Rescuing the Decoupling Literature from Incomparable Chaos

1. Abstract

This report presents results of an assessment of the agricultural economics literature on decoupling farm policies with a view to inform decision makers. We develop a method of comparing scientific estimates in terms of the supply impact per unit of payment and the coupling coefficient, or output effect of a payment relative to an equivalent amount of market returns. Our indicators permit clearer assessment of payment impacts in terms of supply effects, rather than ill-suited proxies such as statistical significance or parameters with no relevance outside of the estimated equation. Going farther, we use a Bayesian model to synthesize findings from these disparate studies in order to move from their case-, time-, and method-specific results to a set of estimates of the impacts of payments on national supply. We find that the implications for markets tend to be constrained by inelastic total area, leading us to identify the focus on crop area, not yield or supply, as a weakness of the literature on U.S. payments. Moreover, we find at this time limited applicability of the literature to actual current U.S. policies. While we also identify several additional improvements to this work, the comparable indicators of impact and relating these effects to national supply represent important contributions.

Authors Wyatt Thompson, Scott Gerlt, Joe Dewbre, and Anne Effland

Affiliations

a. Thompson and Gerlt: Food and Agricultural Policy Research Institute, Division of Applied Social Sciences, University of Missouri
b. Dewbre: private economic consulting
c. Effland: Economic Research Service, United States Department of Agriculture

Acknowledgements

This material is based upon work supported by the U.S. Department of Agriculture, under Agreement Numbers 58-0111-19-011 and 58-0111-18-027, and the USDA National Institute of Food and Agriculture, Hatch project number MO-C1537173. Any opinion, findings, conclusions, or recommendations expressed in this publication are those of the authors and do not necessarily reflect the views of the University of Missouri or the U.S. Department of Agriculture and should not be construed to represent any official USDA or U.S. Government determination or policy.

We received assistance from Ashley E. Hungerford and Emily Scully, but all remaining errors are our own.

2. Introduction

The agricultural economics literature is replete with studies aimed at quantifying the effects of different farm policy choices. Earlier work on the topic, exemplified by Floyd (1965), largely concerned the effects of various policies on farm incomes. In more recent years, emphasis has shifted to potential production and trade distortions created by domestic producer income support measures. In this paper we focus specifically on numerical estimates of the production impacts of the main instruments of U.S. farm commodity support reported in the recent literature. We use those estimates to construct parameters for U.S. national crop supply equations in an agricultural projections and policy simulation model.

Much past literature focused on analysis of policies with reference to various provisions of multilateral trade agreements and not specifically on quantifying policy effects. In particular, for the United States, applied economists have focused on the decoupling that occurred in 1996 that moved much U.S. crop support from an output basis to payments mostly unrelated to current crop production or market conditions. Subsequent policy changes have maintained the decoupling from crop production, but have tied payment levels to market indicators and allowed the occasional updating of the historical area and yield that is the basis for determining payments. For more than twenty years, applied economists have subjected this evolving approach to decoupling to theoretical and empirical examination.

However, this body of analytical work reported in the literature fails to build to results that inform policy for the simple reason that results of different studies tend to be non-comparable and in some cases not closely related to key policy decisions. In addition, it is not easy to build on or extend results from previous analyses because of the wide diversity in the way empirical findings are reported. For example, elasticities of supply response with respect to a payment tend to be extremely sensitive to the initial payment level and magnitude of the change, with results that may look big and take on statistical significance but may be of little economic consequence. Other effects are presented in ways that obscure the fact that the implied impact of the payments exceeds the effect of a like amount of returns from the market.

Many studies also lose their potential for broad relevance because they focus on a subset of producers. Lessons drawn from survey data, regional data, and representative farm simulations may have limited value for aggregating to measure response at the national level. Studies also often focus on only a subset of the potential pathways through which a decoupled payment can affect output. Taken together, these limitations render the literature on decoupling far less useful to policy makers than it could be.

Our objective has been to synthesize findings from prior analyses in ways that make results comparable, quantify the implied national supply effects, and improve the representation of policy in applied economic studies of markets and market impacts of direct payments. In pursuit of that objective, this paper develops and deploys mechanisms that (a) standardize supply-inducing effects of payments reported in the literature, (b) associate standardized results with their characteristics, and (c) measure the appropriateness of each result to be used for modeling national supply.

We compare estimated results from past analyses using three indicators: 1) the induced change in output (acreage, yield or production) per dollar of program payment, which we will refer to subsequently as the *payment impact coefficient*, 2) the induced change in output for the same dollar change in market revenue, and 3) the ratio of the former to the latter, which we will refer to subsequently as the *coupling coefficient*. Very few of the studies we reviewed report these indicators directly. Many of them, however, report sufficient information to allow us to calculate one or more of them.

If reaching our objective only required creating a payment coefficient to plug into a supply equation, the choice between the first and the third indicators would be largely arbitrary. However, since our aim is also to assess distortionary effects of payments, the third indicator - the ratio of payment to market impact - is of direct relevance. In their annual Agricultural Policy Monitoring and Evaluation report (OECD, 2019), the OECD ranks the financial support that member countries provide their producers on a rough scale of most to least distorting based on categories defined by the transfer basis of the support. Countries are judged to have achieved progress in agricultural policy reform if the share of support in the categories ranked as most distorting is declining. Prominent in the list of most distorting measures are those that boost market prices. Thus, shifting from market price support to program payments with coupling coefficients less than unity would be regarded as progress, and vice versa.

Even with the standardization described above, one should still expect differences among the studies resulting from differences in the crop or crops chosen for analysis, the time period and geographic coverage of the data, the method of analysis, and other aspects of study design. As we explain later in the paper, the analytical framework we employ aims to take account of these differences. For the moment it is important to note that regardless of their analytical choices, all of the studies share a focus on a question of broad national and international interest – how do different kinds of government payments differ in their impact on production?

By way of preview, our results show that there remains a critical lack of understanding of the supply effect of payments despite the many scientific studies in this area. Still, based on information available at this time we draw certain tentative conclusions and develop certain tentative results. First, we conclude that the literature is removed from supply-inducing effects of existing agricultural policy as a result of several characteristics: a focus on specific cases or samples, attention to area rather than output, use of estimated or calculated effects that are not related clearly to supply variables in a meaningful way, and analysis of specific programs of the United States that no longer exist. This program set includes fixed direct payments (FDP) tied to historical base without regard to current market conditions.[1] These findings might relate to some aspects of current policies, but not all. Second, we develop two indicators that allow us to compare supply-inducing effects among studies and with respect to market return

---

[1] The studies reviewed for this research refer to fixed direct payments using a variety of program terms. The first of these programs was established by the 1996 Farm Bill and known variously as Production Flexibility Contract (PFC) payments and Agricultural Marketing Transition Act (AMTA) payments. PFC refers to the formal name of the program, whereas AMTA refers to the section of the Farm Bill that authorized them. The 2002 Farm Bill renamed the payments Direct Payments, which they remained until their repeal in 2014.

impacts, finding in many cases different magnitudes of payment effects than those in the originally published work might lead readers to expect. By developing a means of reconciling these effects with national supply, albeit tentatively at this point, we derive from the literature a set of area supply effects of crop payments that we incorporate into a simulation model. Owing in part to inelastic total supply of land for crops and inelastic demand for all crop outputs, this exercise leads to small quantity impacts overall, despite shifting area among crops, with lower prices, lower farm income, and higher taxpayer costs. Indeed, this finding returns us to our observation that the narrow focus on area effects of crop payments seems apt to lead inevitably to modest supply impacts for the United States or, more generally, to any case in which programs are applied across many crops competing for an inelastic amount of area. A focus on yields or output, in contrast, might be more important if the policy question is the supply quantity effects of these programs overall.

The next section provides an overview of the consensus regarding the various channels through which payments may influence production decisions. The subsequent section describes the procedure we adopted to tabulate empirical results from the studies chosen for analysis. That procedure yields a database comprising estimated payment impact and coupling coefficients categorized by source and classified by various criteria characterizing the associated study. The penultimate section explains the method we used to obtain coupling coefficients that might be appropriate for parameterizing supply equations in an agricultural projection and policy model, and uses such a model tests the implications of these coefficients. The final section concludes and offers suggestions for further work on the topic.

3. Channels of payment impact in the literature

Production effects of program payments may come via one or more of multiple channels. U.S. government programs providing support to producers comprise a mix of policy instruments that may change from one Farm Bill to another. Below we define the avenues of payment impacts covered by the studies included in our review. Of these studies, Bhasker and Beghin (2009) and Abler and Blandford (2005) produced the most comprehensive reviews of the various avenues of payment impacts. We discuss some of these avenues and related studies below. We do not focus on the potential direct impacts on effective incentive prices, such as when a policy increases the amount received per unit sold, as such direct impacts are not the focus of this decoupling literature. We also ignore some important elements of the larger literature on payment effects, including those that operate through labor market decisions or planting restrictions because we could not derive estimates of these avenues of payment impact from available studies.

Risk reduction and wealth effects

There are two pathways by which risk considerations may affect producer response to program payments. First, payments that are inversely correlated with market returns reduce producer risk, encouraging producers who are risk averse to increase production (insurance or risk reduction effects). This effect is analogous to the effect of providing insurance against price or other market risks. Second, regardless of the particular instrument employed, financial support to producers increases producer wealth, which may affect willingness to take risks (wealth effects), depending on whether producers are risk averse and if they are, on the nature of their risk aversion.

Theoretical and empirical analyses show that if producers are risk averse and if their preferences display decreasing absolute risk aversion (DARA), then payments may encourage increases in input use and production (Hennessy 1998; Serra, Zilberman, Goodwin and Featherstone, 2005; Sckokai and Moro, 2006; Femenia, Gohin and Carpentier, 2010). Similar derivations reveal that decoupled payments also reduce income variability and thus the implied degree of risk faced by farmers. These studies find that while both the insurance and wealth effects of program payments are positive, the wealth effects are relatively small compared to the insurance effects. They all similarly conclude that the total of wealth and insurance effects is likely small.

Chambers and Voica (2016) challenge the theoretical basis underlying results reported in these studies, concluding that if farmers have off-farm investment and employment opportunities, production decisions are decoupled from lump-sum subsidies in the presence of risk and uncertainty. Burfisher, Robinson, and Thierfelder (2000) and Anton and Le Mouel (2004) study the effects of payments that may be captured through changes in risk premiums. Burfisher et al. estimate the effects on risk premiums of U.S. Production Flexibility Contract (PFC) payments via simulations with a CGE model. Anton and Le Mouel focus on the potential reductions in risk premiums created by the U.S. Counter-Cyclical Program (CCP) payments. They calculate risk premia using OECD Producer Support Estimate (PSE) data to calculate the variance-covariance matrix of the truncated producer price distributions under the 2002 Farm Bill.

Expectations of base updating

Generally, decoupled farm income support programs have been based on fixed historical acreage and yields. Even if producers are risk neutral, expectations of a future updating of the area or yield upon which payments are based may lead them to maintain or increase current production. If producers believe payments will be made according to certain criteria in the future, then they might take actions to meet those criteria. Bhasker and Beghin (2010) and Hendricks and Sumner (2014) each illustrate the behavioral economic linkages through which expectations of future policy changes could affect current period production decisions. Bhasker and Beghin (2010) study the case of a representative Iowa corn producer while the Hendricks and Sumner (2014) study planting decisions of corn and soybeans farmers in three Corn Belt states: Iowa, Illinois, and Indiana. The basic approach is similar in both studies. The authors first posit an optimization problem whereby the producer forms an expectation of the present value of a future updating of entitlements and then use assumed supply elasticities to compute production impacts. Results from both studies show that the key parameter determining production impacts for those entitlements is the expected probability of update.

Entry or exit decisions

The existence of payments could cause some producers who might otherwise exit the industry to remain. Chau and de Gorter (2005) employ a model of the U.S. wheat sector calibrated on data for 1998 to compare the potential production impacts of PFC and Market Loss Assistance (MLA) payments and loan deficiency payments (LDPs). In their model, LDPs are assumed to impact production in the same way as a fully coupled output price subsidy, while PFC and MLA payments have an impact on production only when the possibility of farm exit is included. The authors assume that by increasing a farmer's ability to cover fixed costs the PFC and MLA payments encourage producers who might otherwise exit farming to remain in production. Their theoretical model illustrates the potential that the exit deterrence effect could lead to production distortions from ostensibly decoupled payments that are even greater than those of coupled payments. However, empirical results obtained from model simulations suggested that elimination of the fully coupled LDP payments would have resulted in a production impact over twice as great as elimination of decoupled PFC and MLA payments.

In their review of decoupling studies, Abler and Blandford (2005) note that Chau and de Gorter do not consider the possibility that land and machinery owned by exiting farmers could be rented or sold to other farmers, which would diminish the impact on production of the payments' exit deterrence effect. In similar vein, Kropp and Whittaker (2011) point out that while absent the payment an unprofitable farm may exit the market, agricultural production on the land belonging to the farm does not necessarily cease. Land might be sold or leased to more efficient agricultural producers, leaving aggregate agricultural production unchanged or even increased with the removal of subsidies.

Imperfect Credit Markets

If credit markets are imperfect, decoupled payments may increase the borrowing capacity of credit-constrained producers. The payments also increase land values and rents, which may improve the credit worthiness of credit-constrained producers and provide incentives to retain land in agriculture. Roe, Somwaru, and Diao (2003) undertake analysis using a CGE model to illustrate that if agricultural capital markets are fully integrated with non-agricultural capital markets, decoupled payments have no effect on agricultural production. However, if agricultural capital markets are segmented, simulated production effects of payments were shown to be positive, albeit exceedingly small in the short run falling to zero in the long run.

Girante, Goodwin, and Featherstone (2008) ask whether decoupled payments affect farmer's crop acreage decisions in the presence of credit constraints. They use farm-level data from Kansas to study how production effects may have differed across farmers with varying levels of debt pressure. They also find that decoupled payments have small effects on production.

Studies not identifying specific channels by which payments may affect production

Many of the studies reporting empirical estimates of payment effects do not distinguish the exact channel – risk reduction and wealth effects, expectations of future benefits, entry-exit, or other pathways through which those payments may affect producer decisions. Most of these studies reference the expected utility of future farm profits as the theoretical basis for formulation of their empirical models but estimate regression coefficients that, implicitly, embody totals of potential payment effects that exert their influence through these various avenues.

Goodwin and Mishra (2003, 2006) report results of analysis focusing on, respectively, wheat and barley acreage in the Northern Great Plains region and corn, soybean, and wheat farms in the Corn Belt. They use data collected for the USDA Economic Research Service's Agricultural Resource Management Survey (ARMS) database to estimate acreage response to prices and Agricultural Market Transition Act (AMTA) and MLA payments. The regressions include both AMTA payment variables directly and those variables interacted with debt and wealth indicator variables. The authors conclude that though payments exerted statistically significant impacts on acreage, the estimated effects were very small.

Key and Roberts (2008) use U.S. Census of Agriculture data to examine whether Iowa farmers receiving relatively high levels of PFC payments in 1997 had significantly increased the quantity of land allocated to program crops by 2002. Results indicate that the growth of total program-crop acreage for farmers receiving a high level of payments was 2.6 to 6.7 percentage points above that for farmers with low payments, depending on the model specification and definition of program crops. Weber and Key (2012) also use data from the U.S. Census of Agriculture to examine how Direct Payments (DPs) affect U.S. agricultural production. The study focuses especially on the change implemented in the 2002 Farm Bill making oilseeds eligible for DPs. Their regression analysis uses individual farm data aggregated to zip code geographic areas, for each of three census years: 1997, 2002 and 2007. The authors conclude that government program payments from 2002 to 2007 had little effect on production.

O'Donoghue and Whitaker (2010) analyze the effects of DPs on the total of harvested acres for all crops for the whole of the United States. They model acres harvested as a function of change in DP receipts resulting from the expansion of base acre entitlements under the 2002 Farm Bill. Their dataset comprises farm level data obtained in the 2000, 2001, 2003 and 2004 ARMS. Although they obtained statistically significant estimates coefficients applying to the payment variables, in their concluding remarks the authors emphasize their results say nothing about whether payments caused aggregate acreage to increase or not. The aggregate change in acres depends on many things, including changes in the size of farms.

OECD (2001) reports results of analysis of the market effects of various categories of financial support provided U.S. crop farmers as classified for the PSE. One of those categories, Payments Based on Historical Entitlements, combines AMTA and MLA payments. In the model used to estimate payment impacts, this category of payments is assumed to increase incentives to increase total crop acreage.

4. Calculating impact and coupling coefficients

Based on microeconomic theory, we consider three key supply equations for a crop or an aggregate of crops. Each of the following equations is the optimizing value given prices, payments, and other factors. From theory, we expect that optimal area relates to market returns and payments on the basis of a unit of area and that optimal yield and supply depend on the price or payment per unit of output, so two sets of values for independent variables are required. These are as follows (Table 1).

Table 1 Variable definitions.

Variable definition	Expressed per unit of area	Expressed per unit of output
Market returns	R	P
Payment	H	G
Other factors	Z	Z

Given these variables, we can define our supply equations as follows.

Area:	A(R, H, Z)
Yield:	Y(P, G, Z)
Supply:	S(P, G, Z), which can also be expressed as the product of area and yield.

The *payment impact coefficient* is the derivative of the effect of each kind of payment on the supply variable as reported in (or that can be calculated from information reported in) each of the studies chosen for analysis. For example, if studying the effect of a specific payment, H_i, on area among studies j=1, … J, then our data would consist of a listing of all the first derivative effects of a one unit change in the payment per unit of area on the area planted, or

(1) $$\left\{\left(\widehat{\frac{\partial A}{\partial H_i}}\right)_{j=1}, \left(\widehat{\frac{\partial A}{\partial H_i}}\right)_{j=2}, \dots, \left(\widehat{\frac{\partial A}{\partial H_i}}\right)_{j=J}\right\}.$$

Assuming that we have K studies that generate yield observations, this listing would be

(2) $$\left\{\left(\widehat{\frac{\partial Y}{\partial G_i}}\right)_{k=1}, \left(\widehat{\frac{\partial Y}{\partial G_i}}\right)_{k=2}, \dots, \left(\widehat{\frac{\partial Y}{\partial G_i}}\right)_{k=K}\right\}.$$

The *coupling coefficient* of the payment is the ratio of the *payment impact coefficient* to the like change in returns from the market as estimated in each study. If we have L studies that generate comparable ratios for area and M studies that allow such comparisons for yields, then we have these two sets of comparisons:

(3) $$\left\{\left(\widehat{\frac{\partial A}{\partial H_i}}\Big/\widehat{\frac{\partial A}{\partial R}}\right)_{l=1}, \left(\widehat{\frac{\partial A}{\partial H_i}}\Big/\widehat{\frac{\partial A}{\partial R}}\right)_{l=2}, \dots, \left(\widehat{\frac{\partial A}{\partial H_i}\Big/\frac{\partial A}{\partial R}}\right)_{l=L}\right\}; \text{ and}$$

(4) $$\left\{\left(\widehat{\frac{\partial Y}{\partial G_i}}\Big/\widehat{\frac{\partial Y}{\partial P}}\right)_{m=1}, \left(\widehat{\frac{\partial Y}{\partial G_i}}\Big/\widehat{\frac{\partial Y}{\partial P}}\right)_{m=2}, \dots, \left(\widehat{\frac{\partial Y}{\partial G_i}}\Big/\widehat{\frac{\partial Y}{\partial P}}\right)_{m=M}\right\}.$$

In practice, we expect $J > L > K > M$.

We may expect the magnitude of estimated payment impact and coupling coefficients to vary according to study characteristics such as:

- The method of analysis (econometric, simulation, survey);

- The data used, such as the national or regional scope, or whether producer panel or experimental farm;
- The crop or crops covered and whether cross-effects were estimated;
- Whether it was published and, if so, peer-reviewed;
- When it was published and the period of time to which the data relate;
- To which payment program(s) the results relate; and
- Which potential channels of payment effects are studied (such as risk reduction, expectations of updating, entry and exit decisions, and imperfect credit markets).

Some studies can produce multiple estimates of payment impact and coupling coefficients. Moreover, a given study might provide a distinct quantitative estimate of the supply effect of each of several program payments. The database includes each result to which the authors grant credence. That said, we use published econometric estimates of payment effects without regard to their reported degree of statistical significance.

We ignore judgements authors make about statistical significance of their estimated results for both practical and other reasons. As a practical matter, we want to combine estimates of payment effects from econometric studies with those from model simulations or purely theoretical analyses for which there are no corresponding estimates of coefficient variances. We also do not wish to use statistical significance as an indicator of economic consequence. In reading studies that do so, we see a risk that a value that is not statistically significant is dismissed as unimportant even though it might correspond to a supply effect that is large compared to the impact of a similar amount of market receipts.

The math of statistical significance might mislead if our concern is the supply-inducing effect per dollar spent relative to a dollar of market receipts, perhaps even more so if elasticities are estimated. In the United States, program payments are usually much smaller than market receipts in size, so it might be expected that large percent changes in government payments might cause small percent changes in supply variables and, given other factors, these effects might appear close to zero.

5. Data

As noted earlier, a few studies report estimates of impact or coupling coefficients directly. Others report the base data, assumptions, and estimated results needed to compute them. In some cases, we rely on market or payment data from other sources, primarily USDA or OECD, to convert published results into usable indicators. However, in doing so, we do not impose our own judgments or draw any additional information apart from some data representing market conditions or payment sizes. For example, we do not supplement the half dozen studies that publish payment effects but not the associated market return effects by imposing any economic finding external to that study, such as supply elasticities.

We analyze results for 122 cases from 20 studies (Table 2). Most of the studies were published in peer-reviewed journals, and the average date of publication was 2007 or 2008, depending on whether one averages over studies or cases. The average date of the data used in these studies is 2000. Half of the studies and nearly half the observations are from simulation results, with almost as much from direct estimation. Theoretical results account for a small share of studies and cases. Whereas our focus and policy questions relate to national supply, less than half the studies and an even smaller share of cases relate to that level of aggregation, with about as many representing some or all of the Corn Belt. Likewise, many of the studies estimate only partial effects of payments;

more studies focus on risk reduction, risk and wealth, or expectations of base updating than on the total of the various channels of payment effects. In terms of cases, however, there is a greater focus on the total of all the various channels of payment effects. The vast bulk of published results relate to effects of fixed direct payments (FDP), including AMTA, PFC, and DPs, with few studies on other crop programs.. We are unable to find relevant literature for programs that have been in place since the 2014 Farm Bill, such as Price Loss Coverage (PLC) or Agriculture Risk Coverage (ARC).

Table 2. Summary of data from reviewed studies, characteristics of studies.

	Studies		Cases or results	
Number of observations	20		122	
Published in journal	13	65%	107	88%
Peer-reviewed	12	60%	106	87%
Date of publication, average	2007		2008	
Date of data, average	2000		2000	
Method				
Estimation	9	45%	58	48%
Simulation	10	50%	60	49%
Theory	1	5%	4	3%
Region or scope of supply				
United States	9	45%	47	39%
Part of United States	10	50%	43	35%
of which Corn Belt	5	25%	31	25%
Other than U.S.	1	5%	32	26%
Decoupling effect				
All	8	40%	57	47%
Price effect	2	10%	5	4%
Risk reduction	6	30%	36	30%
Risk and wealth	3	15%	11	9%
Updating and expectations	2	10%	20	16%
Exemptions or exclusions	0	0%	0	0%
Credit, liquidity	1	5%	2	2%
Labor	0	0%	0	0%
Entry or exit	1	5%	1	1%
Program				
Pre-1996 US policy	1	5%	4	3%
Marketing loan program (MLB)	1	5%	12	10%
Fixed direct payment (FDP)	18	90%	89	73%
Market Loss Assistance (MLA)	2	10%	2	2%
Average Crop Revenue Election (ACRE)	0	0%	0	0%
Counter-Cyclical Program (CCP)	2	10%	31	25%
Price Loss Coverage (PLC)	0	0%	0	0%
Agriculture Risk Coverage (ARC)	0	0%	0	0%

Source: author calculations.

The focus of almost half the studies is crop area (Table 3). Production is directly the focus of fewer studies and less than a third of the cases. Very few useful results for crop yields have been identified and there is little information that spans all three crop supply variables. Partly because we restrict ourselves to drawing market effects from the same study as we calculate the payment effects, we are not able to calculate the ratio of payment impact to market impact for one-fifth of the studies and nearly about 15% of the observations.[2]

Table 3. Summary of data from reviewed studies, characteristics of results.

	Studies		Cases or results	
Supply variable				
Area of all crops	4	20%	46	38%
Area of a crop	5	25%	22	18%
Yield	1	5%	12	10%
Production of all crops	6	30%	24	20%
Production of a crop	2	10%	11	9%
All supply variables	2	10%	7	6%
Presence of cross-effects	2	10%	48	39%
Results, number of instances where available				
Change in output per payment	20	100%	98	80%
Ratio of payment impact to market impact	16	80%	105	86%

Source: author calculations.

6. Comparable impact and coupling coefficients from the literature

Data from published studies are used to generate impact and coupling coefficients, as defined earlier. This assessment does not span all studies that relate to FDPs, but only those from which we can calculate comparable indicators of effect that

[2] The exception is in instances where the impact of payments on the supply variable of a study or case is zero. In that case, we assume the ratio of payment impact to market impact is also zero even if the study does not estimate the effect of market returns.

might be relevant to supply effect. In principle, we might hope to find estimates of the supply-inducing effects of all payments related to historical entitlement in the United States during the past few decades (e.g. FDP, MLA, CCP, ACRE, ARC, PLC) on the key crop supply variables (area planted, yield, and output) or policies in other countries (such as the Single Farm Payment of the European Union or the program of direct payments (PROCAMPO) of Mexico).

We find that most estimates of impact and coupling coefficients obtained from past studies analyzed the area effects of FDP. As noted above, this category of program payments was the focus of almost three-fourths of the observations and 90% of the studies available for our analysis.

FDP area impact and coupling coefficients

Tables 4 and 5 refer, respectively, to estimates of area impact and coupling coefficients. Column headings in these tables denote the avenue of payment effects: via price channels, risk reduction, risk and wealth, expectations of base updating, and, in the final column, results from studies that do not distinguish which one of the various channels of payment effects to which the estimated results relate. Studies assigned to this latter category account for most of the studies reporting estimated payment impacts on area planted.

There are five cell entries in each of the columns:

1. (top left) is the number of <u>cases</u> for which numerical estimates of payment effects were made;
2. (top middle) is the total number of <u>studies</u> that analyzed this or that channel of payment effects;
3. (top right) is the median of all cases;

4. (bottom left) is the average of all cases (without weights); and
5. (bottom middle) is the average of all studies (so cases are weighted).[3]

The primary focus is on own effects, meaning the effect of a payment associated in some way with a crop on the area of that crop. This distinction is admittedly vague for FDP payments that are not tied to current area, at least aside from the updating avenue of impact, a point reflected in some of the source studies. For other payments that are tied in some way to crop market conditions, such as PLC or ARC, this distinction is somewhat clearer.

The first tranche of rows, “Region & Own Effect,” denotes regional coverage of the analysis: U.S. National, U.S. Corn Belt, and an aggregate of all other regions outside of the United States. The second tranche, “Methods & Own Effects,” identifies the kind of data and the method used to estimate results. The third major row label, “All & Own Effect,” combines results from all studies reporting estimates of payment impacts on area but ignoring the particular method used to obtain them, in effect, aggregating results reported in the immediately preceding rows. The final tranche of rows contains results characterized by the “Nature of Effect,” specifically whether the result refers to a cross-effect, such as the impact of FDPs associated with corn on soybean area and whether the study relates to an aggregate of crop area or to a single crop.

---

[3] Many studies generate multiple cases, but these are not independent observations. We present an average of all cases from all studies as though they are independent and we also present an average that puts equal weight on each study regardless of the number of cases each study provides.

Table 4. Area impact coefficients of fixed direct payments

	Price Effect	Risk Reduction	Risk and Wealth	Expectations of Base Updating	Other	All
Change in output per change in payment						
Region & Own Effect						
US National		1 1 ~0 ~0 ~0	2 2 ~0 ~0 ~0			7 2 0.039 0.032 0.017
Corn Belt				12 2 0.001 0.001 0.001		5 3 0.002 0.003 0.004
Other						4 1 ~0 ~0 ~0
Methods & Own Effect						
Est., Panel or Survey Data		1 1 0.055 0.055 0.055				19 7 0.004 0.014 0.009
Est., Market Data						3 1 ~0 0.001 0.001
Simulation or Theory		1 1 ~0 ~0 ~0	2 2 ~0 ~0 ~0	12 2 0.001 0.001 0.001		
All & Own Effect						
		2 2 0.027 0.027 0.027	2 2 ~0 ~0 ~0	12 2 0.001 0.001 0.001		22 8 0.002 0.012 0.008
Nature of Effect						
Cross-Effect				8 1 ~0 ~0 ~0		12 1 ~0 ~0 ~0
All Crops		2 2 0.027 0.027 0.027	2 2 ~0 ~0 ~0	20 2 ~0 ~0 ~0		34 8 ~0 0.008 0.008
One Crop		2 2 0.027 0.027 0.027	2 2 ~0 ~0 ~0	20 2 ~0 ~0 ~0		34 8 ~0 0.008 0.008

Table 5. Area coupling coefficients of fixed direct payments

	Price Effect	Risk Reduction			Risk and Wealth			Expectations of Base Updating			Other	All		
Ratio of payment impact to market impact														
Region & Own Effect														
US National		1	1	~0	2	2	0.064							
		~0	~0		0.064	0.064								
Corn Belt								12	2	0.689		1	3	1.037
								0.652	0.665			1.037	1.037	
Other												4	1	0.689
												0.693	0.693	
Methods & Own Effect														
Est., Panel or Survey Data		1	1	0.024								6	7	0.929
		0.024	0.024									0.827	0.96	
Est., Market Data												3	1	0.459
												0.842	0.842	
Simulation or Theory		1	1	~0	2	2	0.064	12	2	0.689				
		~0	~0		0.064	0.064		0.652	0.665					
All & Own Effect														
		2	2	0.012	2	2	0.064	12	2	0.689		9	8	0.92
		0.012	0.012		0.064	0.064		0.652	0.665			0.832	0.931	
Nature of Effect														
Cross-Effect								8	1	0.625		12	1	0.445
								0.625	0.625			0.321	0.321	
All Crops		2	2	0.012	2	2	0.064	20	2	0.689		21	8	0.459
		0.012	0.012		0.064	0.064		0.641	0.665			0.54	0.861	
One Crop		2	2	0.012	2	2	0.064	20	2	0.689		21	8	0.459
		0.012	0.012		0.064	0.064		0.641	0.665			0.54	0.861	

We can calculate the own impact indicator for two studies encompassing seven cases with U.S. National coverage (Table 4, final column of first row), an ultimate target of the present analysis. Those studies reporting econometric estimation results relied mainly on panel or survey data (Table 4, final column of first row under "Methods & Own Effect"). Results from panel or survey data as opposed to market data raise a key question about composition of estimated responses: observed adjustments in planted area due to payments presumably reflect a combination of area expansion or contraction by panel members, but might omit sales, purchases, and rental agreements of producers not in the panel. For a panel that is defined, for example, by maintaining at least some minimum amount of area over time, results might reflect those producers who stay and expand while omitting those who exit.

The greatest number of studies for which payment effects were measured comprised those estimating (implicitly or explicitly) the combined effects of all channels of potential payment impacts (Table 4, last column of "All & Own Effect row"). That is a bit surprising given the fact that much of the general discussion of the different channels has focused on payment effects due to risk reduction – risk reduction is examined in isolation in only two cases examined in two different studies.

Many of the numerical values of estimated payment impact coefficients in Table 4 appear quite small, perhaps supporting a view that payments might have small production effects (Bhaskar and Beghin, 2009). This can be misleading, however, as even quite small per dollar impact coefficients may result in quite substantial area impacts for large payments and planted areas.[4] The estimates of payment impact from studies not distinguishing the particular source of payment effects (final column in the Table) average 0.012 over all observations or 0.008 if averaged by study. The U.S. National numbers average somewhat higher than the Corn Belt, suggesting regional differences that could be important for certain policy questions or for an effort to extrapolate to other payments in other countries. There is a quite high incidence of empty cells revealing that we found no study from which to develop the corresponding (row and column) indicator of area impact per dollar spent on the program.

Coupling coefficients presented in Table 5 relate the area impact of FDP to the impact of an equal amount of market receipts. The table structure is otherwise identical to the preceding table to facilitate comparison – both here and among all calculated indicators for different programs and supply variables presented in the appendix.

Recall, an estimated coupling coefficient equal to zero implies the study found no area effect from FDP. Correspondingly, an estimated value of one means that the area impact of a dollar of FDP is the same as the area impact of a dollar of market receipts.

[4] To illustrate, consider the average payment impact coefficient across all studies, the last entry in the final column of the All & Own Effect row (0.008). In 2014, the total of FDP paid farmers was USD million 4,726 (OECD, 2019). The product, assuming the coefficient applies at all values of payment, implies a total payment impact on area of 0.008*4725=38 million acres or approximately 15% of total program acres in that year.

Here, the median and average values of the estimated coupling coefficients are in the range nearly zero to 1.037. Moreover, there are non-zero estimates of coupling coefficients across the complete list of channels of payment effects.

There are differences between the implications of payment impact coefficients (Table 4) and coupling coefficients (Table 5) for at least two reasons. First, the tables include results from a different set of studies. While we can calculate both indicators from many studies, we cannot calculate impact coefficients from a few studies and we cannot calculate coupling coefficients from 20% of our sample overall. In other words, in one-fifth of the studies reviewed, there is no clear indication of how market receipts affect supply against which to compare the published estimate of payment impacts, so a consistent coupling coefficient cannot be calculated.

Second, a seemingly small payment impact coefficient could still yield a meaningfully large coupling coefficient if the associated market impact coefficient is also small. Comparing the two tables supports this possibility, which raises concerns for any reader of this literature. Authors often use statistical significance or some similar proxy for payment effects which does not have a benchmark that speaks to economic consequence. By standardizing payment area effects on the area effect of a like value of market receipts, our coupling coefficients might strike a note that is closer to policy questions and to the information needed by applied economists who are concerned about supply-inducing impacts of payments in order to assess their market implications.

Impact and coupling coefficients for other programs and other supply variables

Results for other programs and output variables, including FDP impact and coupling coefficients for yield and output, are reported in the appendix. As of yet, we find no relevant estimates of supply-inducing impacts, as we define them, for over half the U.S. programs in the past two decades, including ACRE, ARC, and PLC. We find few estimates relating to other payments, such as CCP, MLA, and MLB. As already noted, studies tend to focus on area impacts, generally speaking, with far fewer estimates available for the impacts of payments on yield or overall crop output.

It is perhaps unsurprising that published analyses of FDP so outnumber those evaluating other program types. FDP payments were largely the focus of policy reforms introduced in the midst of the international discussions aimed at bringing agricultural subsidies under the discipline of global trade rules. Those discussions sparked debate over whether proposed shifts from market support to FDPs would achieve policy reform goals. It is surprising, however, that such a large share of the analytical effort was expended on estimating payment effects focused on induced changes in area planted. Yield is admittedly a difficult area for applied economics, yet potentially critical to long-run supply response (Thompson et al., 2019). Because land is relatively fixed as compared to other factors of production one might expect greater payoff to policy reforms that feature reductions in price support from yield response as opposed to area response.

What about generic base?

Generic base appears to be omitted from the literature despite the focus on payments tied to historical base area, and despite the fact that this rule change seems to create an opportunity for an important case study. Unusual circumstances caused a portion of base area payments to be linked to the crop planted, not historical criteria, and there appeared to be a substantial reallocation of area towards the crop that offered the highest payment (see the policy section of the appendix for background and data). Casual observation of policy and planting is no substitute for serious analysis, yet this case stands out as an instance where an erstwhile decoupled program was briefly coupled to planting decisions and the change appeared to have important consequences. Indeed, generic base provides an important sniff test going forward for decoupling analysis that answers how producers would respond if base acres were replaced with planted acres.

The impact and coupling coefficients presented in this section and in the appendix cannot be applied directly to national supply impacts nor incorporated directly into an economic model of U.S. agricultural policies and markets. In their present form, the impact and coupling coefficients presented here provide input into a process for achieving such an objective. They fall short for reasons suggested earlier: studies often focus on a panel of only some producers, on only part of the United States, or on only a representative or theoretical setting, so the results might not relate to national supply. As such, numerical estimates of coupling coefficients (of the type reported in Table 5)

What's missing? U.S. dairy payments and crop insurance

Our assessment does not include crop insurance at this time. Our focus is on decoupled payments (in the sense that production is not a criterion of payment) under Title 1 Farm Bill programs, with MLBs presented as a benchmark which we expect to have a coupling coefficient near one. Crop insurance could in principle be added to the analysis, but its more complex coupling to production makes it less useful than MLBs as a benchmark and calls for consideration of how risk-related effects of insurance and other programs interact and, as well, crop insurance support is distributed differently.

We also do not include an assessment of dairy programs at this time. Since 2014, dairy payments have been tied to historical benchmark production and as a result are in that sense decoupled from current production, although eligibility still requires an active dairy operation unlike decoupled payments on historical crop base. In addition, prior to the 2018 Farm Bill, payment base could increase by a share of national production growth, potentially providing an indirect incentive to increase production. In any case, while we believe there would be value in analyzing the implications of this type of decoupling in Title 1 dairy programs on production, the literature has not yet addressed these questions and so we have not included those programs in our study. That is likely the result of the limited scope for empirical analysis at this point, since dairy program payments have been quite small in most years relative to production value (OECD, 2019). Moreover, some of the same complexities regarding risk-related effects that must be considered in analyzing crop insurance might also hold for the insurance-like dairy margin programs.

supply equations for a U.S. national agricultural policy and projections model. We should not expect every possible coupling coefficient to be equally likely.

7. Combining coupling coefficients across studies

A Bayesian modeling framework constitutes a suitable method for exploiting the prior knowledge of payment coupling coefficients based on program payment criteria (as summarized in the appendix) and then updating these priors based on observed results drawn from the literature. Moreover, Bayesian methods are adapted to allow us to lend more or less weight to published coupling coefficient based on a measure of how well each coupling coefficient relates to national supply, as defined here.

Test of study appropriateness of coupling coefficients for national supply

We model the distribution of a given study's coupling parameter as:

(5) $$\alpha_j^i|\mu^i \sim N\left(\mu^i, \left(\beta_j^i\right)^2\right)$$

where α_j^i is the coupling coefficient derived from the j^{th} study for program i, μ^i is the mean of the coupling coefficients for program i and β_j^i is a known standard deviation for the study. It is worth noting that each study is treated as a distribution instead of a data point. This is due to the fact the studies are not equally suitable for forward looking-analysis. The β_j^i's allow a measure of confidence in the parameter to be inserted into the framework.

The prior distribution for the mean of the coupling coefficients is modeled by:

(6) $$\mu^i \sim N\left(\mu_0^i, \left(\sigma_0^i\right)^2\right)$$

where μ_0^i is our prior for the mean value for the coupling coefficient and σ_0^i is the prior standard deviation. The μ_0^i's were taken from the FAPRI-MU model. Since the normal is the conjugate prior for the normal, the posterior will also be a normal distribution and can be shown to be:

$$\text{(7)} \qquad \mu^i|\alpha_1^i, \dots, \alpha_{k^i}^i \sim N\left(\frac{\frac{\mu_0^i}{\sigma_0^2}+\sum_{j=1}^{k^i}\frac{\alpha_j^i}{\left(\beta_j^i\right)^2}}{\frac{1}{\sigma_0^2}+\sum_{j=1}^{k^i}\frac{1}{\left(\beta_j^i\right)^2}}, \frac{1}{\frac{1}{\sigma_0^2}+\sum_{j=1}^{k^i}\frac{1}{\left(\beta_j^i\right)^2}}\right)$$

where k^i is the number of studies about the i^{th} program.

Furthermore, it is reasonable to believe in specific rankings of the coupling parameters. For example, the key difference between payments under PLC and CCP and FDP payments is that the former type are tied to the current year price, and thus can be expected to be more coupled than the FDP (see Table 6 and discussion of programs in the appendix). Likewise, ARC seems obviously more coupled than FDP due to its reliance on current yields and the current price, but it is not clearly more or less coupled than PLC. While ARC does contain a local yield component, it has a small cap on payments that PLC lacks which makes it unresponsive to market conditions beyond that point making comparison to PLC difficult. ACRE and MLB are most closely tied to actual plantings of programs studied, but ACRE payments were subject to some historical base limitations, whereas MLB can expand without limit as output rises.

The rankings can be represented as $\mu^i|\alpha_1^i, \dots, \alpha_{k^i}^i;\ \mu^{i-1}, \mu^{i+1}$ where the μ^i's are ranked in ascending order. Gelfand, Smith and Lee, (1992) show that this can be represented by the standard distribution restricted to the (μ^{i-1}, μ^{i+1}) interval. In this case,

$\mu^i|\alpha_1^i,\ldots,\alpha_{k^i}^i;\ \mu^{i-1},\mu^{i+1}$ is still represented by equation 7, but is now a restricted normal. Gibbs sampling of the conditional posteriors can be used to obtain the unconditioned posteriors.

Table 6. Prior distributions

Program	$\boldsymbol{\mu_0^i}$	$\boldsymbol{\sigma_0^i}$	**Restriction**
Fixed direct payments (FDP)	0.05	0.2	$\mu^{DP} \in (-\infty,\ \min(\mu^{PLC},\ \mu^{ARC}))$
Price Loss Coverage (PLC)	0.25	0.2	$\mu^{PLC} \in \left(\mu^{DP},\ \min(\mu^{ACRE},\ \mu^{MLB})\right)$
Agriculture Risk Coverage (ARC)	0.25	0.2	$\mu^{ARC} \in \left(\mu^{DP},\ \min(\mu^{ACRE},\ \mu^{MLB})\right)$
Average Crop Rev. Election (ACRE)	1.00	0.2	$\mu^{ACRE} \in (\max(\mu^{PLC},\ \mu^{ARC}),\ \infty)$
Marketing loan benefits (MLB)	1.00	0.2	$\mu^{MLB} \in (\max(\mu^{PLC},\ \mu^{ARC}),\ \infty)$

The coefficients, β_j^i, are determined using cross-validation to measure a study's appropriateness to our criteria. The reason for this is that the units of study vary widely in the literature- from farm level to national and across a variety of crops and different time periods. For these reasons, we do not expect every result to be equally suitable to use in a national model with multiple commodities. However, the appropriateness of parameters from a study to our conditions can be measured. We do this via cross-validation. Here, the data, equations, and method are defined.

In order to estimate U.S. area equations, we first construct a dataset from multiple sources. Planted area is from the National Agricultural Statistics Service of the U.S. Department of Agriculture (USDA). Variable costs by commodity are published by the Economic Research Service (ERS) of the USDA. Expected government payments per acre are calculated from the FAPRI-MU deterministic crop production model which breaks out area for 15 states. The state numbers are aggregated to a national total via a weighted average. MLB and ACRE payments are weighted by planted acres whereas FDP, ARC, CCP, and PLC payments are weighted by base acres. PLC and CCP payments are given the same parameter since the programs have essentially the same structure. Expected market revenues per state are the product of the state trend yield and the planting-time futures price of the harvest contract adjusted for basis. The revenues are weighted to a national average by planted acres. The data span the years 1996 to 2018. Data prior to 1996 lacks relevance for the analysis as programs that no longer exist placed many restrictions on plantings.

The coupling factors convert the government payments to a market equivalent basis. Consequently, expected market net returns plus the sum of the products of the coupling parameters and corresponding expected payments gives a new expected net returns that has all terms normalized to the market net returns equivalent. Note that actual variable costs are used in the calculation as those are mostly known at the time of planting. Expected net returns are calculated for U.S. corn, soybeans, and wheat. For estimation purposes, the net returns are adjusted for inflation using a GDP deflator with a base year of 2013. We regress U.S. corn, soybean, and wheat area against the real expected net returns of the three and the year of harvest.

Given the limited number of observations, several constraints are imposed on the linear system. First, the cross effects of returns on acreage are non-positive. In other words, the derivate of corn area with respect to the soybean return is less than or equal to zero, and so on. Second, area planted to a crop cannot decrease if all returns increase by an equal amount. This is equivalent to the sum of the derivatives of corn area with respect to corn, soybeans, and wheat returns being non-negative. Note that along with the first assumption, this condition forces planted area with respect to own returns to be non-negative. Finally, it is assumed that the cross effects are symmetric. A dollar increase in corn returns will lower soybean acreage by the same amount that an increase in a dollar of soybean returns would lower corn acreage. This helps ensure consistency of effects. For example, it prevents the case where a dollar increase in corn returns might reduce soybean and wheat acreage more than it increased corn acreage, thereby reducing total acreage even though returns increase. It also reduces the number of parameters to be estimated.

Ordinary Least Squares (OLS) was chosen for the estimator, as Seemingly Unrelated Regression is equivalent to the former when all of the equations in the system have the same independent variables. The OLS estimation with inequality constraints was performed by recasting the problem as a quadratic programming equation and solving with the quadprog package in R. Standard errors were determined by bootstrapping the estimators with 5,000 iterations. A baseline case was initially estimated using a set of coupling coefficients (Table 6). The results from the baseline regression use all the data and verify the incorporation of the constraints (Table 7). Care should be taken when comparing the standard errors with the parameter estimates: the returns coefficients cannot change signs due to restrictions, so hypothesis tests checking for significant differences from zero are complicated and not made available here.

Table 7. Planted acres regressed on returns for the baseline

	Area planted (1,000 acres)		
	Corn	Soybeans	Wheat
Intercept	-1,857,734.7	-989,981.4	1,819,978.1
	(321,610.4)	(286,079.2)	(202,642.0)
Corn real net returns	63.7	-48.7	0.0
	(13.9)	(16.6)	(0.5)
Soybean real net returns	-48.7	48.7	0.0
	(16.6)	(16.9)	(1.8)
Wheat real net returns	0.0	0.0	25.2
	(0.5)	(1.8)	(11.2)
Year	970.4	528.7	-877.8
	(160.8)	(143.1)	(101.0)

Standard errors in parentheses

Table 8: Study and program MSE relative to baseline MSE

Study	Program				
	FDP	ARC	PLC	ACRE	MLB
Anton and Le Mouel (2004)			0.994		
Anton and Le Mouel (2004)					0.995
Becker and Judge (2014)			1.178		
Becker and Judge (2014)	1.021				
Bhaskar and Beghin (2010)	1.009				
Chambers and Voica (2017)			0.980		
Chambers and Voica (2017)		1.009			
Chambers and Voica (2017)				0.998	
Chambers and Voica (2017)	0.999				
Chambers and Voica (2017)					1.000
Chau and de Gorter (2005)	1.003				
Femenia, Gohin and Carpentier (2010)	1.002				
Goodwin and Mishra (2006)	1.027				
Goodwin and Mishra (2003)	1.031				
Hendricks and Sumner (2014)	1.009				
Hendricks and Sumner (2014)			1.012		
OECD (2001)	1.000				
OECD (2003)	1.005				
Roe, Somwaru and Diao (2003)	0.999				
Serra, Zilberman, Goodwin and Featherstone (2005)	0.999				
Weber and Key (2012)	0.988				

The constrained OLS was used to construct appropriateness measures of the coupling parameters through five-fold cross validation. Mean Squared Error (MSE) was calculated for each out of sample fold to determine the predictive ability of different coupling parameters. This method also has less risk of overfitting relative to a single regression result of the full data. With limited post-1995 data, it would be difficult to estimate actual parameters for every coefficient on every payment and market returns – and additional complications are suggested by the various estimation techniques used in past studies. This method allows the use of previous studies with adjustments for appropriateness for our purposes.

The MSE from each study was used to construct the standard deviation for each study via the following formula:

$$\beta_j^i = \left(\frac{MSE_j^i}{MSE_0^i}\right)^{w/2} \sigma_0^i \tag{8}$$

where MSE_j^i is the MSE from j^{th} study for program i, MSE_0^i is the MSE using the prior means for program i and w is an unknown parameter with a flat prior (uninformative). Substitution generates the conditional posterior for the coupling parameter means, namely

$$\mu^i | \alpha_1^i, \ldots, \alpha_{k^i}^i; w;\ \mu^{i-1}, \mu^{i+1} \sim N\left(\frac{\mu_0^i + \sum_{j=1}^{k^i} \alpha_j^i \left(\frac{MSE_0^i}{MSE_j^i}\right)^w}{1 + \sum_{j=1}^{k^i}\left(\frac{MSE_0^i}{MSE_j^i}\right)^w}, \frac{\left(\sigma_0^i\right)^2}{1 + \sum_{j=1}^{k^i}\left(\frac{MSE_0^i}{MSE_j^i}\right)^w}\right);\ \mu^i \in \left[\mu^{i-1}, \mu^{i+1}\right]. \tag{9}$$

The posterior has rather intuitive properties. As a study performs better relative to the others, its MSE will go to zero and the posterior mean will approach the mean from that study and the variance will go to zero. Conversely, if none of the studies perform well, the MSEs will be large and the posterior mean and variance will approach the priors. In other words, the posterior distribution is a combination of the prior assumptions and the relative performance of the studies.

Our belief is that *w* should only be positive, as studies that fit better should have more influence in the posteriors. Therefore, we chose a uniform (flat) prior constrained to be nonnegative. The conditional posterior for *w* has the form:

(10)
$$p\left(w|\alpha_1^i, \ldots, \alpha_{k^i}^m;\ \mu^1, \ldots, \mu^m\right) \propto$$

$$\left[\prod_{i=1}^m \prod_{j=1}^{k^i} \left(\frac{MSE_0^i}{MSE_j^i}\right)\right]^{w/2} exp\left\{\frac{-1}{2\sigma_0^2} \sum_{i=1}^m \sum_{j=1}^{k^i} \left(\frac{MSE_0^i}{MSE_j^i}\right)^w \left(\alpha_j^i - \mu^i\right)^2\right\}$$

where *m* is the number of coupling coefficients and $\sum_{i=1}^m k^i$ is the total number of observations. The form does not correspond to a known kernel, so a Metropolis-Hasting step was included in the Gibbs sampling for *w*. A normal distribution with a standard deviation of 0.1 was used as the sampling distribution, and values of *w* less than zero were rejected as potential jumps.

Simulation results to generate appropriateness-adjusted coupling coefficients

The Markov-Chain Monte Carlo (MCMC) was performed with 15,000 iterations and the first 200 were dropped as burn-in, as shown in the MCMC trace plots (Figure 1).

The summary statistics for the posterior distributions include mean, median, and selected percentiles (Table 9). Bayesian statistics reflects beliefs given evidence and treats parameters as distributions instead of points. Relative to the priors, the posterior means have less dispersion across the programs. FDP are more coupled in the posterior distribution as all of the outcomes are above the prior mean; 97.5% of PLC outcomes were higher than ARC outcomes in the MCMC; and likewise, 98.5% of MLB outcomes were greater than ACRE outcomes. All of the 95% credible intervals are between 0.158 and 1.303, indicating that the programs have a positive effect on acreage. However, this effect per dollar of payment is less than the effect of a comparable amount of money from the market, except for marketing loan benefits.

Figure 1. Trace plots

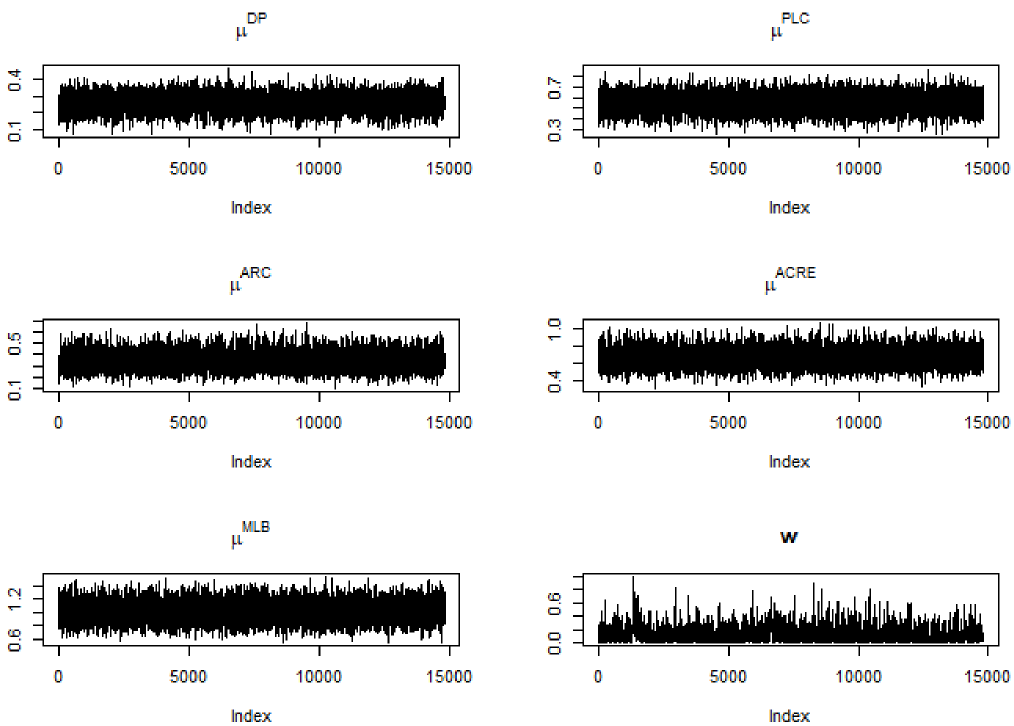


Table 9. Posterior distributions

	DP	PLC	ARC	ACRE	MLB	w
Percentile						
2.5%	0.158	0.393	0.205	0.479	0.750	0.003
25.0%	0.223	0.497	0.281	0.585	0.927	0.041
50.0%	0.257	0.550	0.325	0.648	1.022	0.099
75.0%	0.291	0.603	0.377	0.714	1.118	0.196
97.5%	0.354	0.707	0.496	0.854	1.303	0.502
Mean	0.257	0.550	0.333	0.652	1.023	0.140

Market implications might be a better tool to assess the implications of these coupling coefficients. The changes going from the prior to posterior levels of coupling coefficients might or might not appear "large." We use a large-scale structural economic model of the markets of crops and crop products, livestock and livestock products, and biofuels to assess the impacts of going from the mean of the prior values to the mean of the posterior distributions (see appendix). This exercise highlights several facts that are not immediately germane to the literature focused on the payments but have an impact on our understanding of their potential effects.

PLC and ARC payment impacts appear to be limited despite the increase in coupling coefficients. There are two main reasons for this finding (see the appendix for details). First, payments in the past have been much smaller than market receipts in the United States. As such, changes in coupling coefficients will have small proportional area impacts and moreover, price responses will tend to moderate these area changes. Second, changes to supply-inducing effects of payments on each crop are not in isolation but are instead bound by the inelastic supply of land to crop production overall. While relative payments might encourage reallocation of area from one crop to another, the overall land allocated to crops is fairly inflexible, so total crop output rises by less than the supply of many individual crops.

The price impacts are larger than the area effects, with implications for farm income and government costs. Because total crop demand is also inelastic, price changes must be proportionally larger than the total crop output change to coax buyers to pick up the extra quantities and clear the markets. The consequence of a larger price reduction than the quantity increase, in proportional terms, is less farm income. Taxpayer costs rise if the lower prices trigger increases in PLC and MLB.

8. Conclusions

In recent decades, agricultural policies in the United States and many other countries moved partly away from direct market intervention via tariffs or other mechanisms that raise market prices and towards direct payments to producers, often tied to historical entitlement. This was concurrent with expansion in the scope and depth of international agreements by means of which countries imposed constraints that seemed to push them in this same direction. If the premise of such unilateral and multilateral policy changes was to decrease the output impact while allowing transfers to the income of targeted recipients, then scientific assessment of the impacts of these payments could provide critical input to policy makers. Given that these payments cost many billions of dollars in taxpayer expenditures per year in the United States and recent events have led to new payments with different mechanics, scientific assessment of the production, market, and income impacts of these various policy designs is timely.

The agricultural economics literature is not as helpful in assessing existing payments as one might hope given the policy importance of the topic. We identify several omissions at this stage of our review. First, the scope of programs covered is narrow, with a heavy focus on FDP (Direct Payments, PFC payments, or AMTA payments in the United States) and less, even none, on other types of programs. Second, the literature focuses on the impact of crop payments on crop area planted, potentially missing the mark if the key goal is to estimate supply effects. Third, the data and method used to estimate impacts in many studies might not ensure a strong relationship to national supply. Fourth, idiosyncratic characterizations of published payment impacts sometimes do not inform readers of the supply-inducing effects. Elasticities of a supply variable, like area, with respect to payments might mislead readers: a small elasticity that reflects how large percent changes in payments cause small percent changes in area might be a result of the fact that payments are much smaller than market returns. Depending on the sample, a near-zero elasticity of area with respect to payments is possible even when the per-dollar unit impact of payments is larger than the per-dollar impact of market returns. This weakness in the literature, to which we return below, also relates to the use of statistical significance of a particular parameter as a proxy for economic consequence.

Our first major contribution is to generate over one hundred comparable measures of payment impacts on supply variables. We standardize on two key indicators, (1) the impact coefficient, or per-dollar effect, of a payment on a supply variable and (2) the coupling coefficient, or the supply variable effect of a dollar of payment relative to the per-dollar effect of a dollar from the market on that same supply variable. For the second indicator, we rely on both payment and market effects of each study to ensure that the two are as consistent as in the original material; we do not impose elasticities from other sources or other external measures of market response to standardize study results.

Both indicators allow meaningful comparisons among studies and, as well, meaningful conclusions. While it is not our task to call an effect “big” or “small,” our concern as noted above is confirmed. Results that might be characterized as small – because of a statistical proxy for economic consequence or because an elasticity of a supply variable with respect to payments looks close to zero or even smaller than a price elasticity – might have generated payment impacts that are as large as or larger than the impacts of market receipts. Coupling coefficients range widely in the literature, from close to zero (almost no effect relative to the effect of a like amount of market returns) to far greater than one (one being the point at which a dollar of payment has the same supply impact as a dollar of returns from the market).

The meaning of all these studies for national supply effects of payments and for U.S. policy is unclear. By construction, our indicators are tied to the same sample and case as the source material, focusing on a specific avenue of impact or group of producers, and thus might not relate well to national supply. Even empirical studies based on panel data that implicitly might represent all potential avenues by which payments affect output are set at a distance from supply if the panel is not representative. For example, a panel of crop farmers with a minimum amount of activity in one or more periods by construction ignores compositional effects (Hertel et al., 1996) and more specifically, entry and exit effects. Our indicators render studies comparable to each other and to their own market impacts, but an additional step is necessary to relate them to national supply.

Our second major contribution is that next step: to relate coupling coefficients to national supply. Starting from *a priori* expectations about the level and relationship of coupling coefficients of past programs, we develop a Bayesian method to adjust those priors based on how each coupling coefficient taken from the literature relates to national data. This process puts greater weight on coupling coefficients that are, by this measure, more appropriate in terms of their ability to help explain national data and less weight on coupling coefficients that seem less appropriate in this context. This assessment is driven by the focus of studies on crop area and, we emphasize, is preliminary for reasons given below. We find at this time that the posteriors all have a higher mean than the priors, with the exception of ACRE. Moreover, the more decoupled posteriors have means that increase more than those of the more coupled programs, resulting in a narrowing of the range of coupling coefficients across programs.

We test the implications of changes in coupling coefficients for crop area and markets. The consequence of inelastic total crop area is that revising coupling coefficients reallocates land among crops without inducing much change in overall land use. That said, the inelastic demand for all crops leads to larger proportional price changes to rebalance the market, with negative implications for farm income and the consequence of rising taxpayer costs if certain program thresholds are reached.

Our experiment helps to underscore the importance of omissions in this body of literature, in particular the narrow focus on area. Area is not supply and, as this experiment shows, inelastic total land supply suggests serious limits on the crop market impacts of U.S. payments if measured via the impact on area planted alone, even for larger changes in the coupling coefficients. There is potential for land reallocation and, presumably, land price and rent impacts, but not on total U.S. crop area. Indeed, much greater coupling coefficients for total area might lead to large simulated swings in total crop area that are difficult to reconcile with observed patterns in land use or with the generally accepted view of inelastic total crop land supply. Although area may be more readily assessed by standard research approaches, the scope for payments to affect crop yield or output could be key omissions in this literature. Other expansions of research beyond the case of U.S. FDP effects on crop area could include impacts on area of other commodities. Cases of other countries might differ as well in such ways as total crop area elasticity.

We have highlighted some important advances resulting from our research so far, including by identifying key limitations in the decoupling literature. In order to refine our work, however, we seek studies of U.S. payments, particularly on current policies that can be rendered comparable using our current method, as well as studies of non-U.S. policies that would allow the scope of this work to be expanded beyond the United States. Our efforts thus far have revealed very few studies from which we can develop our indicators. And of course, we are certain that our calculations and methods will benefit from improvements suggested by thorough review. Nevertheless, we believe our work already takes two large steps towards rendering more useful to policy makers the results of a literature that could currently be characterized as a body of chaotically varying expressions of results and assessments of importance without an overall clear relationship to national supply and related policy questions.

9. References

Abler, D., and Blandford, D. (2005). “A Review of Empirical Studies of the Acreage and Production Response to U.S. Production Flexibility Contract Payments under the FAIR Act and Related Payments under Supplementary Legislation.” Paper prepared for the OECD.

Antón, J., and le Mouël, C. (2004). "Do Counter-Cyclical Payments in the 2002 US Farm Act Create Incentives to Produce?" Agricultural Economics 31(2-3): 277-284.

Bhaskar, A., and Beghin J. (2009). “How Coupled are Decoupled Farm Payments? A Review of the Evidence.” Journal of Agricultural and Research Economics 34(1): 130-153.

Bhaskar, A., and Beghin, J. (2010). “Decoupled Farm Payments and the Role of Base Acreage and Yield Updating Under Uncertainty.” American Journal of Agricultural Economics 92: 849-858.

Burfisher, M., Robinson, S., and Thierfelder, K. (2000). “North American Farm Programs and the WTO.” American Journal of Agricultural Economics 82(3):768-774.

Chambers, R., and Voica, D. (2016). “’Decoupled’ Farm Program Payments Are Really Decoupled: The Theory.” American Journal of Agricultural Economics 99(3): 773-782.

Chau, N., and de Gorter, H. (2005). "Disentangling the Consequences of Direct Payment Schemes in Agriculture on Fixed Costs, Exit Decisions, and Output." American Journal of Agricultural Economics 87(5): 1174-1181.

Femenia, F., Gohin, A., and Carpentier, A. (2010). “The Decoupling of farm Programs: Revisiting the Wealth Effect.” American Journal of Agricultural Economics 92(3):836-848.

Floyd, J.E. (1965). ‘The Effects of Farm Price Supports on the Returns to Land and Labor in Agriculture.” Journal of Political Economy 73: 148-158.

Gelfand, A.E., Smith, A.F.M., and Lee, T.M. (1992). “Bayesian Analysis of Constrained Parameter and Truncated Data Problems Using Gibbs Sampling.” Journal of the American Statistical Association 87(418): 523-532.

Girante, M., Goodwin, B.K., and Featherstone, A. (2008). “Farmers' Crop Acreage Decisions in the Presence of Credit Constraints: Do Decoupled Payments Matter?” Selected Paper, American Agricultural Economics Association Annual Meeting, Orlando, Florida, July 27-29.

Goodwin, B.K., and Mishra, A.K. (2003). “Acreage Effects of Decoupled Programs at the Extensive Margin.” Selected Paper, American Agricultural Economics Association Annual Meeting, Montreal, Canada, July 27-30.

Goodwin, B.K., and Mishra, A.K. (2006). “Are ‘Decoupled’ Farm Program Payments Really Decoupled? An Empirical Evaluation.” American Journal of Agricultural Economics 88(1): 73-89.

Hendricks, N., and Sumner D. (2014). “Crop Supply, with an Application to Base Updating.” American Journal of Agricultural Economics 96(3): 903-923.

Hennessy, D.A. (1998). “The Production Effects of Agricultural Income Support Policies under Uncertainty.” American Journal of Agricultural Economics 80(1): 46-57.

Hertel, T.W., Stiegert, K., and Vroomen, H. (1996). “Nitrogen-Land Substitution in Corn Production: a Reconciliation of Aggregate and Firm-Level Evidence.” American Journal of Agricultural Economics 78(1): 30-40.

Key, N., and Roberts, M.J. (2008). “Do Decoupled Payments Stimulate Production? Estimating the Effect on Program Crop Acreage Using Matching.” Selected Paper, American Agricultural Economics Association Annual Meeting, Orlando, Florida, July 27-29.

Kropp, J.D., and Whitaker, J.B. (2011). "The Impact of Decoupled Payments on the Cost of Operating Capital." Agricultural Finance Review 71(1): 25-40.

O’Donoghue, E.J., and Whitaker, J.B. (2010). “Do Direct Payments Distort Producers’ Decisions? An Examination of the Farm Security and Rural Investment Act of 2002.” Applied Economic Perspectives and Policy 32(1): 170-193.

Organization for Economic Cooperation and Development (OECD) (2001). Market Effects of Crop Support Measures. OECD Publishing, Paris. Available at doi.org/10.1787/9789264195011-en.

Organization for Economic Cooperation and Development (OECD) (2019). “Agricultural policy monitoring and evaluation: Producer Support Estimates.” Available at www.oecd.org/agriculture/topics/agricultural-policy-monitoring-and-evaluation.

Roe, T., Somwaru, A., and Diao, X. (2003). “Do Direct Payments have Intertemporal Effects on U.S. Agriculture?” In: Government Policy and Farmland Markets, pp. 115-139, edited by C.B. Moss and A. Schmitz, Iowa State Press.

Sckokai, P., and Moro, D. (2006). “Modeling the Reforms of the Common Agricultural Policy for Arable Crops under Uncertainty.” American Journal of Agricultural Economics 88(1): 43-56.

Serra, T., Zilberman, D., Goodwin, B., and Featherstone, A. (2005). “Decoupling Farm Policies: How Does This Affect Production?” Selected Paper, American Agricultural Economics Association Annual Meeting, Providence, Rhode Island, July 24-27.

Thompson, W., Dewbre, J., Pieralli, S., Schroeder, K., Pérez-Domínguez, I., and Westhoff, P. (2019). “Long-Term Crop Productivity Response and Its Effects on Cereal Markets.” Food Policy 84: 1-9.

Weber, J.G., and Key, N. (2012). “How Much Do Decoupled Payments Affect Production? An Instrumental Variable Approach with Panel Data.” American Journal of Agricultural Economics 94(1): 52-66.

Appendix to accompany

“Rescuing the Decoupling Literature from Incomparable Chaos”

A. Studies from which impact factors or coupling coefficients can be calculated

The studies from which relevant indicators could be derived are listed here.

Anton, J., and C. Le Mouel. 2004. Do counter-cyclical payments in the 2002 U.S. Farm Act create incentives to produce? *Agricultural Economics* 31:277-284.

Becker, A.D., and R.P. Judge. 2014. Evidence of Distortionary Effects of Decoupled Payments in U.S. Indica Rice Production. *Atlantic Economic Journal* 42(3):265-275.

Bhaskar, A., and J. Beghin. 2010. Decoupled farm payments and the role of base acreage and yield updating under uncertainty. *American Journal of Agricultural Economics* 92(3):849-858.

Burfisher, M., S. Robinson, and K. Thierfelder. 2000. North American Farm Programs and the WTO. *American Journal of Agricultural Economics* 82 (3):768–774.

Chambers, R.G., and D.C. Voica. 2017. "Decoupled" Farm Program Payments Are Really Decoupled: The Theory. *American Journal of Agricultural Economics* 99(3):773–782.

Chau, N., and H. de Gorter. 2005. Disentangling the Consequences of Direct Payment Schemes in Agriculture on Fixed Costs, Exit Decisions, and Output. *American Journal of Agricultural Economics* 87(5):1174-1181.

Femenia, F., A. Gohin and A. Carpentier. 2010. The Decoupling of farm Programs: Revisiting the Wealth Effect. *American Journal of Agricultural Economics* 92(3):836-848.

Girante, M., B.K. Goodwin and A. Featherstone. 2008. Farmers' Crop Acreage Decisions in the Presence of Credit Constraints: Do Decoupled Payments Matter? Selected Paper, American Agricultural Economics Association Annual Meeting, Orlando, Florida.

Goodwin, B. K., and A.K. Mishra. 2003. Acreage Effects of Decoupled Programs at the Extensive Margin. Selected Paper, American Agricultural Economics Association Annual Meeting, Montreal, Canada.

Goodwin, B. K., and A.K. Mishra. 2006. Are 'Decoupled' Farm Program Payments Really Decoupled? An Empirical Evaluation. *American Journal of Agricultural Economics*: 88(1):73–89.

Hendricks, N.P., and D.A. Sumner. 2014. The Effects of Policy Expectations on Crop Supply, with and Application to Base Updating. *American Journal of Agricultural Economics* 96(3):902-923.

Hennessy, D.A. 1998. The Production Effects of Agricultural Income Support Policies under Uncertainty. *American Journal of Agricultural Economics* 80(1):46-57.

Key, N. and M. Roberts. 2008. Do Decoupled Payments Stimulate Production? Estimating the Effect on Program Crop Acreage Using Matching. Selected Paper, American Agricultural Economics Association Annual Meeting, Orlando, Florida.

O'Donoghue, E.J., and J.B. Whitaker. 2010. Do direct payments distort producers' decisions? An examination of the Farm Security and Rural Investment Act of 2002. *Applied Economic Perspectives and Policy* 32(1): 170-193.

Organization for Economic Cooperation and Development (OECD). 2001. Market effects of crop support measures.

Organization for Economic Cooperation and Development (OECD). 2003. Risk Effects of PSE Crop Measures.

Roe, T., A. Somwaru, and X. Diao. 2003. Do direct payments have intertemporal effects on U.S. agriculture? In: *Government Policy and Farmland Markets*, pages 115–139. Edited by C.B. Moss and A. Schmitz, Iowa State Press.

Sckokai, P., and D. Moro. 2006. Modeling the Reforms of the Common Agricultural Policy for Arable Crops under Uncertainty. *American Journal of Agricultural Economics* 88(1):43-56.

Serra, T., D. Zilberman, B.K. Goodwin and A.M. Featherstone. 2005. Decoupling farm policies: How does this affect production? Selected Paper, American Agricultural Economics Association Annual Meeting, Providence Rhode Island.

Weber, J. G., and N. Key. 2012. How much do decoupled payments affect production? An Instrumental Variable Approach with Panel Data. *American Journal of Agricultural Economics* 94(1):52-66.

B. Brief description of relevant U.S. programs

As summarized in Gerlt, Thompson, and Dewbre (2019), U.S. agricultural policy includes programs that deliver payments or other transfers to producers. A number of programs of varying designs have been used to effect those transfers, some of which include eligibility criteria for payments that have been presumed to have potential effects on production. Because thorough reviews are available elsewhere CRS, 2019; ERS, 2019a; ERS, 2019b; Zulauf and Orden, 2016), we summarize here the programs of this type that have been examined in the decoupling literature, focusing on the differing characteristics and mechanisms that presumably have some relationship to production effects.

Transfer mechanisms for programs associated with crops

Programs that provide transfers associated with crops are listed according to how tightly linked the basis for payment seems to be with production decisions (Table B1). This listing is based on our impressions from the decoupling literature, although there is a degree of subjectivity because not all programs have been assessed in terms of their supply-inducing effects.

The least associated to production decisions of programs in this category are fixed direct payments (FDP), the amount and recipients of which are least tied to crop markets and their permutations. We include in this category the Production Flexibility Contract (PFC) program established by the 1996 Farm Bill, (variously referred to in the literature as Production Flexibility Contract payments, contract payments, and Agriculture Market Transition Act payments) and the Direct Payment (DP) program that replaced it under the

2002 and 2008 Farm Bills. These program payments were made on fixed historical base area and yields with fixed payment rates unrelated to market conditions. Certain land use changes or production choices could terminate or suspend the payment: Base area had to be kept in a condition that could allow for continued agricultural activity, rather than conversion to non-agricultural uses; and producers who grew fruits, vegetables, and wild rice on base acres could have payments on that base suspended for that crop year.

We focus largely on FDPs because they are most studied, and in part because they were the first U.S. program established that based payments on historical area and yield unaffected by a producer's planting choices. Subsequent programs that have paid on historical base area and yield include the Counter-Cyclical Program (CCP), Average Crop Revenue Election (ACRE), Price Loss Coverage (PLC), and Agriculture Risk Coverage-County (ARC-CO). While base area and yield remained key components of these programs, payment triggers and levels were linked to some indicator(s) of market conditions, such as changes in county and/or farm revenue or national price relative to some benchmark. Although the payments depended on market conditions, eligibility for the payment was determined by base area linked to historical plantings. As such, producer decisions about which crop to plant in the current year would not affect eligibility for the payment, provided base area was not used for restricted practices.

Base acres were established in 1996 and built on previous farm program entitlements. Subsequent Farm Bills permitted various limited updates to base area and base yield. Updates could be affected by practices since the original historical base period but remained fixed and unaffected by a participant's current production decisions. If assessed purely as a question of contemporaneous price effects for a risk neutral producer without credit constraints or preferences relating to work activities, one might expect such payments to have little effect on supply decisions, although the literature we reviewed (see the main text) goes beyond those assumptions.

A different type of program associated with crop production is the Marketing Assistance Loan Program. Payments or transfers under this program, often referred to in aggregate as marketing loan benefits (MLB) occur through Loan Deficiency Payments (LDPs) or through repayment of nonrecourse marketing assistance loans at market prices lower than the original loan rate (known as marketing loan gains). The rate of benefit depends entirely on the difference between the market price and the loan rate. Payments are made on harvested production and thus are tied directly to production decisions. Moreover, the larger the production the larger the potential benefit. Given this direct connection to output, the *a priori* expectation based on price effects alone is for an effect on plantings and yield.

While these programs have varying degrees of association to production, the association is relevant in certain ranges. For instance, the programs often have limits on payments to individual producers. Once the limit is reached, payments are invariant which forces the marginal correlation of programs to farm conditions to zero. Additionally, certain programs, such as ACRE and ARC, have caps on the payments that can be made per base acre. Likewise, payments which are at least somewhat tied to market conditions have a lower bound of zero. For PLC, if farm prices are above reference prices the marginal effect of an increasing farm price on PLC payments is zero. This also breaks the link between the programs and current market conditions or production decisions.

Table B1. Crop programs and their benefit basis

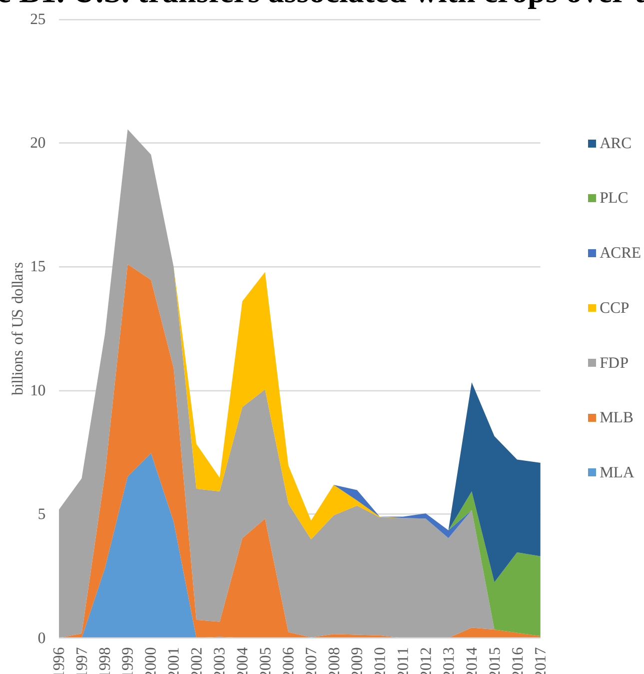
Link to production and markets	Program	Links to production decisions
LESS ↑	FDP (includes Direct Payments and Production Flexibility Contract payments)	Historical farm plantings Historical farm yields
	Counter-Cyclical Program (CCP) and Price Loss Coverage (PLC)	Historical farm plantings Historical farm yields Current national prices
	Agriculture Loss Coverage-County (ARC-CO)	Historical farm plantings Current county yields Current county prices
	Average Crop Revenue Election (ACRE)	Historical farm plantings Current farm plantings Historical farm yields Current farm yields Historical state yields Current state yields Current national prices
↓ *MORE*	Marketing Loan Benefits	Current farm plantings Current farm yields Current county prices

Scale of transfers from programs associated with crops

Budgetary expenditures used here to indicate the scale of FDP are drawn from the Producer Support Estimates (PSE) database produced by the OECD (2019), a source that tracks transfers resulting from agricultural policy support. Our research focuses only on PSE-identified support generated by government expenditures, omitting market price support – support that operates by increasing the domestic price relative to border or external prices. Policies that provide market price support until recently played the primary role in U.S. dairy support and currently play an important role in sugar support policy, but that has not been the case for other U.S. crops, at least in recent years. OECD (2019) data representing expenditures are presented here

The OECD budget data suggest that payments associated with crop area range between $5 and $10 billion a year, with one instance of transfers above $20 billion dollars (Figure B1). Payment composition shows FDP beginning in 1996 and carrying through 2014 when they were terminated. Associated MLA payments, which were ad hoc, appear for only four years (1999-2001). CCP was introduced the following year ACRE in 2008, and although both remained in place through 2014, high prices reduced payments under both programs to low levers. PLC and ARC were introduced in 2014 and overlapped for a year with FDPs. Throughout the period, MLBs endured, albeit with changes in the loan rates that trigger for benefits with noticeable variation in expenditures depending on those prices.

Figure B1. U.S. transfers associated with crops over time



Source: calculated from OECD (2019) PSE data, excluding market price support and input subsidies except those based on land.

C. Initial values for coupling coefficients

The main text reproduces prior values and ranges that are assumed for U.S. farm program coupling coefficients. Ranges are defined by central values, dispersion and boundaries, each of which reflects an early take on these impacts, before this literature review was undertaken, and our understanding of eligibility criteria for payment or other transfer (as summarized above) and how they relate to the avenues of impacts (as characterized in other reviews and summarized in the main text). FDPs are assumed to have a coupling coefficient of 0.05, PLC and ARC have 0.25, and ACRE and MLB have 1.00 coupling coefficients. The ranges are wide, allowing vastly different values and even negative values given the potential for labor-leisure trade-offs to reduce production.

The hierarchy might seem clear. For example, fixed direct payments tied to historical base area in the U.S. that began following legislation in 1996 seemed unrelated to market conditions, yet subsequent programs tied to the historical base area allowed payment amounts to vary inversely with some measure of market price or market returns. As such, these later programs might be presumed to span all avenues of impact of the original fixed payments and then add on any additional effects, like risk reduction, that might come with the tie to market conditions. In practice, however, program rules are complicated, the importance of different avenues of impact are unclear, and there is at least some subjectivity to these judgments. Indeed, it is for this reason that we develop and apply the Bayesian updating to these initial values and hierarchies according to what we learn from the literature and how well those results apply to national supply.

D. Is generic base the forgotten test case of coupling?

In the settlement of the disputes brought by Brazil to the World Trade Organization over U.S. cotton policies in 2004 and 2007 (Schnepf, 2008), the United States Congress redesigned several upland cotton programs to achieve compliance with the ruling. One of those redesigns, implemented in the 2014 Farm Bill, removed upland cotton as a covered commodity eligible for the new Agriculture Risk Coverage (ARC) and Price Loss Coverage (PLC) programs. Historical base area that had formerly been identified with upland cotton was re-designated as "generic base" and became eligible for payments under the ARC and PLC programs on rules different from those applying to other base.

Because the new generic base was eligible for payments only when covered commodities were planted on that area, those acres were directly recoupled to production decisions. As a result, this seems an important potential case for testing payment coupling effects. While ARC and PLC disassociate payment from current production decisions, the rules for generic base acres provided what turned out to be a temporary exception. As far as we know, this special case has not been exploited to analyze the effects of recoupling the payment basis for a formerly decoupled program; we are unaware of any scientific studies to see if program changes had an impact on the degree to which support can affect supply.

Generic base acres could become eligible for ARC or PLC payments if the program triggers were met for the covered commodity that was planted on those generic acres. Eligibility could change from year to year based on a producer's decision on what commodity to plant on generic base in a given year, allowing producers to consider the likelihood of program payments in their production decisions. For example, if a producer had 100 corn base acres and planted 20 acres of generic base acres in corn for the year, the producer could receive ARC or PLC payments (depending on their election) on 120 base acres for that year.[5]

The practical effect of the coupled nature of generic base was to encourage the planting of covered commodities with high expected payments, all else equal. Average ARC and PLC payments were not equal among the main covered commodities during the years of this program (Figure D1). Peanuts averaged over $140 per base acre in ARC and PLC payments during this period. Likewise, rice payments were also high at nearly $120 per base acre.

Rice was not grown on many farms with generic base acres and the levee and irrigation needs of rice limit quick, temporary expansion. However, unlike rice, peanuts did not face such limitations and acres could be expanded relatively quickly (Figure D2). Despite lower prices, peanut acres in 2015 through 2017 were at some of the highest

---

[5] Payments to generic base acres were more complicated if a producer planted more than one covered commodity. In that case, the payments were prorated, depending on the share of base assigned to each of the commodities based on shares in planted acres. For example, if a producer planted 150 acres of corn and 50 acres of soybeans, 75% of the producer's generic acres would be assigned to corn and 25% to soybeans. If a producer had 100 generic acres and PLC or ARC were triggered for corn, the producer would receive payments on 75% of generic base, or 75 acres. If this producer also had 100 acres of corn base, then the corn PLC or ARC payment would be for 175 acres.

levels of the decade. The plantings rose concurrently with the availability of generic base. The ratio of generic base to plantings was 57% for peanuts. The next highest was sorghum with 18%. No other crop exceeded 5%. After generic base acres had to be designated seed cotton base or permanently allocated to another covered commodity (if historical production supported the allocation) under the Bipartisan Budget Act of 2018, peanut acreage immediately dropped.

Figure D1. Program payments during the period of generic base

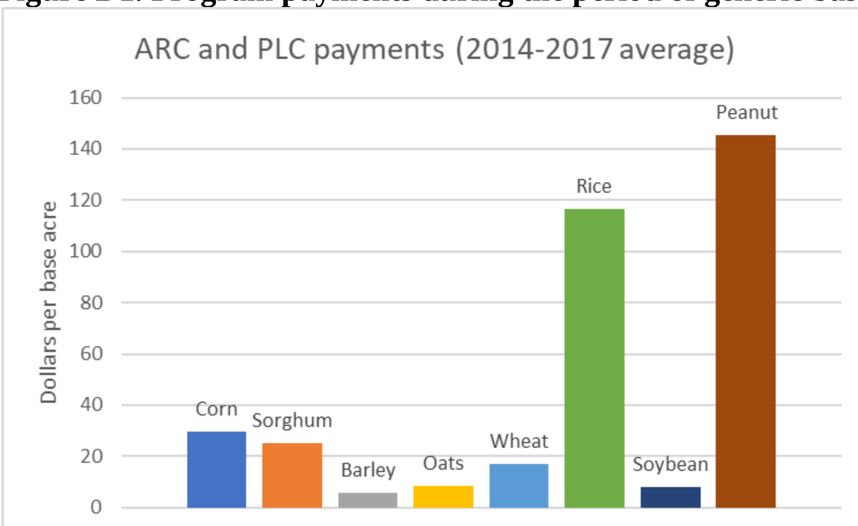
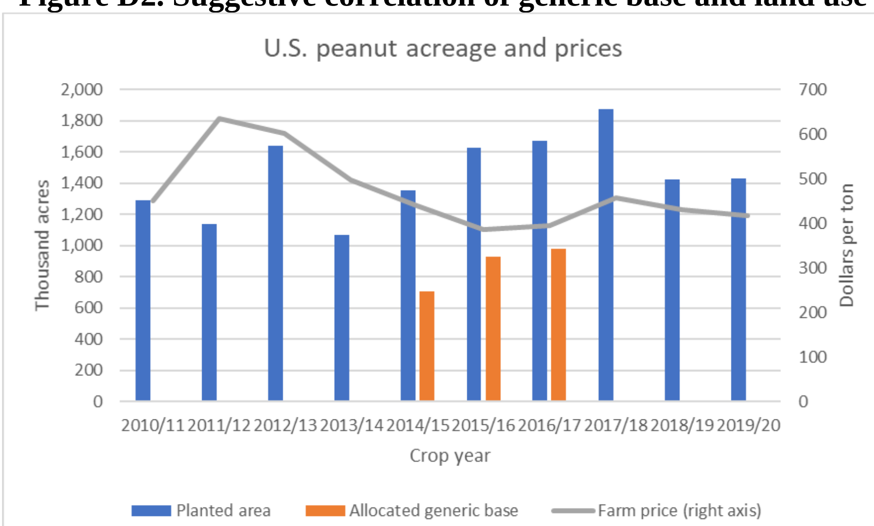


Figure D2. Suggestive correlation of generic base and land use



Notes: 2017/18 generic base plantings of covered commodities were not reported by USDA. The 2019/20 farm price is from FAPRI's 2020 baseline.

The timeframe during which generic base acres operated was too short to conduct time-series analysis. Likewise, confidentiality of farm-level data for farms with and without generic base acres is protected by USDA, preventing the use of panel or cross-sectional analysis. Even so, the pattern of concentrated plantings of a covered commodity eligible for large average payments over a short period of time appears to provide a case study to test how directly coupling payments can lead to shifts in production.

E. Tables of standardized payment impacts drawn from the literature

We generate tables for combination of program and output variable for which we have usable material in the published studies. The case presented in the main text is the one with the most observations, namely direct payments (DP, including various incarnations of these payments) effects on area planted. This is a potentially large number of tables is reduced by our choice not to produce the many tables that show the absence of usable results from published studies. Omissions are important, and these are identified (Table E1). Crop insurance and dairy program payments (MILC, MPP, and DMC) are not included at this time.

For each table where there are data, we provide these two tables: *impact coefficients* of the program indicates the impact on the output variable per unit of payment, as defined in the text; and *coupling coefficients* of the program indicates the output impact relative to the effect of an equal amount of market returns. The example tables presented in the main text consist of the most populated two tables: “area impact coefficients of fixed direct payments” and “area coupling coefficients of fixed direct payments”.

Table E1. Presence of usable studies, with table numbers, or absence of such studies

	Area planted	Yield	Output quantity
Pre-1996 payments	NONE	Tables E2, E3	NONE
Fixed direct payment (FDP)	E4, E5	E6, E7	E8, E9
Market Loss Assistance (MLA)	E10, E11	NONE	NONE
Counter-Cyclical Payments (CCP)	E12, E13	No impact coefficients, Coupling coefficients E14	No impact coefficients, Coupling coefficients E15
Average Crop Rev. Election (ACRE)	NONE	NONE	NONE
Price Loss Coverage (PLC)	NONE	NONE	NONE
Supplemental Coverage Option (SCO)	NONE	NONE	NONE
Agriculture Risk Coverage (ARC)	NONE	NONE	NONE
Marketing loan program (MLB)	No impact coefficients, Coupling coefficients E16	No impact coefficients, Coupling coefficients E17	No impact coefficients, Coupling coefficients E18

Table E2. Yield impact coefficients of pre-96 policies

		Price Effect	Risk Reduction	Risk and Wealth	Expectations of Base Updating	Other	All
Change in output per change in payment							
Region & Own Effect							
	US National						
	Corn Belt		4 1 0.012 0.014 0.014	4 1 0.012 0.014 0.014			
	Other						
Methods & Own Effect							
	Est., Panel or Survey Data						
	Est., Market Data						
	Simulation or Theory		4 1 0.012 0.014 0.014	4 1 0.012 0.014 0.014			
All & Own Effect							
			4 1 0.012 0.014 0.014	4 1 0.012 0.014 0.014			
Nature of Effect							
	Cross-Effect						
	All Crops						
	One Crop		4 1 0.012 0.014 0.014	4 1 0.012 0.014 0.014			

Table E3. Yield coupling coefficients of pre-96 policies

	Price Effect	Risk Reduction	Risk and Wealth	Expectations of Base Updating	Other	All
Ratio of payment impact to market impact						
Region & Own Effect						
US National						
Corn Belt		4 1 0.808 0.896 0.896	4 1 0.808 0.896 0.896			
Other						
Methods & Own Effect						
Est., Panel or Survey Data						
Est., Market Data						
Simulation or Theory		4 1 0.808 0.896 0.896	4 1 0.808 0.896 0.896			
All & Own Effect						
		4 1 0.808 0.896 0.896	4 1 0.808 0.896 0.896			
Nature of Effect						
Cross-Effect						
All Crops						
One Crop		4 1 0.808 0.896 0.896	4 1 0.808 0.896 0.896			

Table E4. Area impact coefficients of FDP

	Price Effect	Risk Reduction			Risk and Wealth			Expectations of Base Updating			Other	All		
Change in output per change in payment														
Region & Own Effect														
US National		1	1	~0	2	2	~0					7	2	0.039
		~0	~0		~0	~0						0.032	0.017	
Corn Belt								12	2	0.001		5	3	0.002
								0.001	0.001			0.003	0.004	
Other												4	1	~0
												~0	~0	
Methods & Own Effect														
Est., Panel or Survey Data		1	1	0.055								19	7	0.004
		0.055	0.055									0.014	0.009	
Est., Market Data												3	1	~0
												0.001	0.001	
Simulation or Theory		1	1	~0	2	2	~0	12	2	0.001				
		~0	~0		~0	~0		0.001	0.001					
All & Own Effect														
		2	2	0.027	2	2	~0	12	2	0.001		22	8	0.002
		0.027	0.027		~0	~0		0.001	0.001			0.012	0.008	
Nature of Effect														
Cross-Effect								8	1	~0		12	1	~0
								~0	~0			~0	~0	
All Crops		2	2	0.027	2	2	~0	20	2	~0		34	8	~0
		0.027	0.027		~0	~0		~0	~0			0.008	0.008	
One Crop		2	2	0.027	2	2	~0	20	2	~0		34	8	~0
		0.027	0.027		~0	~0		~0	~0			0.008	0.008	

Table E5. Area coupling coefficients of FDP

	Price Effect	Risk Reduction	Risk and Wealth	Expectations of Base Updating	Other	All
Ratio of payment impact to market impact						
Region & Own Effect						
US National		1 1 ~0 ~0 ~0	2 2 0.064 0.064 0.064			
Corn Belt				12 2 0.689 0.652 0.665		1 3 1.037 1.037 1.037
Other						4 1 0.689 0.693 0.693
Methods & Own Effect						
Est., Panel or Survey Data		1 1 0.024 0.024 0.024				6 7 0.929 0.827 0.96
Est., Market Data						3 1 0.459 0.842 0.842
Simulation or Theory		1 1 ~0 ~0 ~0	2 2 0.064 0.064 0.064	12 2 0.689 0.652 0.665		
All & Own Effect						
		2 2 0.012 0.012 0.012	2 2 0.064 0.064 0.064	12 2 0.689 0.652 0.665		9 8 0.92 0.832 0.931
Nature of Effect						
Cross-Effect				8 1 0.625 0.625 0.625		12 1 0.445 0.321 0.321
All Crops		2 2 0.012 0.012 0.012	2 2 0.064 0.064 0.064	20 2 0.689 0.641 0.665		21 8 0.459 0.54 0.861
One Crop		2 2 0.012 0.012 0.012	2 2 0.064 0.064 0.064	20 2 0.689 0.641 0.665		21 8 0.459 0.54 0.861

Table E6. Yield impact coefficients of FDP

		Price Effect	Risk Reduction	Risk and Wealth	Expectations of Base Updating	Other	All
Change in output per change in payment							
Region & Own Effect							
	US National		1 1 ~0 ~0 ~0	2 2 ~0 ~0 ~0			
	Corn Belt						
	Other						
Methods & Own Effect							
	Est., Panel or Survey Data						
	Est., Market Data						
	Simulation or Theory		1 1 ~0 ~0 ~0	2 2 ~0 ~0 ~0			
All & Own Effect							
			1 1 ~0 ~0 ~0	2 2 ~0 ~0 ~0			
Nature of Effect							
	Cross-Effect						
	All Crops						
	One Crop		1 1 ~0 ~0 ~0	2 2 ~0 ~0 ~0			

Table E7. Yield coupling coefficients of FDP

		Price Effect	Risk Reduction	Risk and Wealth	Expectations of Base Updating	Other	All
Ratio of payment impact to market impact							
Region & Own Effect							
	US National		1 1 ~0 ~0 ~0	2 2 0.068 0.068 0.068			
	Corn Belt						
	Other						
Methods & Own Effect							
	Est., Panel or Survey Data						
	Est., Market Data						
	Simulation or Theory		1 1 ~0 ~0 ~0	2 2 0.068 0.068 0.068			
All & Own Effect							
			1 1 ~0 ~0 ~0	2 2 0.068 0.068 0.068			
Nature of Effect							
	Cross-Effect						
	All Crops						
	One Crop		1 1 ~0 ~0 ~0	2 2 0.068 0.068 0.068			

Table E8. Output impact coefficients of FDP

	Price Effect			Risk Reduction			Risk and Wealth			Expectations of Base Updating			Other Effect			All		
Change in output per change in payment																		
Region & Own Effect																		
US National	5 0.118	2 0.118	0.07	4 0.082	3 0.071	0.083	2 0.016	2 0.016	0.016				2 0.03	1 0.03	0.03	1 -0.716	1 -0.716	-0.716
Corn Belt																1 0.173	1 0.173	0.173
Other																4 0.001	1 0.001	0.001
Methods & Own Effect																		
Est., Panel or Survey Data																6 -0.09	2 -0.135	0.001
Est., Market Data																		
Simulation or Theory	5 0.118	2 0.118	0.07	4 0.082	3 0.071	0.083	2 0.016	2 0.016	0.016				3 0.023	2 0.019	0.008			
All & Own Effect																		
	5 0.118	2 0.118	0.07	4 0.082	3 0.071	0.083	2 0.016	2 0.016	0.016				3 0.023	2 0.019	0.008	6 -0.09	2 -0.135	0.001
Nature of Effect																		
Cross-Effect																12 ~0	1 ~0	~0
All Crops	5 0.118	2 0.118	0.07	4 0.082	3 0.071	0.083	2 0.016	2 0.016	0.016				3 0.023	2 0.019	0.008	18 -0.03	2 -0.136	~0
One Crop	5 0.118	2 0.118	0.07	4 0.082	3 0.071	0.083	2 0.016	2 0.016	0.016				3 0.023	2 0.019	0.008	18 -0.03	2 -0.136	~0

Table E9. Output coupling coefficients of FDP

	Price Effect			Risk Reduction			Risk and Wealth			Expectations of Base Updating			Other Effect			All		
Ratio of payment impact to market impact																		
Region & Own Effect																		
US National	5	2	0.265	3	3	0.265	2	2	0.066				1	1	~0			
	0.306	0.329		0.295	0.221		0.066	0.066					~0	~0				
Corn Belt																		
Other																4	1	0.356
																0.356	0.356	
Methods & Own Effect																		
Est., Panel or Survey Data																4	2	0.356
																0.356	0.356	
Est., Market Data																		
Simulation or Theory	5	2	0.265	3	3	0.265	2	2	0.066				2	2	0.091			
	0.306	0.329		0.295	0.221		0.066	0.066					0.091	0.091				
All & Own Effect																		
	5	2	0.265	3	3	0.265	2	2	0.066				2	2	0.091	4	2	0.356
	0.306	0.329		0.295	0.221		0.066	0.066					0.091	0.091		0.356	0.356	
Nature of Effect																		
Cross-Effect																12	1	0.301
																0.258	0.258	
All Crops	5	2	0.265	3	3	0.265	2	2	0.066				2	2	0.091	16	2	0.323
	0.306	0.329		0.295	0.221		0.066	0.066					0.091	0.091		0.282	0.282	
One Crop	5	2	0.265	3	3	0.265	2	2	0.066				2	2	0.091	16	2	0.323
	0.306	0.329		0.295	0.221		0.066	0.066					0.091	0.091		0.282	0.282	

Table E10. Area impact coefficients of MLA

		Price Effect	Risk Reduction	Risk and Wealth	Expectations of Base Updating	Other		All	
Change in output per change in payment									
Region & Own Effect									
	US National								
	Corn Belt						1 0.008	1 0.008	0.008
	Other								
Methods & Own Effect									
	Est., Panel or Survey Data						2 0.007	2 0.007	0.007
	Est., Market Data								
	Simulation or Theory								
All & Own Effect									
							2 0.007	2 0.007	0.007
Nature of Effect									
	Cross-Effect								
	All Crops						2 0.007	2 0.007	0.007
	One Crop						2 0.007	2 0.007	0.007

Table E11. Area coupling coefficients of MLA

		Price Effect	Risk Reduction	Risk and Wealth	Expectations of Base Updating	Other	All
Ratio of payment impact to market impact							
Region & Own Effect							
	US National						
	Corn Belt						1 1 3.119 3.119 3.119
	Other						
Methods & Own Effect							
	Est., Panel or Survey Data						2 2 1.84 1.84 1.84
	Est., Market Data						
	Simulation or Theory						
All & Own Effect							
							2 2 1.84 1.84 1.84
Nature of Effect							
	Cross-Effect						
	All Crops						2 2 1.84 1.84 1.84
	One Crop						2 2 1.84 1.84 1.84

Table E12. Area impact coefficients of CCP

	Price Effect	Risk Reduction	Risk and Wealth	Expectations of Base Updating	Other	All
Change in output per change in payment						
Region & Own Effect						
US National						
Corn Belt				8 1 ~0 ~0 ~0		
Other						
Methods & Own Effect						
Est., Panel or Survey Data						
Est., Market Data						3 1 0.002 0.002 0.002
Simulation or Theory				8 1 ~0 ~0 ~0		
All & Own Effect						
				8 1 ~0 ~0 ~0		3 1 0.002 0.002 0.002
Nature of Effect						
Cross-Effect				8 1 ~0 ~0 ~0		
All Crops				16 1 ~0 ~0 ~0		3 1 0.002 0.002 0.002
One Crop				16 1 ~0 ~0 ~0		3 1 0.002 0.002 0.002

Table E13. Area coupling coefficients of CCP

	Price Effect	Risk Reduction	Risk and Wealth	Expectations of Base Updating	Other	All
Ratio of payment impact to market impact						
Region & Own Effect						
US National		3 1 1.044 40.874 40.874				
Corn Belt				8 1 0.625 0.625 0.625		
Other						
Methods & Own Effect						
Est., Panel or Survey Data						
Est., Market Data						3 1 2.35 2.258 2.258
Simulation or Theory		3 1 1.044 40.874 40.874		8 1 0.625 0.625 0.625		
All & Own Effect						
		3 1 1.044 40.874 40.874		8 1 0.625 0.625 0.625		3 1 2.35 2.258 2.258
Nature of Effect						
Cross-Effect				8 1 0.625 0.625 0.625		
All Crops		3 1 1.044 40.874 40.874		16 1 0.625 0.625 0.625		3 1 2.35 2.258 2.258
One Crop		3 1 1.044 40.874 40.874		16 1 0.625 0.625 0.625		3 1 2.35 2.258 2.258

Table E14. Yield coupling coefficients of CCP

	Price Effect	Risk Reduction	Risk and Wealth	Expectations of Base Updating	Other	All
Ratio of payment impact to market impact						
Region & Own Effect						
US National		3 1 ~0 ~0 ~0				
Corn Belt						
Other						
Methods & Own Effect						
Est., Panel or Survey Data						
Est., Market Data						
Simulation or Theory		3 1 ~0 ~0 ~0				
All & Own Effect						
		3 1 ~0 ~0 ~0				
Nature of Effect						
Cross-Effect						
All Crops						
One Crop		3 1 ~0 ~0 ~0				

Table E15. Output coupling coefficients of CCP

		Price Effect	Risk Reduction	Risk and Wealth	Expectations of Base Updating	Other	All
Ratio of payment impact to market impact							
Region & Own Effect							
	US National		3 1 ~0 ~0 ~0				
	Corn Belt						
	Other						
Methods & Own Effect							
	Est., Panel or Survey Data						
	Est., Market Data						
	Simulation or Theory		3 1 ~0 ~0 ~0				
All & Own Effect							
			3 1 ~0 ~0 ~0				
Nature of Effect							
	Cross-Effect						
	All Crops		3 1 ~0 ~0 ~0				
	One Crop		3 1 ~0 ~0 ~0				

Table E16. Area coupling coefficients of MLB

	Price Effect	Risk Reduction	Risk and Wealth	Expectations of Base Updating	Other Effect	All
Ratio of payment impact to market impact						
Region & Own Effect						
US National		3 1 2.016 41.546 41.546				
Corn Belt						
Other						
Methods & Own Effect						
Est., Panel or Survey Data						
Est., Market Data						
Simulation or Theory		3 1 2.016 41.546 41.546				
All & Own Effect						
		3 1 2.016 41.546 41.546				
Nature of Effect						
Cross-Effect						
All Crops		3 1 2.016 41.546 41.546				
One Crop		3 1 2.016 41.546 41.546				

Table E17. Yield coupling coefficients of MLB

		Price Effect	Risk Reduction	Risk and Wealth	Expectations of Base Updating	Other Effect	All
Ratio of payment impact to market impact							
Region & Own Effect							
	US National	3 41.546	1 41.546	2.016			
	Corn Belt						
	Other						
Methods & Own Effect							
	Est., Panel or Survey Data						
	Est., Market Data						
	Simulation or Theory	3 41.546	1 41.546	2.016			
All & Own Effect							
		3 41.546	1 41.546	2.016			
Nature of Effect							
	Cross-Effect						
	All Crops						
	One Crop	3 41.546	1 41.546	2.016			

Table E18. Output coupling coefficients of MLB

	Price Effect	Risk Reduction	Risk and Wealth	Expectations of Base Updating	Other Effect	All
Ratio of payment impact to market impact						
Region & Own Effect						
US National		3 1 2.016 41.546 41.546				
Corn Belt						
Other						
Methods & Own Effect						
Est., Panel or Survey Data						
Est., Market Data						
Simulation or Theory		3 1 2.016 41.546 41.546				
All & Own Effect						
		3 1 2.016 41.546 41.546				
Nature of Effect						
Cross-Effect						
All Crops		3 1 2.016 41.546 41.546				
One Crop		3 1 2.016 41.546 41.546				

F. Market implications of changing coupling coefficients

In this section, we explore effects of incorporating the coupling coefficients from the posterior distributions into U.S. crop models. The appropriateness tests developed coupling coefficients for different payments based on certain assumptions and results of the literature review. Summarizing, priors about initial values of coupling coefficients for existing studies were updated based on findings in the literature, where comparable, based on the apparent appropriateness of these numbers for determining national supply historically.

Market results are simulated for the case that coupling coefficients are increased for payments tied to historical base (PLC and ARC), yet decreased for the marketing loan program (MLB) relative to initial conditions. The method of analysis is to generate a baseline projection for markets for the next ten years subject to certain assumptions (Westhoff et al. 2020). A partial equilibrium model representing markets for crops and crop products, biofuels, livestock and livestock products, with focus on the U.S., is used (Gerlt and Westhoff 2011; Westhoff and Meyers 2010). This model has been applied to study agricultural policy, biofuel and climate policy, and trade (Debnath et al. 2017; Thompson et al. 2010; Thompson et al. 2017; Whistance et al. 2017).

Key results are summarized here, setting aside a great many details in the model output. The model is stochastic: specific values for key input variables are replaced with distributions, often correlated, from which inputs are drawn for *Monte Carlo* simulation. (While Bayesian treats parameters are stochastic, this section uses the expected values from the posterior distributions due to the model treating the parameters as deterministic.)

This method allows us to capture a wide range of possible market outcomes, as is to accurately measure the costs of programs, such as PLC, ARC, and MLB, under uncertainty. The average results shown here reflect a wide range of possible payment levels, such as very low or even zero PLC and MLB amounts if prices are higher than trigger levels to many billions of dollars of expenditures in the event prices are persistently below the thresholds for payment. Although the representation estimates year-by-year impacts, the average of the last five years is presented here to discourage focus on any short-run or transitory effects. Results are expressed in terms of the changes in market variables and other indicators going from the base case with initial coupling values to the alternative case with the results of the appropriateness test imposed on existing policies.

Results suggest that the changes in coupling coefficients do cause changes in market outcomes (Table F1). The greater PLC and ARC coupling coefficients imply that these payments have a larger supply-inducing impact per dollar than in the initial assumptions; there is more incentive to plant crops than in the initial case. A key limiting factor is the limited scope to affect overall crop area, which increases by 0.1%. In contrast, land is reallocated from one crop to another, reflecting relative amounts paid per acre planted. The changes in area planted to a specific crop range as high as 1.3%, although the larger changes are associated with crops that account for a small share of area while those that dominate area in the U.S., like corn, soybeans, and wheat to a lesser extent, see smaller proportional changes.

The reallocation of land has price implications. As expected, these changes tend to have an inverse relationship with area changes, but are mostly negative. In cases where area planted to a crop contracts, the price is bid higher as domestic and foreign buyers compete for smaller volume. Where area expands, there is more supplied to the market so the price is bid lower. Because area and output is higher overall, prices tend to fall.

Table F1. Impact of changing coupling coefficients on key indicators.

	Farm price		Area planted
Crop market indicators			
Corn	-1.0%		0.2%
Soybeans	0.2%		-0.2%
Wheat	-0.7%		0.1%
Upland cotton	-0.8%		0.3%
Sorghum	-1.3%		0.8%
Barley	-1.0%		0.1%
Oats	0.1%		-1.0%
Rice	-0.8%		1.1%
Sunflowers	-0.1%		1.3%
Peanuts	-2.8%		0.5%
10 crop planted area			0.1%
Farm income indicators			
Farm receipts	Crops		Livestock
from sales of	-0.2%		-0.1%
Government payments			
Total		3.0%	
Net income	Cash		Farm
in terms of	-0.1%		-0.1%
Net government outlays			
ARC		-1.4%	
PLC		5.9%	
Marketing loans		8.2%	
Crop insurance		-0.4%	

The price changes are larger than the area changes in proportional terms. Just like total land available to plant crops is unlikely to change much, total demand for all crops and crop products is also fairly rigid. Inelastic aggregate demand leads to a large price reduction to rebalance markets when more quantity of these goods, in total, is produced. These results for area and prices could be quite different if the coupling coefficient for payments associated with only a single crop were changed. However, given the nature of the programs, piecemeal experiments that assume a policy change that can focus on a crop seems farfetched. Such policy change would be dramatic and likely imply new coupling coefficients more generally.

Net cash and farm income indicators are lower. The net effect of a crop output increase and a proportionally larger decrease in output prices is lower crop receipts. The lower prices are passed on to livestock producers, and some part of the reduction in feed costs is passed on to consumers. Transfers from taxpayers to producers rise. The lower prices induce higher PLCs and MLBs. (As noted earlier, these averages of stochastic analysis include many possible market outcomes, in some of which PLC or MLB might be zero in both base case and alternative, while others see prices below trigger levels and, consequently, payments). Reduced receipts lead over time to lower ARC and crop insurance outlays or net payments, but these reductions are more than offset by greater PLC and MLB payouts. Other program costs represented here are not affected very much by the change in market conditions induced by the higher coupling coefficients.

Clearly, these results are subject to certain caveats. Different coupling coefficients would yield some differences in results. While the stochastic analysis covers a range of possibilities, it does not include all possibilities. In particular, the baseline was generated just before the global pandemic and related responses took shape. If for this reason or any other the baseline started with lower crop prices overall, then the larger starting payments could interact with changing coupling coefficients to generate at least somewhat larger results. That said, the inelasticity of total land supplied to planting crops and the inelasticity of demand for all crops and crop products likely combine to limit the overall quantity impacts of alternative scenarios, although the price impacts and farm income implications could become larger.

G. References

Anton, J., and C. Le Mouel. 2004. Do counter-cyclical payments in the 2002 U.S. Farm Act create incentives to produce? Agricultural Economics 31:277-284.

Becker, A.D., and R.P. Judge. 2014. Evidence of Distortionary Effects of Decoupled Payments in U.S. Indica Rice Production. Atlantic Economic Journal 42(3):265-275.

Bhaskar, A., and J. Beghin. 2010. Decoupled farm payments and the role of base acreage and yield updating under uncertainty. American Journal of Agricultural Economics 92(3):849-858.

Burfisher, M., S. Robinson, and K. Thierfelder. 2000. North American Farm Programs and the WTO. American Journal of Agricultural Economics 82 (3):768–774.

Chambers, R.G., and D.C. Voica. 2017. "Decoupled" Farm Program Payments Are Really Decoupled: The Theory. American Journal of Agricultural Economics 99(3):773–782.

Chau, N., and H. de Gorter. 2005. Disentangling the Consequences of Direct Payment Schemes in Agriculture on Fixed Costs, Exit Decisions, and Output. American Journal of Agricultural Economics 87(5):1174-1181 .

Congressional Research Service (CRS). 2019. Farm Bill Primer Series: A Guide to Agriculture and Food Programs in the 2014 Farm Bill. CRS report R44913. Available at crsreports.congress.gov/product/pdf/R/R44913.

Debnath, D., J. Whistance, W. Thompson, and J. Binfield. 2017. Complement or substitute: ethanol's uncertain relationship with gasoline under alternative petroleum price and policy scenarios. Applied Energy 191:385–397.

Economic Research Service (ERS) of the U.S. Department of Agriculture. 2019a. Analysis of Previous Farm Bills. Website available at www.ers.usda.gov/topics/farm-economy/farm-commodity-policy/analysis-of-previous-farm-bills.

Economic Research Service (ERS) of the U.S. Department of Agriculture. 2019b. Farm Policy Glossary. Website available at www.ers.usda.gov/topics/farm-economy/farm-commodity-policy/farm-policy-glossary.aspx.

Farm Service Agency (FSA) of the U.S. Department of Agriculture. 2018. What's New: FSA and the 2018 Farm Bill. Website available at www.farmers.gov/sites/default/ files/documents/FSA-FarmBill2018_WhatsNew-19.pdf.

Femenia, F., A. Gohin and A. Carpentier. 2010. The Decoupling of farm Programs: Revisiting the Wealth Effect. American Journal of Agricultural Economics 92(3):836-848.

Gerlt, S., and P. Westhoff. 2011. FAPRI-MU stochastic US crop model documentation. FAPRI-MU Report 09-11. Available at www.fapri.missouri.edu/wp-content/uploads/2015/02/FAPRI-MU-Report-09-11.pdf.

Girante, M., B. Goodwin and A. Featherstone. 2008. Farmers' Crop Acreage Decisions in the Presence of Credit Constraints: Do Decoupled Payments Matter? Selected Paper, American Agricultural Economics Association Annual Meeting, Orlando, Florida.

Goodwin, B.K., and A.K. Mishra. 2003. Acreage Effects of Decoupled Programs at the Extensive Margin. Selected Paper, American Agricultural Economics Association Annual Meeting, Montreal, Canada.

Goodwin, B.K., and A.K. Mishra. 2006. Are 'Decoupled' Farm Program Payments Really Decoupled? An Empirical Evaluation. American Journal of Agricultural Economics: 88(1):73-89.

Hendricks, N.P., and D.A. Sumner. 2014. The Effects of Policy Expectations on Crop Supply, With and Application to Base Updating. American Journal of Agricultural Economics 96(3):902-923.

Hennessy, D.A. 1998. The Production Effects of Agricultural Income Support Policies under Uncertainty. American Journal of Agricultural Economics 80(1):46-57.

Key, N. and M. Roberts. 2008. Do Decoupled Payments Stimulate Production? Estimating the Effect on Program Crop Acreage Using Matching. Selected Paper, American Agricultural Economics Association Annual Meeting, Orlando, Florida.

O'Donoghue, E.J., and J.B. Whitaker. 2010. Do direct payments distort producers' decisions? An examination of the Farm Security and Rural Investment Act of 2002. Applied Economic Perspectives and Policy 32(1): 170-193.

Organization for Economic Cooperation and Development (OECD). 2001. Market effects of crop support measures.

Organization for Economic Cooperation and Development (OECD). 2003. Risk Effects of PSE Crop Measures.

Organization for Economic Cooperation and Development (OECD) 2019. Agricultural policy monitoring and evaluation. Producer Support Estimates. Available at www.oecd.org/agriculture/topics/agricultural-policy-monitoring-and-evaluation.

Roe, T., A. Somwaru, and X. Diao. 2003. Do direct payments have intertemporal effects on U.S. agriculture? In: Government Policy and Farmland Markets, pages 115–139. Edited by C.B. Moss and A. Schmitz, Iowa State Press.

Schnepf, R. 2014. U.S. Dairy Programs after the 2014 Farm Bill (P.L. 113-79). Congressional Research Service (CRS) report R43465.

Schnepf, R. 2008. Brazil's WTO Case Against the U.S. Cotton Program. Congressional Research Service (CRS) report RL32571.

Sckokai, P., and D. Moro. 2006. Modeling the reforms of the Common Agricultural Policy for arable crops under uncertainty. American Journal of Agricultural Economics 88(1):43-56.

Serra, T., D. Zilberman, B.K. Goodwin, and A.M. Featherstone. 2005. Decoupling farm policies: How does this affect production? Selected Paper, American Agricultural Economics Association Annual Meeting, Providence Rhode Island.

Weber, J. G., and N. Key. 2012. How much do decoupled payments affect production? An Instrumental Variable Approach with Panel Data. American Journal of Agricultural Economics 94(1):52-66.

Westhoff, P., S. Gerlt, J. Whistance, W. Thompson, J. Binfield, S. Chiuchiarelli, Y. Kim, S. Meyer, A. Meffert, and J.I. Kim. 2020. "U.S. agricultural market outlook: Missouri trade friction baseline and a Phase 1 scenario." FAPRI-MU Report 1-20.

Westhoff, P., and W. Meyers. 2010. The FAPRI approach: A few key principles. Journal of International Agricultural Trade and Development 6(1):133–135.

Thompson, W., S. Meyer, and P. Westhoff. 2010. The new markets for renewable identification numbers. Applied Economic Perspectives and Policy 32(4):588–603.

Thompson, W., S. Gerlt, J.E. Campbell, L.M. Kueppers, Y. Lu, and M.A. Snyder. 2017. A cost of tractability? Estimating climate change impacts using a single crop market understates impacts on market conditions and variability. Applied Economic Perspectives and Policy 39(2):346–362.

Whistance, J., S. Meyer, and W. Thompson. 2017. Interactions between California's low carbon fuel standard and the national renewable fuel standard. Energy Policy 101: 447-455.

Zulauf, C.,and D. Orden. 2016. 80 Years of Farm Bills-Evolutionary Reform. Choices 31(4):1-6.