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# Technical efficiency in developing country agriculture: a meta-analysis

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**Abstract**

A meta-analysis is performed to review empirical estimates of technical efficiency (TE) in developing country agriculture. The objective of the study is to contribute to a better understanding of the factors that influence estimates of mean TE. A data set of 51 observations of TE from 32 studies is used in order to test if specific characteristics of the data and econometric specifications account for systematic differences in the efficiency estimates. Results using the two-limit Tobit procedure indicate that factors such as primal versus dual, number of fixed inputs and number of variable inputs increase average TE estimates. On the other hand, using the Cobb–Douglas functional form and cross-sectional data yields a lower level of TE. Other factors, including the number of variables in the model, crop type, stochastic versus deterministic frontiers and sample size, do not seem to significantly affect estimates of TE across studies. 

*JEL classification:* Q12

*Keywords:* Production economics; Frontier functions; Technical efficiency; Meta-analysis; Developing country agriculture

## 1. Introduction

The importance of the agricultural sector in the economic development of poor countries has been recognised for years (Kuznets, 1966; Hayami and Ruttan, 1985). The potential importance of efficiency as a means of fostering production has yielded a substantial number of studies focusing on agriculture.

Since Farrell's original work in 1957, the frontier methodology has become a widely used tool in applied production analysis, due mainly to its consistency with the textbook definition of a production, profit or cost function (i.e. with the notion of maximisation or minimisation). This popularity is evidenced by the proliferation of methodological and empirical frontier studies over the last two decades. Reviews of applications of the frontier methodology literature to examine technical efficiency (TE) in agriculture have been published by Battese (1992) and by Bravo-Ureta and Pinheiro (1993). These reviews underscore the efforts that have been devoted to measuring efficiency in developing country agriculture using the broad arsenal of available frontier models.

Despite this wide array of applied work, the extent to which empirical measures of efficiency are sensitive to the choice of methodology remains a matter of controversy. Thus, an important task ahead in this field of inquiry is a more systematic effort to evaluate the performance of various efficiency estimators. This study is an attempt to narrow this gap. For this purpose, a meta-analysis of 35 TE studies focusing on the agricultural sector of developing countries is undertaken.

Meta-analysis is an approach that uses empirical estimates of some indicator from several studies, average TE in this case, and attempts to explain the

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variation of these estimates based on differences across studies as explanatory variables in a regression model. Meta-analysis has been used extensively in education, psychology and health sciences. More recently, some economists have used this technique (e.g. Espey et al., 1994; Phillips, 1994). However, there appears to be no application of this methodology to the analysis of TE.

First we consider different approaches to estimating TE. Next we present a summary of TE measures reported in the literature for a wide range of developing countries. We then present the empirical model and discuss, on the basis of our results, some key methodological issues that arise from the empirical analysis of TE using frontiers. Finally, a summary is presented along with some suggestions for further research.

## 2. Frontier function methodology: some highlights

TE can be defined as the ability of a decision-making unit (e.g. a farm) to produce maximum output given a set of inputs and technology. According to Farrell (1957), TE is one component of economic efficiency (EE) where the latter is defined as the product of TE and allocative efficiency (AE). In turn, AE refers to the ability to produce a given level of output using cost-minimising input ratios.

The large number of frontier models that have been developed based on Farrell's work can be classified into two basic types: parametric and non-parametric. Parametric frontiers, which rely on a specific functional form, can be separated into deterministic and stochastic. The deterministic model assumes that any deviation from the frontier is due to inefficiency, while the stochastic approach allows for statistical noise. Therefore, a fundamental problem with deterministic frontiers is that any measurement error, and any other source of stochastic variation in the dependent variable, is embedded in the one-sided component. As a consequence, outliers can have profound effects on the estimates and any shortcoming in the specification of the model could translate into increased inefficiency measures (Greene, 1993).

The stochastic frontier production model incorporates a composed error structure with a two-sided symmetric term and a one-sided component. The one-sided component reflects inefficiency, while the two-sided error captures the random effects outside the control of the production unit including measurement errors and other statistical noise typical of empirical relationships. Hence, stochastic frontier models address the noise problem that characterised early deterministic frontiers.

Stochastic frontiers also make it possible to estimate standard errors and to test hypotheses, which was problematic with deterministic frontiers because of their violation of certain maximum likelihood (ML) regularity conditions (Schmidt, 1976). Subsequent work by Jondrow et al. (1982) provided an approach for calculating individual firm efficiency using the stochastic frontier model. A major criticism that still afflicts stochastic frontier models is the lack of a priori justification for the selection of a particular distributional form for the one-sided inefficiency term.

Another issue surrounding parametric frontiers relates to the choice of functional form. Several studies, from both developing and developed countries, have used the Cobb–Douglas functional form to analyse farm efficiency despite its well-known limitations (Battese, 1992; Bravo-Ureta and Pinheiro, 1993). Koop and Smith (1980) concluded that functional form has a discernible but rather small impact on estimated efficiency. Ahmad and Bravo-Ureta (1996) rejected the Cobb–Douglas functional form in favour of a simplified translog form, but concluded that TE measures do not appear to be affected by the choice of the functional form.

Econometric techniques for the estimation of efficiency can be separated into primal and dual approaches, depending on the underlying behavioural assumptions that are made. The primal approach, or the direct estimation of the production function, has been the more common route used for frontier estimation. A major problem with the primal approach is that parameter estimates may be biased and inconsistent if the standard behavioural postulates of either profit maximisation or cost minimisation are valid (Coelli, 1995). The reason is that input levels are not independent of the error term, leading to simultaneous equation bias. However, there are several situations where the primal approach remains valid. Also, as shown by Zellner et al. (1966), direct estimation can be pursued when expected, rather than actual, profit is being maximised.

Recently, empirical frontier studies have turned more to alternative representations of the production function or dual approaches using cost or profit functions. Coelli (1995) provides the following three reasons for the application of the dual approach: (1) to reflect alternative behavioural objectives (cost minimisation or profit maximisation); (2) to account for multiple outputs and (3) to simultaneously estimate both TE and AE.

However, the validity of dual models has been controversial for some time (Junankar, 1989; Sevilla-Siero, 1991). More recently, Kumbhakar and Bhattacharyya (1992), Ali et al. (1994), and Wang et al. (1996) showed that the conventional assumption of profit maximisation based on market prices is inappropriate in the context of developing country agriculture. In addition, Greene (1993) has argued that the interpretation of the technical inefficiency measures derived from dual models is not straightforward.

Econometric estimation of frontier functions can also be categorised, according to the type of data, as cross-section or panel data studies. Cross-section data correspond to the observation of different units (e.g. firms or farms) at one point in time, while panel data consist of observations of some or all units across different time periods. The ability to observe each unit more than once can translate into more accurate estimates of efficiency than can be obtained from a single cross-section (Greene, 1993; Lovell, 1993).

From an econometric perspective, the estimation of stochastic frontiers with panel data avoids some of the limitations present in cross-sectional studies. A key element is that technical inefficiency can be consistently estimated when adding more observations on the same unit, while adding more units to a given cross-sectional data set does not solve the consistency problem. Another advantage of panel data is that it opens up the opportunity of computing efficiency by estimating the fixed effects model, which avoids the need for imposing distributional assumptions on the one-sided error term and also circumvents the assumption that the inefficiency term is uncorrelated with the regressors (Schmidt and Sickles, 1984).

A major feature of panel data is the ability to decompose productivity growth into technological change and TE. Moreover, TE can be modelled as time-variant or time-invariant and suitable statistical tests can be applied to determine which alternative is consistent with the data at hand (Ahmad and Bravo-Ureta, 1996).

Non-parametric TE models, often referred to as data envelopment analysis (DEA), are based on mathematical programming techniques. A relatively small but growing number of agricultural applications have used the DEA approach to frontier estimation (Just, 2000; Shafiq and Rehman, 2000). The main feature of DEA methods is that they do not require the specification of a functional form. Nevertheless, a major drawback of these methods is that they do not allow for random noise or measurement error as do deterministic frontiers. Another characteristic of DEA methods is the potential sensitivity of efficiency scores to the number of observations as well as to the number of outputs and inputs. Nunamaker (1985) concluded that variable set expansion can be expected to produce an upward trend in efficiency scores.

The various efficiency models available suggest several hypotheses that could be tested within a meta-analysis framework. Meta-analysis offers the possibility to relate the summary information of several frontier studies represented by their average TE to a set of characteristics of these studies. Average TE is considered here as a summary measure which characterises the entire sample for any particular study (Greene, 1993).

How sensitive the efficiency estimates are to the specification and assumptions imposed on the model is an issue not completely discussed. Authors such as Coelli (1995) and Hjalmarsson et al. (1996) have discussed the advantages and limitations of the different methodological approaches to the measurement of efficiency. In this paper we examine the effects of using different methodologies and the impacts of study-specific characteristics on average TE estimates.

The specific issues to be investigated in this study are: (1) whether deterministic frontiers produce higher average TE than stochastic frontiers; (2) whether more restricted functional forms (such as Cobb–Douglas) produce lower average TE; (3) whether panel data frontier models produce higher average TE than their cross-sectional counterparts and (4) whether primal specifications lead to lower efficiency estimates than dual specifications. In addition to these methodological issues, we are interested in examining whether study-specific characteristics, such as the location of the study, the year of publication or the number of variables utilised in the model, have a systematic effect on average farm level TE.

Table 1
Empirical estimates of technical efficiency

| Authors and year of publication | Country | Product | Sample size | TE % |
|---|---|---|---|---|
| I. Deterministic production frontiers | | | | |
| (a) Parametric frontiers | | | | |
| Ali and Chaudry (1990) | Pakistan | Crops | 220 | 84 |
| Belbase and Grabowski (1985) | Nepal | Whole farm | 537 | 80 |
| Belbase and Grabowski (1985) | Nepal | Rice | – | 84 |
| Belbase and Grabowski (1985) | Nepal | Maize | – | 67 |
| Dawson et al. (1991) | Philippines | Rice | 22 | 59 |
| Huang and Kalirajan (1997) | China | Maize | 1061 | 68 |
| Huang and Kalirajan (1997) | China | Rice | 770 | 78 |
| Huang and Kalirajan (1997) | China | Wheat | 314 | 73 |
| Kalaitzandonakes and Dunn (1995) | Guatemala | Maize | 82 | 52 |
| Shapiro (1983) | Tanzania | Cotton | 37 | 66 |
| Average | | | | 71 |
| (b) Non-parametric frontiers | | | | |
| Llewelyn and Williams (1996) | Indonesia | Crops | 61 | 97 |
| Kalaitzandonakes and Dunn (1995) | Guatemala | Maize | 82 | 93 |
| Average | | | | 95 |
| II. Stochastic production frontiers | | | | |
| (a) Cross-sectional frontiers | | | | |
| Bravo-Ureta and Evenson (1994) | Paraguay | Cotton | 87 | 58 |
| Bravo-Ureta and Evenson (1994) | Paraguay | Cassava | 101 | 59 |
| Bravo-Ureta and Pinheiro (1997) | Dominican Republic | Crops | 60 | 70 |
| Ekanayake and Jayasuriya (1987) | Sri Lanka | Rice (head) | 63 | 100 |
| Ekanayake and Jayasuriya (1987) | Sri Lanka | Rice (tail) | 61 | 50 |
| Huang and Bagi (1984) | India | Whole farm | 151 | 89 |
| Kalaitzandonakes and Dunn (1995) | Guatemala | Maize | 82 | 74 |
| Kalirajan (1990) | Philippines | Rice | 103 | 79 |
| Kalirajan (1986) | Philippines | Rice 1 | 73 | 60 |
| Kalirajan (1986) | Philippines | Rice 2 | 73 | 63 |
| Kalirajan (1986) | Philippines | Maize | 73 | 71 |
| Kalirajan (1984) | Philippines | Rice | 81 | 63 |
| Kalirajan and Flinn (1983) | Philippines | Rice | 79 | 50 |
| Kalirajan and Shand (1986) | Malaysia | Rice (inside) | 210 | 63 |
| Kalirajan and Shand (1986) | Malaysia | Rice (outside) | 172 | 67 |
| Kumbhakar (1994) | India | Rice | 227 | 75 |
| Phillips and Marble (1986) | Guatemala | Maize | 1384 | 76 |
| Rawlins (1985) | Jamaica | Crops | 152 | 69 |
| Rawlins (1985) | Jamaica | Crops (IRDPII) | 80 | 71 |
| Rawlins (1985) | Jamaica | Crops (non-IRDPII) | 72 | 75 |
| Squires and Tabor (1991) | Indonesia | Rice | 812 | 70 |
| Squires and Tabor (1991) | Indonesia | Cassava | 161 | 58 |
| Squires and Tabor (1991) | Indonesia | Peanuts | 177 | 69 |
| Squires and Tabor (1991) | Indonesia | Beans | 69 | 55 |
| Tadesse and Krishnamoorthy (1997) | India | Rice | 129 | 83 |
| Taylor and Shonkwiler (1986) | Brazil | Crops (part.) | 181 | 71 |
| Taylor and Shonkwiler (1986) | Brazil | Crops (non part.) | 252 | 70 |
| Average | | | | 69 |

Table 1 (*Continued*)

| Authors and year of publication | Country | Product | Sample size | TE % |
|---|---|---|---|---|
| (b) Panel data | | | | |
| Battese and Coelli (1995) | India | Whole farm | 15 | 82 |
| Battese et al. (1986) | Pakistan | Wheat | 499 | 68 |
| Battese and Tessema (1993) | India | Crops | 35 | 84 |
| Dawson et al. (1991) | Philippines | Rice | 22 | 89 |
| Kalirajan (1991) | India | Rice | 30 | 69 |
| Kalirajan and Shand (1989) | India | Rice | 34 | 70 |
| Average | | | | 77 |
| (c) Dual frontiers | | | | |
| Abdulai and Huffman (1998) | Ghana | Rice | 120 | 73 |
| Ali and Flinn (1987) | Pakistan | Rice | 120 | 72 |
| Ali et al. (1994) | Pakistan | Crops | 436 | 24 |
| Taylor et al. (1986) | Brazil | Crops (part.) | 181 | 18 |
| Taylor et al. (1986) | Brazil | Crops (non part.) | 252 | 17 |
| Wang et al. (1996) | China | Whole farm | 1889 | 61 |
| Average | | | | 44 |
| Overall average | | | | 68 |

## 3. Frontier function studies in LDC agriculture

This study extends the work of Bravo-Ureta and Pinheiro (1993) who conducted a critical narrative review of the frontier literature dealing with farm level efficiency in developing countries. By contrast, this article applies meta-analysis to conduct a more rigorous review where TE is regressed against inter-study differences (Wolf, 1986).

Of the 30 studies reviewed by Bravo-Ureta and Pinheiro, 20 reported the type of information required for the analysis undertaken below. The combination of these 20 studies with twelve new studies published since 1993 yields a total of 51 data points, given that some studies reported more than one TE estimate. Only studies published in major journals are included in this analysis except for Abdulai and Huffman (1998), which was included to increase the number of studies from Africa.

The studies included in the meta-analysis are divided, according to the type of methodology used, into two major groups: (I) deterministic production frontiers and (II) stochastic production frontiers. In turn, the studies using deterministic models are subdivided into: (a) parametric and (b) non-parametric frontiers. Those based on stochastic models are subdivided into: (a) cross-sectional; (b) panel data and (c) dual frontiers.

Some key characteristics of all the studies reviewed are presented in Table 1. The overall average level of TE computed from all the studies listed in this table is 68%.[1] This table also shows that there are eight deterministic, six parametric and two non-parametric studies. The parametric studies, all relying on the Cobb–Douglas functional form, reported TE measures ranging from 52 to 84% with an average of 71%, while the average efficiency was 95% for the two non-parametric studies.

Table 1 includes 27 stochastic frontier studies, 13 of which used the Cobb–Douglas functional form while the remaining 14 employed a translog specification. The average TE for the 16 studies using cross-sectional data was 69%, with a low of 50% and a high of 100%. Panel data frontiers were estimated in six studies that yielded an average TE of 77%, and a range from 69 to 89%. Finally, there are five dual frontier studies with efficiency indices between 17 and 73% with an average TE of 44%. All together, 19 studies used the Cobb–Douglas functional form against 14 that specified a translog functional form. Asian countries were the focus of the largest number of studies (25) while rice was the most studied crop.

[1] As an example, the 68% TE level means that, on average, the sample of farmers included in a study attains a mean level of output equal to 68% of what could be achieved under full TE.

## 4. Empirical model

The basic hypothesis of this paper is that the variation in the TE indices reported in the literature can be explained by the attributes of the studies, including functional form, sample size, product analysed, number of variables in the model, and estimation technique. To investigate this issue formally, the following model is estimated:

$$\begin{aligned}\mathrm{TE} = f(&\mathrm{YRSTUD, ASIANC, CWFARM, RICE,}\\ &\mathrm{STO, CD, CS, PRIMAL, SIZE, NVAR,}\\ &\mathrm{NFINP, NVINP, RANGE})\end{aligned}$$

where TE is the average technical efficiency reported in a study; YRSTUD is the year the study was published; ASIANC is a dummy variable equal to one for Asian countries and zero otherwise; CWFARM is a dummy variable equal to one if the model used in the analysis is the total value of farm output or the value of crops, and zero otherwise; RICE is a dummy variable equal to one if the model is for rice and zero otherwise, and the excluded output category is other individual crops (e.g. wheat, cassava, maize, etc.); STO is a dummy variable equal to one if the model is a stochastic frontier and zero otherwise; CD is a dummy variable equal to one if the Cobb–Douglas functional form is used and zero otherwise; CS is a dummy variable equal to one if the data is cross-sectional and zero otherwise; PRIMAL is a dummy variable equal to one if a primal model is estimated and zero otherwise; SIZE is the number of observations used in the study and NVAR, NFINP, and NVINP represent the number of variables, the number of fixed inputs, and number of variable inputs included, respectively. The last variable, RANGE, stands for the difference between the minimum and the maximum TE scores reported in the study. No variable was included to account for the distinction between parametric and non-parametric frontiers because of the limited number of non-parametric studies. The model is estimated using the two-limit Tobit procedure of LIMDEP (Greene, 1991) given that the efficiency scores are bounded between zero and one. However, ordinary least squares (OLS) estimates are also presented for comparison.

Table 2
OLS and ML of the two-limit Tobit equation for technical efficiency

| Variable | OLS (S.E.) | ML (S.E.) |
|---|---|---|
| Intercept | 37.636 (15.460)[a] | 37.248 (14.450)[a] |
| YRSTUD | 0.594 (0.624) | 0.627 (0.571) |
| ASIANC | −4.016 (5.791) | −4.233 (5.350) |
| CWFARM | 5.225 (6.462) | 5.627 (5.908) |
| RICE | 4.184 (5.141) | 4.385 (4.634) |
| STO | −2.553 (5.407) | −2.696 (5.009) |
| CD | −7.830 (5.397) | −8.739 (5.081)[b] |
| CS | −10.637 (6.362)[b] | −11.215 (5.878)[b] |
| PRIMAL | 23.871 (7.686)[a] | 24.553 (7.066)[a] |
| SIZE | 0.001 (0.005) | 0.001 (0.005) |
| NVAR | −0.024 (0.018) | −0.064 (0.048) |
| NFINP | 5.341 (3.676) | 5.713 (3.396)[b] |
| NVINP | 4.625 (2.058)[b] | 4.909 (1.89)[a] |
| RANGE | −0.010 (0.009) | −0.010 (0.01) |
| $\sigma$ | | 11.229 (1.227)[a] |
| $R^2$ log-likelihood | 0.45 | −192.104 |

[a] Significance at the 5% level.
[b] Significance at the 10% level.

## 5. Empirical results

According to the results presented in Table 2, the OLS estimates are very similar to the Tobit model that is estimated using ML procedures. However, slight differences in terms of smaller standard errors and higher significance of the parameter estimates, and the fact that the dependent variable is indeed truncated suggests that one should focus on the ML results.

As highlighted by Espey et al. (1994), in meta-analysis the values of the dependent variable across observations are not independent of each other, since some studies provide more than one data point. This lack of independence could bias the standard errors and hence invalidate tests of hypotheses. However, no study included in our analysis reports more than four TE estimates; therefore, we conclude that the lack of independence of estimates within a given study is not a serious problem in this analysis.[2]

The parameter estimate of the year of the study, while positive, is not statistically significant. This suggests that reported average TE indices have not increased significantly over time. The parameter

[2] According to Espey et al. (1994), a minimum of five estimates is needed before the lack of independence within a given study can become a problem.

estimates for the dummy variables for Asian countries, value of crops and whole farm output and rice are not statistically significant.

Models using stochastic frontiers do not generate significantly different TE indices than deterministic models. This finding contradicts a priori expectations that inefficiency scores are higher for deterministic models than stochastic frontiers. Moreover, in an empirical analysis, Ekanayake and Jayasuriya (1987) found that deterministic procedures have a tendency to overestimate the average level of technical inefficiency and that the extent of the bias is unknown. Further, these authors concluded that even though stochastic frontiers enable the separation of random noise from deviations arising from technical inefficiency, the smaller this noise, the closer the efficiency estimates from these two procedures will be.

Studies using the Cobb–Douglas functional form yield significantly lower average TE indices than those relying on the translog specification, which implies that more restricted functional forms lead to lower average TE. In contrast, Koop and Smith (1980), and Ahmad and Bravo-Ureta (1996) concluded that functional form has a discernible, but rather small impact on estimated efficiency. Therefore, the results of our meta-analysis suggest that formal tests of alternative functional forms in efficiency studies is warranted.

Studies based on cross-sectional data exhibit significantly lower TE estimates than those using panel data. According to Greene (1993), models relying on panel data are likely to yield more accurate efficiency estimates given that there are repeated observations on each unit. However, no a priori expectations regarding the impact of data type (i.e. cross-sectional versus panel) on the magnitude of efficiency scores have been developed.

The econometric results shown in Table 2 also reveal that the primal approach leads to significantly higher TE estimates than those obtained from dual frontiers. Nevertheless, this result should be interpreted with caution given the relatively limited number of dual studies included in the meta-analysis. Furthermore, dual frontiers use price distortions to model allocative inefficiency and TE is modelled parametrically rather than entered as a random component. In one of the few empirical papers that compare primal to dual models, Greene (1993) estimated deterministic and stochastic frontiers for primal and dual (cost) functions to analyse efficiency. He obtained lower inefficiency estimates with the cost function, for both the deterministic and stochastic approaches, than with the primal models. He concluded that this results is unexpected and without any obvious cause.

Sample size, the range of TE reported, and the number of variables in the model do not significantly affect TE estimates across studies. In general, the number of variables in parametric models has been an issue in the literature for functional form selection because of the possible effect of multicollinearity on the estimated parameters (Griffin et al., 1987). Finally, there is a positive association between the number of inputs-fixed and variable-included, and TE. Even though, as discussed above, the expansion of the input set may be an issue with DEA methods, the literature on econometric frontier analyses has been silent on this matter.

## 6. Summary and concluding comments

A total of 32 frontier studies using farm level data from 15 different developing countries were analysed. These studies yielded 51 observations, given that some studies reported more than one TE estimate. By far, the countries that have received most attention from frontier researchers are in Asia (India and the Philippines) which accounts for 12 of the 32 studies. In addition, 16 of the studies reviewed focused specifically on rice, making this the most studied agricultural product by frontier researchers. The farm level TE scores from all the studies reviewed range from 17 to 100% with an average of 68%. The key results of this study, which have implications for future efficiency work, relate to the impact of stochastic versus deterministic models, the effect of functional form, and the effect of type of data (i.e. panel versus cross-sectional).

This study represents the first attempt to use meta-analysis to examine TE estimates. Thus, more work is needed to get a better understanding of the major determinants of TE estimates. As concluded by Bauer (1990) in a review of new developments in frontier function methodology, additional empirical as well as theoretical work is needed to arrive at a clearer picture of the effects that alternative methodological assumptions might have on measures of efficiency.

Recent advances in panel data methodologies, along with models that enable the joint estimation of efficiency and its determinants, offer an exciting area for further research. However, to make these methodologies truly useful, it will be necessary to assemble suitable data sets, which is likely to be a challenging undertaking.

From a policy standpoint, more accurate TE estimates are crucial in guiding policy decisions dealing with farm extension and training programs, among others. Finally, further meta-analysis research of TE seems warranted. In our view, additional work that incorporates a larger set of studies with broader geographical and/or sectoral coverage would produce a better understanding of the association between measures of TE and the attributes of the studies reporting these measures.

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