Bias and Scale Effects of Decoupled Farm Payments

Motivation

Farm support programs such as direct payments were initially considered a "green box" policy at the GATT/WTO negotiation since it was thought to be least trade distorting. These payments are based on historical yields and acreage and thus considered to be decoupled from production decisions. The extent to which these payments are truly decoupled from production decision has come under intense scrutiny during recent years. The large size of US agriculture implies that the absolute amount of these support payments can be substantial. As these payments are delivered to farmers they have the potential to significantly impact the income and wealth of the recipients. Thus these payments have the potential to create distortions in trade and the efficient allocation of resources and production decision. A market allocation system that is truly decoupled should not affect farm activities. It is of general interest to quantify the impact associated with such payments.

Figure 1

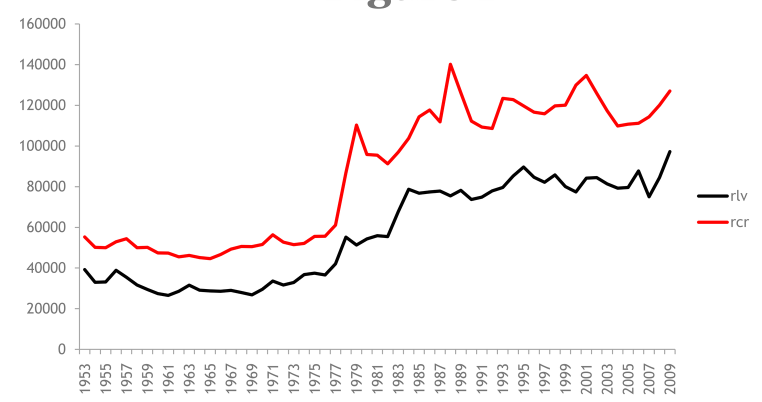
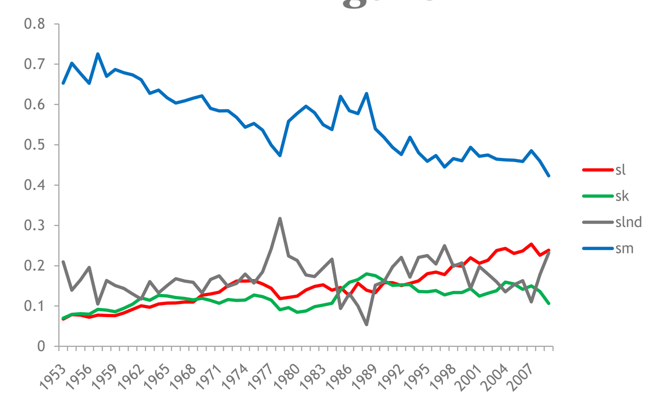


Figure 2



These government payments may potentially induce factor bias, altering the proportional input usage, alter the scale of production, and or cause adjustment in optimal out mix (output bias). Recognizing and estimating these effects would play crucial role in the formulation of future policy. If, for example, direct payments are dis-favorable for fertilizer usage, then it might impact the input supply chain. On the other hand if such policy is dis-favorable to labor usage, then it might cause migration of labor out of farming and impact urban-rural wage gap. Understanding the primary impacts of direct payments in production (scale and bias effects) would help us gauge the secondary effects of such policy.

This research will explore the impact of "green box" payments on the use of labor, capital, material, and land in the aggregate production of crop and livestock in US agriculture for the years 1953-2009. Depending on the sign and magnitude of these bias impacts it will help us present the tendency of such effects as relevant consideration in the formulation of future policy. In order to address this goal we will use the standard translog cost function approach and adapt measures of input and output bias first proposed by Binswanger (1974, 1978) and Antle (1984) and later further developed by Antle and Capalbo (1988) for categorizing the impacts of technical change.

Method

$$(1)\quad LogTC = f(\tilde{Q},\tilde{W},DP)$$

Where Q is a vector of output quantities, W is a vector if input prices, and DP is the farm payment variable. We can use Shepherd's Lemma to derive the relevant input cost share and revenue share of cost equations.

$$(2)\quad S_i = \frac{\partial LogTC}{\partial LogW_i}$$, is the input factor share of total cost , and

$$(3)\quad R_i = \frac{\partial LogTC}{\partial LogQ_i}$$, is the revenue share of total cost .

Equations (1), (2), and (3) is our system of equation. Just like any well behaved cost function we impose the homogeneity, cross equation symmetry, and adding up restriction. We estimate the system using iterative SUR. Since the cost shares add up to one, we drop one share equation to avoid singularity problem. Our results are invariant to the share equation dropped.

Our preliminary results suggested serial correlation. In order to address this issue we re-estimated the first differenced form of the model. Also, in order to address simultaneity bias of output, we use one period lagged output as expected future output. Following Antle and Capalbo (1988), we estimate input bias as follows:

$$(4)\quad MB_i^{ce} = MB_i^{c} - \left[\sum_j \left(\frac{\partial \log S_i(\tilde{Q},\tilde{W},DP)}{\partial \log Q_j}\right)\left(\frac{\partial LogTC}{\partial LogQ_j}\right)^{-1}\right]\frac{\partial LogTC}{\partial DP}$$

where $MB_i^c = \frac{\partial Log\, S_i(\tilde{Q},\tilde{W},DP)}{\partial DP}$. The first term of (4) measures the total bias caused by technological change and the second term measures the scale effect. Thus after accounting for the scale effect we are left with pure factor bias due to farm payments.

Results

Variable	Coefficient Estimates & Standard Errors		
dlogq1	-0.187731451 (0.147248158)	dlogq1w3	-0.015698452 (0.013850412)
dlogq2	-0.440278962*** (0.120286023)	dlogq1w4	0.006913751 (0.019401796)
dlogq1q1	-0.205627117 (0.142902970)	dlogq2w1	0.015427998*** (0.007308681)
dlogq1q2	0.024934778 (0.057246438)	dlogq2w2	0.005564036 (0.003993922)
dlogq2q2	0.225376266*** (0.081891228)	dlogq2w3	-0.053322687*** (0.014256129)
dlogw1	0.211997560*** (0.041346441)	dlogq2w4	0.032330654*** (0.011204648)
dlogw2	0.189332913*** (0.034590626)	dlogcons	0.315827050*** (0.065079255)
dlogw3	0.290193842*** (0.031178520)	dlogconssq	-0.026740137*** (0.005207597)
dlogw4	0.396300989*** (0.048099889)	dlogconslogq1	-0.018817786 (0.012396119)
dlogw1w1	0.125158820*** (0.005225336)	dlogconslogq2	0.055509182*** (0.016202536)
dlogw1w2	-0.026061651*** (0.002519410)	dlogconslogw1	0.004869005*** (0.001548517)
dlogw1w3	-0.017341674*** (0.001991382)	dlogconslogw2	0.002362468*** (0.000877431)
dlogw1w4	-0.081755495*** (0.005668863)	dlogconslogw3	-0.025605442*** (0.004191326)
dlogw2w2	0.108067374*** (0.002703598)	dlogconslogw4	0.018373968*** (0.002945229)
dlogw2w3	-0.015507278*** (0.001119638)		
dlogw2w4	-0.066498444*** (0.003408863)		
dlogw3w3	0.100236578*** (0.005397655)		
dlogw3w4	-0.067387625*** (0.003693111)		
dlogw4w4	0.215641564*** (0.007639273)		
dlogq1w1	0.012439233 (0.015108598)		
dlogq1w2	-0.003654532 (0.008400753)		

BIAS	Estimate & SE at Average
Total Bias-Labor	0.03226975* (0.01628012)
Total Bias-Capital	0.01905790 (0.01124057)
Total Bias-Land	-0.1498382*** (0.04074535)
Total Bias-Materials	0.03315012*** (0.008920924)
Scale Effect-Labor	5.611047e-05 (0.0003171795)
Scale Effect-Capital	1.376131e-05 (0.0004464773)
Scale Effect-Land	-0.0001447942 (0.0007979811)
Scale Effect-Materials	2.628956e-05 (0.0002671071)
Pure Bias-Labor	0.03221364* (0.01627715)
Pure Bias-Capital	0.01904414 (0.01124896)
Pure Bias-Land	-0.1496934*** (0.04072912)
Pure Bias-Materials	0.03312383*** (0.00892428)

Our results suggest that there is substantial farm payment induced hicksian bias in the US agriculture during the period 1953-2009. Our hicksian bias indicates that technological change was biased to towards labor, capital, and materials. Though capital using bias is not statistically significant and labor using bias is significant only at the 10% level. There appears to be substantial land saving bias.

Data

Our data was obtained from ERS. We have two output indexes, livestock (q1) and crop (q2), and four input price indexes, labor (w1), capital (w2), land (w3), and material (w4). We also have information on total cost and value of direct payment (DP).

Author Information

*Samiul Haque

Department of Agricultural Economics , Purdue University.

Contact via phone: (765) 307-0109, or email: shaque@purdue.ed

*Dr. Roman Keeney

Department of Agricultural Economics, Purdue University.

Contact via phone: (765) 494-4273 or email: rkeeney@purdue.edu

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