Measuring Rice Competitiveness: New Evidence Using an **Extension of the Policy Analysis Matrix** Fazleen Abdul Fatah^{1,2} and Stephan von Cramon-Taubadel¹ ¹Department of Agricultural Economics and Rural Development, Georg-August University of Goettingen, Germany ²Faculty of Plantation and Agrotechnology, Universiti Teknologi MARA, Malaysia

INTRODUCTION

The advent of free trade agreements, including the Asean Free Trade agreement (AFTA) and WTO accession, pose challenges for the Malaysian rice sector as it must compete with low-cost exporting countries. This implies not only structural changes in trade, but also adjustments at the farm level to improve efficiency and competitiveness. Further developments in the rice sector will therefore depend on the availability of sufficient, relatively low-cost and high-quality rice, or in other words, on the competitiveness of rice production. However, the measurement of competitiveness in agriculture is often based on average farms. If the farms that are summarised in this manner



STUDY AREA

- Agricultural Development Muda Authority (MADA), which is the largest granary area (Fig.1)
- The farm level data is collected twice a year and each survey period includes a balanced sample of 675 farming households (~6750 households)
- The panel is composed of ten crosssections covering main and off-

are heterogeneous, inferences based on aggregated measures can be misleading. Therefore, we propose an extension to the Policy Analysis Matrix by Monke and Pearson (1989). This extension allows us to take farm-level heterogeneity into account and draws distribution of competitiveness scores for each rice farm.

seasons, from 2010 to 2014 This data set provides comprehensive information, including input use, output and corresponding prices

To understand the driving forces behind competitive rice production in Malaysia using an extension to the Policy Analysis Matrix To examine factors influencing rice competitiveness using dynamic panel regression or System of Generalized Method of Moment (SGMM)

AIMS

METHODOLOGY	RESULTS		
Our approach relies on the extension to the 'Policy Analysis Matrix' proposed by	rix' proposed by Table 1: Summary of SCB results by share of individual farms and total rice production		
Monke and Pearson, (1984). This extension makes it possible to determine for each	Year Distribution by	Competitive (SCB<1)	Uncompetitive (SCB>1)
product a) the proportion of the farms that producing it that is competitive and b) the	Weighted average SCB	0.65	2.33
proportion of the total production that derives from competitive/uncompetitive farms.	2010 Share of the individual farms in the sample (%)	69.19	30.81
Correspondingly, the proceeding and results presented here are part of a sequence	Share of the total production volume in the sample (%)	86.14	13.86
of the following necessary stens:	Weighted average SCB	0.61	2.30
Social Cost One of the indicators that can be calculated to measure	2011 Share of the individual farms in the sample (%)	73.04	26.96
	Share of the total production volume in the sample (%)	89.89	10.11
competitiveness using the PAM framework:	Weighted average SCB	0.66	2.66
SCB = $\left[\sum_{j=1}^{k} a_{ij} P_j^s + \sum_{j=k+1}^{n} a_{ij} W_j^s\right] / P_i^s$	2012 Share of the individual farms in the sample (%)	60.74	39.26
- ratio of the social cost of producing one unit of an output	Share of the total production volume in the sample (%)	81.83	18.17
to the social value of that unit of output.	Weighted average SCB	0.67	2.28
$- 0<5CB<1 \rightarrow Competitive$	2013 Share of the individual farms in the sample (%)	62.37	37.63
	Share of the total production volume in the sample (%)	83.49	16.51
	Weighted average SCB	0.67	2.28
Reputsional properties of the	2014 Share of the individual farms in the sample (%)	47.70	52.30
indicators and thus allow the calculation of standard deviations	Share of the total production volume in the sample (%)	71.13	28.87





and compared intervals for PAW indicators. Using kernel methods proposed by Cramon-Taubadel and Nivyevskyi (2008, 2009), we estimate SCB distributions for each rice farms and estimate the proportion of farms that produces competitively for each product and the proportion of the total production of that product that is produced competitively.

Results were transformed into kernel distribution (Figure 2) and summarised in (Table 1).

System Generalized Method of Moment (SGMM)

Kernel

distribution

identify factors variation in that explain the 10 competitiveness between rice farms and that could be used to improve the competitiveness of individual farms, we use a dynamic panel regression model defined by:

 $Y_{it} = B_1 Y_{it-1} + B_2 X_{it-1} + a_i + \varepsilon_{it}$ where Y_{it} is farm *i*'s SCB score in period *t*, X_{it-1} is a vector of exogenous explanatory variables (farm size, distance to milling factories, access to credit, off-farm income, landownership, hired cost labor, farmers' organization, land ownership and a time trend), and a_i and ε_{it} are error terms (*a_i* captures unobserved and time constant farm specific effects and ε_{it} is an idiosyncratic error term) (Figure 3).

Fig. 2. Distribution of competitiveness scores (SCB) for the rice farms, 2010-2014

73%

Ava = 0.8







SCB 2014 52% 48%

SCB 2011

27%

Avg is the average SCB values -Numbers in the figures indicate the percentages of the competitive/ uncompetitive farms

CONCLUSION

- Our results demonstrate that considering the aggregate data or average Social Cost • Benefit alone may conceal important variations across the farms.
- Many farmers are shown to be competitive; however these competitive farms account for a disproportionately large share of rice production when using disaggregate data.
- For example, in 2013, the average ton of paddy was produced at a SCB of 1.02, i.e. not competitive (Fig. 2). This result obscures the fact that more than half of the farms (62%) in this region were competitive, and that these competitive farms together accounted for 83% of the total rice production (Tab. 1).
- We concluded participation in the farmers' organization, gender and farm size are the major determinants of rice competitiveness, while the increasing distance to rice mills, off-farm income and the use of hired labor may reduce competitiveness (Fig. 3).

kemel = epanechnikov, bandwidth = 0.2501

kemel = epanechnikov, bandwidth

Dependent variable: SCB score			
Explanatory variables	Coefficient	Standard errors	
SCB_{it-1}	-0.294	0.400	
Hired cost labor	4.e-04***	6.e-05	
Distance to the rice mill	0.077**	0.025	
Access to credit	2.e-05	1.e-05	
Landowner	0.038	0.035	
PPK member	-0.354**	0.159	
Male	-0.077*	0.046	
Off income	5.e-05*	3.e-05	
Farm size	-0.081***	0.011	
Input subsidies _{it-1}	-2.e-04	0.001	
Bonus payment _{it-1}	-4.e-04	0.001	
Main season	-0.268***	0.055	
Observations	5400		
Number instruments	29		
Year and system control	Yes		
Arellano-Bond test AR(1)	-1.84	[0.065]	
Arellano-Bond test $AR(2)$	-0.74	0.459	
Difference-in-Hansen tests of exogeneity	2.61	[0.855]	
of instrument subsets			

Fig. 3. Results of SGMM for rice competitiveness

UNIVERSITI

ſeknologi

References

Monke, E. A., & Pearson, S. R. (1989). The Policy Analysis Matrix For Agricultural Development. Ithaca, NY: Cornell University Press.

von Cramon-Taubadel, S., & Nivyevskyi, O. (2008). Ukraine-Ag-Competitiveness-Policy Note - Final. von Cramon Taubadel, S., & Nivyevskyi, O. (2009). Belarus Agricultural Productivity and Competitiveness: Impact of State Support and Market Intervention.





Contact: Fazleen Abdul Fatah

