Analysis for aggregation Error). FAE is in line with LF representation, as in both of them the basic principle is to identify the set of heterogeneous micro units and perform the aggregation analysis on these alone. In LF the units are preliminarily divided into homogeneous sets on which the aggregation properties are verified. Similarly, in FAE the co-movements of the individual series are extracted and then the aggregation analysis focuses on micro heterogeneous components.
From equation (14) it is also possible to trace the similarities of FAE with Theil’s approach. Theil’s compositional stability in equation (14) corresponds to null \( \hat{\sigma}_{\xi_i}^2 \), but as by construction \( \xi_i \) cannot be constant, the condition becomes that all the micro \( \xi_i \)'s are absent. The absence of idiosyncratic components is a rather extreme and special case which implies compositional stability. The micro homogeneity, too, can be seen in the FAE framework, since the micro individual parameters cancel out in the quadratic term of equation (14), so that the whole error vanishes.

There are also differences. FAE representation is based on unobserved components, which should be estimated in empirical research, while in SAE the representation is on observable series. This has advantages and drawbacks. On the one hand, in estimating the components there is a problem of measurement error arising.\(^6\) On the other hand, extracting unobserved components gives a variety of information on the multivariate structural properties of the variables that is of economic interest, besides the statistical interest of the aggregation error.\(^7\) The FAE analysis, for example sheds light on the unit source of the aggregation error, which in a cross-country analysis can provide useful economic information.

In addition, the need to estimate the two fundamental components has some advantages. First of all, when \( m \) is a small number the factor model can be estimated by maximum likelihood methods (Stock and Watson, 1981, Engle and Watson, 1981, Quah and Sargent, 1993).\(^8\) Second, it is possible to conceive a strategy to test for the aggregation error in a different way from the standard approach (SAE): besides testing on the micro homogeneity hypothesis, a test on the micro specific component can be performed.

Another point worth stressing concerns the different hypothesis needed for specification with SAE and FAE. In the former we need both the aggregate and the disaggregate models to be exactly specified, otherwise the criteria and test just described are not appropriate. By contrast with FAE only the disaggregate specification is needed, since the study is essentially

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\(^6\) See Aigner and Goldfeld (1974) for an analysis of the effect of measurement errors on the aggregation error.

\(^7\) On the use of factor models to construct cyclical and inflation indicators, for the euro area see Altissimo, Bassanetti, Cristadoro, Forni, Lippi, Reichlin and Veronese (2001) and Cristadoro, Forni, Reichlin and Veronese (2001).

\(^8\) When \( m \) is large the model can be identified and estimated as proposed by Forni, Hallin, Lippi and Reichlin (2002).
on the disaggregate model properties, such that any corresponding aggregate model would be affected by the bias.

To conclude, FAE is consistent with the SAE approach. The main difference is that FAE uses unobservable estimated components, with the advantages and drawbacks we described above. In practice, FAE is feasible with a small number of micro-units and, unlike the SAE, gives an insight into the economic sources of non-perfect aggregation. SAE provides instruments for an empirical comparison of aggregate versus disaggregate models that are reliable only in the case of correct specification of both; in FAE the correct specification of the disaggregate model is sufficient to recover the conditions for the potential bias in the corresponding aggregate model.

With SAE we detect if there is a problem of aggregation, whether with FAE we identify separately the two main heterogeneity components in terms of the data or the model coefficient or both.

FAE can thus be seen as a complementary tool for aggregation analysis, designed to detect the economic causes of non-perfect aggregation and intended for a of small number of micro units. The economic interpretation of FAE makes the approach particularly useful in country pooling, as the estimated unobservable components are of some economic interest regardless of the econometric problem of aggregation bias. We therefore use it in the euro area context.

4. Aggregation bias for EMU: an application with two small models

Some practical issues in the choice between classes of models for the euro area are worth noting. First of all the set of economies adopting the same currency is of recent definition and we can easily foresee that it will change in the future. In addition, we should note that before the euro most macroeconomic applied studies were on single countries, and therefore there exists a huge stock of literature for national economies. Last but not least, the quality of the data is better at country than at international level because the statistics are collected by the national statistical offices.9 Issues on the euro area data construction are beyond the aim of this

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9 At the beginning of EMU the problem of suitable statistics was posed for the harmonization of the series relating to monetary policy, like HICP and M3, but for all the rest of the macroeconomic data there is still much work to be done (See Issing, Angeloni, Gaspar and Tristani, 2001). Methodological issues remain to be solved and different options are available, for example on the share to be used: fixed or variable, using nominal exchange
paper, but the lack of debate on the construction of time series for the area points to the scanty interest in methodological issues concerning the shift from national to European studies. On macro modelling there are some notable exceptions: Fagan and Henry (1998), Mayes and Viren (2000), Fabiani and Morgan (2003), Marcellino, Stock and Watson (2003) and Sbrana (2003).

The option between DEAM and AEAM was available for the main structural models of international institutions. The ECB adopted both classes of models (the Area Wide Model is documented in Fagan, Henry and Mestre (2001), while the IMF moved from a version of the MULTIMOD, in which the main European economies were separately specified, to a new version, in which there is a single block (see Hunt and Laxton, 2002).

The following is an exercise of aggregation error assessment for the main euro countries. We estimate two small structural models, a DEAM and an AEAM, and we compare their properties with SAE and their forecasting ability. We therefore add to these findings those based on the factor representation (FAE).

The DEAM is a standard macro model similar to other backward-looking models already used to assess the optimality of monetary policy (i.e. Rudebusch and Svensson, 1999). The countries represented are Germany, France and Italy, together covering about 70 per cent of euro-area GDP. There is a supply equation, where the inflation rate depends on the lagged endogenous variable, on import prices from the other countries (expressed in domestic currency) and on output gap. The unitary restriction on the sum of the coefficients on lagged domestic prices and on foreign prices is tested and accepted, then an accelerationist version of the Phillips curve is embodied. The demand equation specifies the output gap as a function of the real interest rate and the gap of the other countries, only if it is found to be statistically significative.10 The model takes into account the trade links among the economies, either on the supply side with import prices, or on the demand side.

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10 It is expected that in the demand equation there is an effect of relative prices with the other countries, but we statistically tested and accepted the hypothesis that for this model there are no effects, and for parsimony we excluded this term.
The general formulation of the model has the following form:

$$
\pi^j_{t+1} = \sum_{k=1}^{p} \alpha_{j,k} \pi^j_{t+1-k} + \sum_{i \neq j}^{p} \sum_{k=0}^{p} \beta_{j,i,k} (\pi^i_{t+1-k} + e^i_{t+1-k}) + \sum_{k=0}^{p} \eta_{j,k} y^j_{t+1-k} + u^j_{t+1},
$$

$$
y^j_{t+1} = \sum_{k=1}^{p} \theta_{j,k} y^j_{t+1-k} + \sum_{i \neq j}^{p} \sum_{k=0}^{p} \varphi_{j,i,k} y^i_{t+1-k} + \sum_{k=1}^{p} \psi_{j,k} (i^j_{t+1-k} - 4 \cdot \pi^j_{t+1-k}) + v^j_{t+1},
$$

where:

$$y^j_{t+1} = \text{output gap, band-pass filter (see Baxter and King, 1995) of GDP (ESA 95 National Accounts) of country } j;$$

$$\pi^j_{t+1} = \text{quarter–on–quarter consumer inflation rate (ESA 95 consumption deflator) in country } j;$$

$$e^i_{t+1-k} = \text{quarter–on–quarter rate of change of the exchange rate (quarterly averages of bilateral rates of the Bank of Italy data-base) between country } i \text{ and country } j;$$

$$i^j_{t+1} = \text{short-term interest rate (three-month interbank rate from the BIS data base) in country } j;$$

$$i^j_{t+1} - 4 \cdot \pi^j_{t+1-k} = r^j_{t+1} \text{ real interest rate (ex-post) in country } j.$$

The DEAM also includes two identities to determine inflation and output gap as the average of the three countries’ variables, using the same weights as are used to construct the aggregate series.\textsuperscript{11}

In the case of multi-country models, simultaneous linkages are obviously to be expected, therefore we opted for a 3SLS method. It is assumed that the interest rate does not affect the output gap contemporaneously, hence the model does not contain an estimate of the monetary policy reaction function. The sample period is 1978.Q1 to 1998.Q4 and we employed a general-to-specific approach. The initial starting specification included six lags of any exogenous variable; then we removed the statistically insignificant lags with the result presented in Table 1 (Table 2 contains the residual correlation matrix).

\textsuperscript{11} The weights (for GDP and consumer prices, respectively) are the following: Germany: 0.43, 0.44; France: 0.29, 0.27; Italy: 0.28, 0.29.
The AEAM is similar in structure to the DEAM. With no cross-country terms and import prices the AEAM structure is as follows:

\[
\pi_{t+1} = \alpha_1 \pi_t + (1 - \alpha_1) \pi_{t-3} + \eta y_t + u_{t+1}, \\
y_{t+1} = \theta y_t + \psi(i_t - 1 - 4 \cdot \pi_{t-1}) + v_{t+1}.
\]

The specification approach and the estimate sample period are the same as the DEAM. To take into account demand and supply residual correlation the model is estimated with SURE. The full listing of the model is in Table 3.

These models have also been employed in two papers on the role of national information in the conduct of euro-area monetary policy. In Angelini, Del Giovane, Siviero and Terlizzese (2002) the use of a monetary policy reaction function specified on country-specific variables is compared with a rule specified on area-wide variables, using the DEAM developed here as a representation of the economy. In Monteforte and Siviero (2002) there is an assessment of the welfare losses incurred with a monetary policy implemented with a rule optimized subject to the AEAM versus a rule subject to the DEAM.

The DEAM and AEAM were estimated with data for the period pre-dating the introduction of the euro. There is therefore concern that, notwithstanding their performance in the estimation period, they might be affected by structural discontinuity following the introduction of the single currency. Taking 1997 as the beginning of the euro era allows us to use a reasonably sized sample (twenty quarterly observations) to test for stability.\(^{12}\) Accordingly, both models were re-estimated using pre-euro data as defined above (1978.Q1 to 1996.Q4). For both models, the parameter estimates are basically the same as those found with the original sample (1978.Q1 to 1998.Q4).

The results of out-of-sample stability testing are shown in Table 4 and Figures 1 and 2. For both models, the empirical evidence overwhelmingly rejects the hypothesis of parameter instability; the figures show no detectable signs of convergence of the DEAM parameters.

\(^{12}\) While the euro was officially introduced only on January 1st, 1999, one may argue that, at least since late 1996, the monetary policies of the three countries we consider had been tightly constrained: the bilateral exchange rates remained basically constant at about the same level as the irrevocable exchange rates with which those countries joined the euro area two years later; the financial markets considered it to be highly probable that those countries would participate in the single currency (with the exception, for 1997, of Italy); moreover, fiscal policies were also tightly constrained by the convergence process.
Although one cannot rule out the possibility of sizeable changes in the future, these results at least indicate that no such change is detectable yet, even though there is scarcely any doubt that the introduction of the euro represented a major breaking point in the policy framework.

Figures 3, 4 and 5 show the impulse responses of both models to a number of shocks. Since the Phillips curve is vertical in both models, neither of them would be stable if they were not augmented with a stabilizing policy rule. To compute impulse responses, both models were supplemented with the same monetary policy reaction function (a Taylor-type rule with coefficients 1.5, 0.5 and 0.5 for current inflation, the output gap and the lagged interest rate, respectively). As shown by the results reported in the figures, both models are stable, although even temporary shocks may result in very persistent deviations from equilibrium.\textsuperscript{13}

The results show some common patterns between the AEAM and the DEAM. First, in both models the effects of the shocks are rather long-lasting. Second, a shock to the aggregate supply equation induces a (dampened) oscillatory response of both inflation and the nominal interest rate. Third, the general pattern of responses is similar across the models: e.g. a Phillips curve shock induces a contraction in output that peaks, in both models, in the third and fourth years after the shock; similarly, a (temporary) increase in the policy-controlled interest rate results in a temporary contraction of output that reaches its maximum at the end of the first year after the shock (moreover, the size of the contraction is not too dissimilar in the two models). Fourth, the response of inflation to a monetary policy shock comes with a further lag with respect to the reaction of output (the lag is somewhat more pronounced in the case of the DEAM).

The results, however, also signal several major differences. First, according to the DEAM the economy takes longer to get back to equilibrium after being hit by a shock. Second, the size of the responses is usually larger for the DEAM model (e.g. while the contractionary effect of an aggregate supply shock reaches a maximum, for both models, in the third and fourth years after the shock, the reaction of output in the DEAM is about three times as large as in the AEAM; also, the DEAM is more reactive to monetary policy as far as inflation is concerned, while it is somewhat less sensitive than the AEAM if one considers the effects on the output gap). Third, because the impact of aggregate supply and aggregate demand shocks

\textsuperscript{13} For both the aggregate demand and aggregate supply equations, the shock amounts to one standard deviation of the corresponding estimation residuals. In the case of a monetary policy shock, the short-term interest rate is raised (for just one period) by 100 basis points.
on the economy is more pronounced overall, monetary policy is more activist in the DEAM, even though both models were augmented with exactly the same Taylor-type rule.

The AEAM and DEAM representation of the three largest economies in the euro area is admittedly rather crude. Would our conclusions below be dramatically different if larger models were considered, which include a more detailed description of the entire euro-area economy? To answer this question we explore whether the main features of the AEAM and DEAM are in accordance with those of some of the main macro models used by policy-making and economic analysis institutions. From our viewpoint, therefore, it is of particular interest to ascertain whether the differences between the main properties of the AEAM and DEAM can be deemed representative of the effects of aggregation in larger and more detailed models.

From a qualitative viewpoint, the features of the AEAM and DEAM are reasonably similar to those of the (average of the) other models we consider. In most models, the full effects of a monetary policy shock on demand, output and prices unfold fully only with some lag. The impact is initially stronger on demand and production (reaching its maximum intensity in the course of the first two years); inflation tends to react more slowly (the largest fall occurring, in general, in the course of years two and three). In the AEAM and DEAM, while the effects of the shock take about one year longer to unfold fully, the lag between the reaction of the output gap and that of inflation is about the same. Moreover, according to most disaggregate models, the asymmetries in the individual-country responses to shocks are far from trifling (and are in fact sizeable according to both the Mark III model and the results reported in van Els, Locarno, Morgan and Villettelle, 2001), the only exception being the Quest.

To add some quantitative evidence to our analysis, let us focus on the IMF’s Mark III (which includes a disaggregate euro-area block) and Mark IIIb (aggregate) models only. There are two main reasons for this choice: first, the Mark III and Mark IIIb were developed by the same modeling team and thus presumably share the same theoretical underpinnings and

---

14 Specifically, the discussion in the text reflects a comparison of the AEAM and DEAM with the following models: the ECB’s Area Wide Model (Fagan, Henry and Mestre, 2001; Dieppe and Henry, 2002); the IMF’s Multimod Mark III (disaggregate) and Mark IIIb (aggregate) versions (Hunt and Laxton, 2002); the European Commission’s Quest (Roeger and in’t Veld, 2002); the National Institute’s NiGem (Barrell, Gottschalk, Hurst, and Welsum, 2002). Furthermore, the results presented in van Els, Locarno, Morgan and Villettelle (2001) — based on the models of the individual euro-area economies developed and maintained by the respective NCBs— were also taken into consideration. Since the information available is considerably less detailed than needed for a systematic model comparison exercise (a notoriously difficult and tricky task), the evidence below should be viewed as only indicative.
estimation techniques. Therefore, any difference between the two models can be interpreted—more safely than in the case of other models— as largely stemming from what the data themselves indicate, rather than, say, from differences in the theoretical framework or in the way the empirical models are specified and estimated. Second, while the Mark III and Mark IIIb differ in the way the euro area is modeled, there are only minor differences in the way the blocks for all the other countries or regions are modeled. This is not the case for the rest of the models (e.g. while some of them include a description of the rest of the world, others do not).

Table 5 reports the effects of a four-quarter 100 basis points nominal interest rate shock in the AEAM, DEAM, Mark IIIb and Mark III models. Comparing the results for the latter pair of models, the effects of the shock on euro-area real GDP is initially stronger in the aggregate model; from year 3 onwards the differences between Mark III and Mark IIIb are negligible. By contrast, the fall in inflation is higher in the Mark III (disaggregate) than in the Mark IIIb (aggregate), the average difference between the two being between -0.05 (euro-area shock only) and -0.07 per cent (world-wide shock). Exactly the same pattern is found in the case of our models: the decline in the output gap is initially more pronounced in the AEAM; the differences between the AEAM and DEAM become negligible from year 3 onward. By contrast, the effects on inflation are sensibly more marked in the DEAM (by 0.04 per cent on average). While the comparison also highlights some differences (partly attributable to the fact that the effects of the shock in the Mark III and Mark IIIb models are by construction stronger and more front-loaded, at least as far as inflation is concerned, than in the AEAM and DEAM), the salient features associated with aggregate and disaggregate modeling approaches clearly

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15 In interpreting the results, it should be noted that the effects of the shock in the Mark III and Mark IIIb models are a priori likely to be stronger, at least as far as inflation goes, than in the AEAM and DEAM, as indeed confirmed by the figures (for the real economy effects, the sign of the distortion is not obvious). The main differences between the two sets of simulation results are the following: (a) both Mark III and Mark IIIb include a description of the rest-of-the-world economy, pointing to a number of spillover and feedback mechanisms that are absent in the AEAM and DEAM; (b) the real economy variable in our models is the output gap, while for the Mark III and Mark IIIb models only data for real GDP are available; (c) the simulation results for the Mark III and Mark IIIb refer to the case of endogenous euro exchange rates. More specifically, Hunt and Laxton (2002) report the effects of two monetary policy simulations: (i) shock to the euro-area policy interest rate only (resulting in a considerable initial appreciation of the effective euro exchange rate); (ii) shock to the world policy interest rate (the reaction of the euro exchange rate is relatively muted here; however, the monetary policy shock itself is implicitly stronger than in simulation (i) because it occurs world-wide). In either case, the effects of the shock are likely to be more pronounced in the Mark III and Mark IIIb models than in the DEAM and AEAM; (d) the two pairs of models are supplemented with different monetary policy reaction functions. Indeed, if one corrects the Mark III and Mark IIIb outcomes on the basis of the effects of exchange rate movements as estimated in other models (e.g. the simulation experiments in van Els, Locarno, Morgan and Villetelle, 2001), the numerical results commented in the text become very similar across the two pairs of models.
go in the same direction in both pairs of models: a disaggregate model tends to result in more pronounced effects of monetary policy on inflation, while the opposite applies to output.

5. Aggregation bias diagnostics on the two models

We now compare the two models in terms of aggregation bias. Following SAE we computed different estimators of the error variances and we provide a measure of the forecasting ability.

The PPK test of perfect aggregation is unfeasible as the small number of micro units makes it impossible to compute the statistic. We computed instead the GG and the PPK criterion, respectively corresponding to equation (5) and equation (6) and (7). In interpreting the result we remark that the PPK criterion is an unbiased estimator of the standard error; GG is a small sample biased estimator of the variances. Both criteria (in Tables 6 and 7) indicate smaller DEAM errors than AEAM, thus indicating the existence of a non-negligible aggregation bias. The output gap residuals seem to be less affected by the bias than the inflation residuals.

The choice between aggregate and disaggregate models can also be made on the basis of the forecasting ability, as in Zellner and Tobias (2000) and in Baltagi, Griffin and Xiong (2000). To assess the predicting performances we simulated the models from 1978.Q1 to 2001.Q4 and we computed the RMSE with one to eight steps ahead (Tables 8). We also computed the RMSE on the shorter, out-of-sample range (Table 9). On the basis of the entire available sample, the DEAM sharply outperforms the AEAM, especially in the case of the aggregate supply equation. Out-of-sample results are mixed: in particular, for relatively long forecast horizons the AEAM aggregate demand equation performs slightly better than the corresponding DEAM equations; in the case of aggregate supply equations, by contrast, the performance of the DEAM remains consistently better than that of the AEAM (note, however, that the number of out-of-sample observations is very small and that there are reasons to believe that in-sample tests are more reliable than out-of-sample ones; see Inoue and Kilian, 2002).

These findings suggested investigating the possibility that DEAM predictions encompass the information contained in the AEAM. Therefore we performed a forecast encompassing test, projecting output gap and inflation actual values over the forecast values at different steps ahead with both the DEAM and AEAM. The results, in Table 10, show that for supply
equations the DEAM values encompass the information of the AEAM, as the restriction (unitary coefficient for the disaggregate simulated values and zero for the constant and the AEAM) is always accepted, while the contrary does not apply. For the demand equation we have unacceptable results, as in both cases the restriction is refused and, in general, the encompassing equation is not satisfactory, with some not acceptable signs.

From the SAE analysis we conclude that the DEAM has a better fit than the AEAM and is better for forecasting purposes. This dominance is overwhelming for price equations, while for demand it is less striking. From this analysis we do not know the causes of the DEAM dominance, either in terms of categories (parameters, variables or dynamics) or in terms of micro units (which country is more heterogeneous). We can retrieve this information using FAE.

In the previous section we showed that FAE representation decomposes the aggregation error in terms of the parameter heterogeneity and idiosyncratic components of the disaggregate regressors. Consequently, to identify the sources of non-perfect aggregability we need to look at both the differences in the micro parameters across units (micro heterogeneity) and the relevance of the national specific components in the data.

Concerning the difference in parameters, since we performed system estimation, we can apply the standard test to the micro homogeneity of the DEAM coefficients. In Table 11 we show the test results for the structural regressors: interest rate and import prices. We observe a clear homogeneity not only for the common regressors (across-country equations), but also considering all variables included in the system. Given the small number of micro units of the system, we can also check which unit seems to differ more from the others by testing the parameters in pairs. The results confirm the homogeneity hypothesis for the supply equation, while for the demand equation the pairs including Italy seem more heterogeneous than those including Germany and France.

In our DEAM, the country equations are similar in structure but not in dynamics and there are bilateral differences in the international regressors. Thus, a comparison between structural coefficients would be affected by national peculiarities in specification. A possible solution to this asymmetry is to compute the test on the interim multipliers of the explanatory variables of the system at different lags. This test refers to the same regressors entering in the relationship with the same lag and also takes into account the endogeneity of the output.
gap as inflation regressors. The test results on the multiplier equality are shown in Table 12. We observe that for the first two lags and in the long run there is a substantial homogeneity, while at some intermediate steps there are indications of non-homogeneous responses. This finding, although consistent with the difference in dynamic elasticities we observed in the previous section, do not modify the broad assessment of substantial homogeneity of the DEAM parameters.

Now we turn to the second component of the aggregation error in the FAE representation (equation 14), the idiosyncratic components. To assess the relevance of this component we estimate a factor model for the two non-restricted system regressors: the output gap, as explanatory of inflation, and the interest rate, as explanatory of the gap. Here the aim is explicitly focused to the aggregability conditions, but the extracted loadings could be of economic interest in their own right.

Given the small number of micro units in the DEAM, the factor model is necessarily identified with only one common component. The factor specification is auto regressive with the order determined maximizing the likelihood. We assume static factors and gaussian stochastic components; therefore the likelihood can be computed with kalman filter algorithm (see Engle and Watson, 1981; Harvey, 1989; and Stock and Watson, 1991). The general functional form is the following:

\[
\begin{pmatrix}
    x_{t1} \\
    x_{t2} \\
    x_{t3}
\end{pmatrix}
= \begin{pmatrix}
    \alpha_1 \\
    \alpha_2 \\
    \alpha_3
\end{pmatrix} X_{t,c} + \begin{pmatrix}
    \xi_{t1} \\
    \xi_{t2} \\
    \xi_{t3}
\end{pmatrix},
\]

\[X_{t,c} = \phi_1 X_{t-1,c} + \phi_2 X_{t-2,c} + v_t.\]

The common component of the interest rate is an AR(1), while for the output gap is an AR(2), consistently with the cyclical path produced by the latter process.

The model estimates are in Tables 13 and 14. The coefficient values are reasonable and both models seem to capture the data variability, as the scatter diagrams of common components and national variables show (Figures 6 and 7). We see that, except for the German

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16 The adoption of static factors, even if sub-optimal, is supported in Doz and Lenglart (1999), where it is shown that static factor models estimated with maximum likelihood are consistent with dynamic factor models even in presence of autocorrelation. The static factor model is adopted by the European Commission for the construction of a confidence index for the euro area (see Deroose, Mills and Saint Aubin, 2001).
gap, the estimated unobservable components approximate the country macro data quite well. Notwithstanding the good fit of the model, the country-specific components explain more than 30 per cent of the total variance, both for the gap and for the interest rate. These components are so relevant that in every possible test they would be different from zero. Given our interest in aggregability conditions we deduce that with such high country-specific components in the data it would be difficult for any an area-wide model to be not affected by aggregation bias. Concerning the countries, we see that the German data are the least tailored to the common factor model. Either for the output gap or for the interest rate the share of the variance explained by the idiosyncratic component is considerably higher than for the other two economies.

Having assessed the two sources of aggregation error we can conclude that the DEAM non-aggregability (detected with SAE) seems to come from the country variables more than from the model parameters. There is, in fact, weak evidence of the possibility that coefficients are responsible for the non-aggregation: structural parameters do not seem heterogeneous, while some interim multipliers differentiate. Looking at the national results, we see that only Italy’s demand coefficients are statistically different from the Franco-German bulk. On the other hand, according to the factor model estimates we find evidence of sizeable country-specific components in explaining the macro data, in particular for Germany. The conclusion that the source of heterogeneity that matters for aggregation comes in particular from the German data could have quite striking consequences. In fact one could deduce that every area-wide model, using output gap and interest rate, is in danger of being affected by non-negligible aggregation bias.

6. Conclusions

The issue of aggregation in structural models is a methodological point that, up to now, has not received widespread consideration in empirical studies for the euro zone.

In this paper we suggest complementing the standard representation of the aggregation error (SAE perspective) with the representation based on factor model decomposition (FAE). We show that the two approaches are theoretically consistent, even if they might lead to different figures in practice: SAE is designed for a large number of micro units, while FAE is feasible and recommended for a few units; SAE applications are based on tests and criteria
on observable variables, while FAE requires the estimation of unobservable components, hence the coherence between the two depends on the statistical consistency of the estimated components. FAE is therefore suggested as an SAE complementary instrument for analysis with a small number of units and designed to explain the sources of heterogeneity. The economic interpretation of FAE analysis means it is strongly recommended in the case of country pooling.

In the empirical study we developed and compared a disaggregate and an aggregate model. With SAE techniques we see that DEAM dominates both in the fit and in the prediction of the data. With FAE we were able to decompose the components of non-perfect aggregation. The structural parameters look homogeneous although once adjusted for the dynamics they show some divergences. On the contrary, the system regressors show large country-specific components. This implies potential risks of aggregation errors in models using the same macro data. Looking at the country results, Italy seems to differ as regards the parameters of demand equations, while German macro data present specific components that are much larger than those of the other two countries.

In our empirical study we used a small model and did not consider all the euro countries. We think that if more complex structural models are adopted and the set of economies is enlarged the aggregation error could be greater than reported here, given that, arguably, the heterogeneity of the system would increase. Therefore, we suspect the euro-area aggregation bias reported here is a lower bound and we encourage a systematic and preliminary verification of the relevance of the aggregation error in empirical studies on the euro area.
### ESTIMATE OF THE DEAM

<table>
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<tr>
<th>Input from:</th>
<th>Equations for: Germany</th>
<th>Equations for: France</th>
<th>Equations for: Italy</th>
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<td>0.036 [0] (restr.)</td>
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<td>r</td>
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<table>
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<tr>
<td>y</td>
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<th>Equations for: Italy</th>
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<tr>
<td>y</td>
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<td>r</td>
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</table>

|          | R² | 0.514 | 0.635 | 0.902 | 0.730 | 0.960 | 0.752 |
|          | R² | 0.483 | 0.622 | 0.894 | 0.720 | 0.958 | 0.740 |
|          | σ  | 0.411 | 0.799 | 0.332 | 0.443 | 0.259 | 0.490 |
|          | DW| 2.160 | 2.059 | 2.050 | 1.888 | 2.024 | 1.815 |

In brackets: standard error of the coefficients.
In square brackets: lag with which the variables enter the equations.
CORRELATION MATRIX OF STOCHASTIC DISTURBANCES OF THE DEAM

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<th>Aggregate supply</th>
<th>Aggregate demand</th>
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<tr>
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<tr>
<td>France</td>
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<td>Italy</td>
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ESTIMATE OF THE AEAM

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<th>$y$</th>
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<td>(0.075)</td>
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<td>$0.769$ [-1]</td>
<td>(0.035)</td>
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<td>(0.022)</td>
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<td>$R^2$</td>
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<tr>
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<td>$\sigma$</td>
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<td>DW</td>
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The correlation between the demand and supply disturbances is 0.031.

In brackets: standard error of the coefficients.

In square brackets: lag with which the variables enter the equations.
## CHOW FORECAST TEST ON DEAM AND AEAM

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<tr>
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<tr>
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<th>F-stat</th>
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<tr>
<td>Aggregate supply</td>
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<td>Aggregate demand</td>
<td>0.568</td>
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### Table 5

Comparison of MARK III/MARK III B models and DEAM/AEAM

(100 b.p. shock to policy short-term interest rate for four quarters)

<table>
<thead>
<tr>
<th>Models</th>
<th>Years</th>
<th>Inflation</th>
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<th></th>
<th></th>
<th></th>
<th>Real activity&lt;sup&gt;(1)&lt;/sup&gt;</th>
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<td></td>
<td></td>
<td>-0.00</td>
<td>-0.09</td>
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<td>-0.14</td>
<td>-0.11</td>
<td>-0.09</td>
<td>-0.16</td>
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<td>0.00</td>
</tr>
<tr>
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<td></td>
<td></td>
<td>-0.01</td>
<td>-0.08</td>
<td>-0.16</td>
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<td>-0.21</td>
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<tr>
<td>DEAM-AEAM</td>
<td></td>
<td></td>
<td>-0.01</td>
<td>0.01</td>
<td>-0.02</td>
<td>-0.07</td>
<td>-0.10</td>
<td>0.01</td>
<td>0.04</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Shock to euro-area interest rate&lt;sup&gt;(2)&lt;/sup&gt;</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MARK III B</td>
<td></td>
<td></td>
<td>-0.18</td>
<td>-0.04</td>
<td>-0.07</td>
<td>-0.09</td>
<td>-0.09</td>
<td>-0.38</td>
<td>-0.18</td>
<td>-0.03</td>
<td>-0.03</td>
</tr>
<tr>
<td>MARK III</td>
<td></td>
<td></td>
<td>-0.14</td>
<td>-0.12</td>
<td>-0.16</td>
<td>-0.16</td>
<td>-0.13</td>
<td>-0.20</td>
<td>-0.14</td>
<td>-0.02</td>
<td>-0.04</td>
</tr>
<tr>
<td>MARK III - MARK III B</td>
<td></td>
<td></td>
<td>0.04</td>
<td>-0.08</td>
<td>-0.09</td>
<td>-0.07</td>
<td>-0.04</td>
<td>0.18</td>
<td>0.04</td>
<td>0.01</td>
<td>-0.01</td>
</tr>
<tr>
<td>Shock to world interest rate&lt;sup&gt;(2)&lt;/sup&gt;</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MARK III B</td>
<td></td>
<td></td>
<td>-0.05</td>
<td>-0.10</td>
<td>-0.12</td>
<td>-0.11</td>
<td>-0.10</td>
<td>-0.35</td>
<td>-0.21</td>
<td>-0.01</td>
<td>0.00</td>
</tr>
<tr>
<td>MARK III</td>
<td></td>
<td></td>
<td>-0.11</td>
<td>-0.18</td>
<td>-0.20</td>
<td>-0.18</td>
<td>-0.14</td>
<td>-0.17</td>
<td>-0.22</td>
<td>-0.02</td>
<td>-0.02</td>
</tr>
<tr>
<td>MARK III - MARK III B</td>
<td></td>
<td></td>
<td>-0.06</td>
<td>-0.08</td>
<td>-0.08</td>
<td>-0.07</td>
<td>-0.04</td>
<td>0.18</td>
<td>-0.01</td>
<td>-0.01</td>
<td>-0.02</td>
</tr>
</tbody>
</table>

Notes:

(1) Output gap for AEAM and DEAM; real GDP for MARK III and MARK III B
(2) Endogenous exchange rates.
Table 6

GRUNFELD GRILICHIES CRITERIUM ON PERFECT AGGREGATION

<table>
<thead>
<tr>
<th>GG Criterium</th>
<th>DEAM</th>
<th>AEAM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aggregate supply</td>
<td>3.856</td>
<td>6.5231</td>
</tr>
<tr>
<td>Aggregate demand</td>
<td>15.948</td>
<td>18.961</td>
</tr>
</tbody>
</table>

The GG criterium is the residual sum of squares of equation (5).

Table 7

PPK CRITERIUM ON PERFECT AGGREGATION

<table>
<thead>
<tr>
<th>PPK Criterium</th>
<th>DEAM</th>
<th>AEAM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aggregate supply</td>
<td>5.062</td>
<td>8.180</td>
</tr>
<tr>
<td>Aggregate demand</td>
<td>20.160</td>
<td>23.717</td>
</tr>
</tbody>
</table>

The PPK criterium refers to the statistic in equation (6) for the AEAM and equation (7) for the DEAM
Table 8
RMSE OF N-STEP AHEAD DYNAMIC ERRORS ON DEAM AND AEAM
(1978:1 2001:4)

<table>
<thead>
<tr>
<th>DEAM</th>
<th>Aggregate supply</th>
<th>Aggregate demand</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.219</td>
<td>0.463</td>
</tr>
<tr>
<td>2</td>
<td>0.273</td>
<td>0.607</td>
</tr>
<tr>
<td>3</td>
<td>0.303</td>
<td>0.687</td>
</tr>
<tr>
<td>4</td>
<td>0.344</td>
<td>0.764</td>
</tr>
<tr>
<td>8</td>
<td>0.470</td>
<td>0.846</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>AEAM</th>
<th>Aggregate supply</th>
<th>Aggregate demand</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.283</td>
<td>0.468</td>
</tr>
<tr>
<td>2</td>
<td>0.327</td>
<td>0.620</td>
</tr>
<tr>
<td>3</td>
<td>0.370</td>
<td>0.701</td>
</tr>
<tr>
<td>4</td>
<td>0.394</td>
<td>0.771</td>
</tr>
<tr>
<td>8</td>
<td>0.552</td>
<td>0.834</td>
</tr>
</tbody>
</table>

Table 9
RMSE OF N-STEP AHEAD DYNAMIC ERRORS ON DEAM AND AEAM
(1999:1 2001:4)

<table>
<thead>
<tr>
<th>DEAM</th>
<th>Aggregate supply</th>
<th>Aggregate demand</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.278</td>
<td>0.289</td>
</tr>
<tr>
<td>2</td>
<td>0.331</td>
<td>0.460</td>
</tr>
<tr>
<td>3</td>
<td>0.258</td>
<td>0.601</td>
</tr>
<tr>
<td>4</td>
<td>0.366</td>
<td>0.676</td>
</tr>
<tr>
<td>8</td>
<td>0.339</td>
<td>0.540</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>AEAM</th>
<th>Aggregate supply</th>
<th>Aggregate demand</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.357</td>
<td>0.277</td>
</tr>
<tr>
<td>2</td>
<td>0.382</td>
<td>0.439</td>
</tr>
<tr>
<td>3</td>
<td>0.325</td>
<td>0.538</td>
</tr>
<tr>
<td>4</td>
<td>0.407</td>
<td>0.582</td>
</tr>
<tr>
<td>8</td>
<td>0.439</td>
<td>0.459</td>
</tr>
</tbody>
</table>
### Table 10

**FORECAST ENCOMPASSING TEST REGRESSIONS**

<table>
<thead>
<tr>
<th>Aggregate supply</th>
<th>Step ahead of the prediction (years)</th>
<th>( \pi_0 )</th>
<th>( \pi_1 )</th>
<th>( \pi_2 )</th>
<th>( \pi_3 )</th>
<th>( \pi_4 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>\textit{cost}</td>
<td></td>
<td>0.022</td>
<td>0.103</td>
<td>0.268</td>
<td>0.412</td>
<td>0.354</td>
</tr>
<tr>
<td>( S_{AEAM} )</td>
<td></td>
<td>0.118</td>
<td>0.236</td>
<td>0.270</td>
<td>0.225</td>
<td>-0.216</td>
</tr>
<tr>
<td>( S_{DEAM} )</td>
<td></td>
<td>0.867</td>
<td>0.685</td>
<td>0.472</td>
<td>0.322</td>
<td>0.755</td>
</tr>
</tbody>
</table>

| \( R^2 \)        |                                     | 0.918   | 0.743   | 0.546   | 0.378   | 0.265   |

\( C(S_{AEAM}) = 1^* \)

\( F - statistic \) \( p-value \% \)

\begin{align*}
    &33.10 \quad 5.52 \quad 4.18 \quad 10.26 \quad 36.92 \\
    &0 \quad 0 \quad 0 \quad 0 \quad 0
\end{align*}

\( C(S_{DEAM}) = 1^{**} \)

\( F - statistic \) \( p-value \% \)

\begin{align*}
    &0.70 \quad 0.56 \quad 1.11 \quad 3.39 \quad 6.24 \\
    &55.4 \quad 64.3 \quad 34.9 \quad 2.2 \quad 0
\end{align*}

<table>
<thead>
<tr>
<th>Aggregate demand</th>
<th>Step ahead of the prediction (years)</th>
<th>( y_0 )</th>
<th>( y_1 )</th>
<th>( y_2 )</th>
<th>( y_3 )</th>
<th>( y_4 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>\textit{cost}</td>
<td></td>
<td>-0.006</td>
<td>0.004</td>
<td>-0.035</td>
<td>-0.037</td>
<td>-0.018</td>
</tr>
<tr>
<td>( S_{AEAM} )</td>
<td></td>
<td>0.231</td>
<td>0.627</td>
<td>0.877</td>
<td>0.521</td>
<td>0.619</td>
</tr>
<tr>
<td>( S_{DEAM} )</td>
<td></td>
<td>0.781</td>
<td>0.102</td>
<td>-0.550</td>
<td>-0.232</td>
<td>-0.249</td>
</tr>
</tbody>
</table>

| \( R^2 \)        |                                     | 0.723   | 0.176   | 0.071   | 0.017   | 0.021   |

\( C(S_{AEAM}) = 1^* \)

\( F - statistic \) \( p-value \% \)

\begin{align*}
    &1.12 \quad 34.8 \quad 0.63 \quad 2.21 \quad 2.73 \quad 1.78 \\
    &34.8 \quad 60.0 \quad 9.3 \quad 4.9 \quad 15.8
\end{align*}

\( C(S_{DEAM}) = 1^{**} \)

\( F - statistic \) \( p-value \% \)

\begin{align*}
    &0.12 \quad 0.39 \quad 3.26 \quad 4.14 \quad 3.71 \\
    &94.9 \quad 76.3 \quad 2.6 \quad 0.8 \quad 1.3
\end{align*}

In brackets: heteroskedasticity and autocorrelation consistent (Newey West) standard error of the coefficients.

* The test is on the unitary restriction on AEAM coefficients and zero for the constant and for the DEAM coefficient.

** The test is on the unitary restriction on DEAM coefficients and zero for the constant and for the AEAM coefficient.
<table>
<thead>
<tr>
<th>Aggregate supply</th>
<th>$\chi^2$</th>
<th>p-value %</th>
</tr>
</thead>
<tbody>
<tr>
<td>COST</td>
<td>0.17</td>
<td>92.0</td>
</tr>
<tr>
<td>$\pi A(L)$</td>
<td>RESTR</td>
<td>-</td>
</tr>
<tr>
<td>$y$</td>
<td>0.52</td>
<td>77.0</td>
</tr>
<tr>
<td>common regressors</td>
<td>3.12</td>
<td>79.3</td>
</tr>
<tr>
<td>all regressors</td>
<td>7.34</td>
<td>39.4</td>
</tr>
<tr>
<td>Test in pairs</td>
<td></td>
<td></td>
</tr>
<tr>
<td>all regressors</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Germany-France</td>
<td>5.46</td>
<td>24.3</td>
</tr>
<tr>
<td>Germany-Italy</td>
<td>2.69</td>
<td>44.2</td>
</tr>
<tr>
<td>France-Italy</td>
<td>4.89</td>
<td>29.9</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Aggregate demand</th>
<th>$\chi^2$</th>
<th>p-value %</th>
</tr>
</thead>
<tbody>
<tr>
<td>COST</td>
<td>0.75</td>
<td>68.9</td>
</tr>
<tr>
<td>$yA(L)$</td>
<td>5.63</td>
<td>6.0</td>
</tr>
<tr>
<td>$r$</td>
<td>0.91</td>
<td>63.6</td>
</tr>
<tr>
<td>common regressors</td>
<td>6.74</td>
<td>34.6</td>
</tr>
<tr>
<td>all regressors</td>
<td>11.5</td>
<td>11.8</td>
</tr>
<tr>
<td>Test in pairs</td>
<td></td>
<td></td>
</tr>
<tr>
<td>all regressors</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Germany-France</td>
<td>1.5</td>
<td>68.4</td>
</tr>
<tr>
<td>Germany-Italy</td>
<td>9.7</td>
<td>4.5</td>
</tr>
<tr>
<td>France-Italy</td>
<td>10.5</td>
<td>0.3</td>
</tr>
</tbody>
</table>

Note: Wald test on micro-homogeneity restriction
Common regressors row reports the test for parameters of variables included in every country regression.

Table 12

<table>
<thead>
<tr>
<th>$\pi^*$</th>
<th>$\chi^2$</th>
<th>p-value %</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1.91</td>
<td>38.3</td>
</tr>
<tr>
<td>1</td>
<td>0.44</td>
<td>80.3</td>
</tr>
<tr>
<td>2</td>
<td>7.48</td>
<td>2.4</td>
</tr>
<tr>
<td>3</td>
<td>15.94</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>1.43</td>
<td>49.0</td>
</tr>
<tr>
<td>5</td>
<td>0.79</td>
<td>67.3</td>
</tr>
<tr>
<td>6</td>
<td>2.82</td>
<td>24.5</td>
</tr>
<tr>
<td>$\propto$</td>
<td>RESTR</td>
<td>-</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>$r$</th>
<th>$\chi^2$</th>
<th>p-value %</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>1</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>2</td>
<td>11.45</td>
<td>0.4</td>
</tr>
<tr>
<td>3</td>
<td>10.69</td>
<td>0.5</td>
</tr>
<tr>
<td>4</td>
<td>9.54</td>
<td>0.8</td>
</tr>
<tr>
<td>5</td>
<td>8.27</td>
<td>1.6</td>
</tr>
<tr>
<td>6</td>
<td>7.04</td>
<td>2.9</td>
</tr>
<tr>
<td>$\propto$</td>
<td>1.66</td>
<td>43.5</td>
</tr>
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</table>
## Table 13

**FACTOR ANALYSIS ON OUTPUT GAP**

<table>
<thead>
<tr>
<th>SIGNAL EQUATIONS</th>
<th>Factor loading</th>
<th>$\sigma^2_{\xi_i}$</th>
<th>$\sigma^2_{\eta}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Germany</td>
<td>0.903</td>
<td>0.906</td>
<td>1.583</td>
</tr>
<tr>
<td></td>
<td>(0.121)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>France</td>
<td>0.534</td>
<td>0.384</td>
<td>0.645</td>
</tr>
<tr>
<td></td>
<td>(0.083)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Italy</td>
<td>1</td>
<td>0.158</td>
<td>0.952</td>
</tr>
<tr>
<td></td>
<td>(restr.)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>STATE EQUATIONS</th>
<th>Common component</th>
</tr>
</thead>
<tbody>
<tr>
<td>coefficient lag 1</td>
<td>1.530</td>
</tr>
<tr>
<td></td>
<td>(0.155)</td>
</tr>
<tr>
<td>coefficient lag 2</td>
<td>-0.689</td>
</tr>
<tr>
<td></td>
<td>(0.134)</td>
</tr>
<tr>
<td>residual variance</td>
<td>0.082</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>STATE EQUATIONS</th>
<th>Common component</th>
</tr>
</thead>
<tbody>
<tr>
<td>coefficient lag 1</td>
<td>0.952</td>
</tr>
<tr>
<td></td>
<td>(0.031)</td>
</tr>
<tr>
<td>residual variance</td>
<td>0.325</td>
</tr>
</tbody>
</table>

### Table 14

**FACTOR ANALYSIS ON REAL INTEREST RATE**

<table>
<thead>
<tr>
<th>SIGNAL EQUATIONS</th>
<th>Factor loading</th>
<th>$\sigma^2_{\xi_i}$</th>
<th>$\sigma^2_{\eta}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Germany</td>
<td>0.261</td>
<td>3.630</td>
<td>4.360</td>
</tr>
<tr>
<td></td>
<td>(0.064)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>France</td>
<td>0.761</td>
<td>2.197</td>
<td>7.911</td>
</tr>
<tr>
<td></td>
<td>(0.049)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Italy</td>
<td>1</td>
<td>1.129</td>
<td>11.059</td>
</tr>
<tr>
<td></td>
<td>(restr.)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Standard error of the coefficients in brackets.

Note: the system is estimated with the Kalman filter algorithm and solved with Berndt, Hall, Hall, and Hausman (BHHH) optimization method; starting conditions for the AR coefficient in the common component are imposed to be equal to the OLS estimation of AR models for the Italian variables.
Figure 1


Legend: co1: coeff. of German inflation (lag 1) in German AS curve; co2: coeff. of German inflation (lag 4) in German AS curve; co3: coeff. of German output gap (lag 1) in German AS curve; co4: coeff. of German output gap (lag 1) in German AD curve; co5: coeff. of real interest rate in German AD curve; co6: coeff. of French inflation (lag 1) in French AS curve; co7: coeff. of French output gap (average of lags 2-5) in French AS curve; co8: coeff. of French output gap (lag 1) in French AD curve; co9: coeff. of real interest rate in French AD curve; co10: coeff. of Italian inflation (lag 1) in Italian AS curve; co11: coeff. of Italian output gap (lag 1) in Italian AS curve; co12: coeff. of Italian output gap (lag 1) in Italian AD curve; co13: coeff. of German output gap in Italian AD curve; co14: coeff. of real interest rate in Italian AD curve

Legend: co1: coeff. inflation (lag 1) in AS curve; co2: coeff. of output gap (lag 1) in AS curve; co3: coeff. of output gap (lag 1) in AD curve; co4: coeff. of real interest rate (lag 2) in AD curve
Figure 3

Impulse responses to a temporary monetary policy shock (+100 b.p.)

(a) Response of euro area inflation rate

(b) Response of euro area output gap

(c) Response of euro area real interest rate

(d) Response of euro area nominal interest rate
Figure 4

Impulse responses to a temporary Phillips curve shock (+1 per cent)

(a) Response of euro area inflation rate

(b) Response of euro area output gap

(c) Response of euro area real interest rate

(d) Response of euro area nominal interest rate
Impulse responses to a temporary aggregate demand shock (+1 per cent)

(a) Response of euro area inflation rate

(b) Response of euro area output gap

(c) Response of euro area real interest rate

(d) Response of euro area nominal interest rate
Figure 6

Scatter diagram of national output gap and common component
Scatter diagram of national interest rate and common component

Figure 7
References


The interaction between face-to-face and electronic delivery: the case of the Italian banking industry, by E. Bonaccorsi di Patti, G. Gobbi and P. E. Mistrulli (July 2004).

Bad loans and entry into local credit markets, by M. Bofondi and G. Gobbi (July 2004).

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