Estimating Elasticities Via Market Share Impacts for Crop Insurance Coverage Options

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Abstract

Over the last three decades, crop insurance has moved from the wings to become the farm safety net centerpiece. In recent years, the costs and benefits of the premium subsidy expansion that largely drove this movement have received increased scrutiny. The crux of this debate has been the estimated elasticities of farmer insurance choice responses to potential policy changes in the support provided. To better understand and predict these responses, we derive elasticity measures in terms of total crop insurance subsidy expenditures and the average coverage level based on the changes in the subsidy rates at buyup coverage levels. These measures are then evaluated by using crop insurance data and econometric estimates of market share impacts for crop insurance coverage level options. The estimations are made for corn and soybeans at the countrywide level covering the period 2001-2020. To elicit farmers' responses, the focus is given to the policy change on enterprise units that took place in 2009. Econometric findings suggest an auto-regressive structure in how coverage option market shares change over time. Previous price elasticity studies of crop insurance demand that did not account for autoregression typically inferred inelastic demand. Allowing for long-term effects of a policy change as well as considering a broader set of coverage level options point to more elastic price responses.

1. Introduction

The origins of the federal multiple peril crop insurance (MPCI) program in the U.S. go back to the 1934-36 drought. However, only in the late 1990s did the program gain prominence as a means of securing farm financial stability (Collins, 2013). It took several Acts for Congress to restructure the program and increase premium subsidies—all with the intent of replacing costly

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disaster aid payments.[1] In the end, the 2014 Farm Bill marked, and the 2018 Farm Bill reaffirmed, the shift in the farm policy towards risk-management and cemented crop insurance at the farm safety net's center.[2] All the while, crop insurance premium subsidies—which are projected by the Congressional Budget Office (CBO, 2020) to constitute about 78% of all government support to this program over the next decade—have been questioned and there have been many calls for reductions amid policy and budget issues (Goodwin and Smith, 2013; Glauber, 2013; Bekkerman, Belasco and Smith, 2019). Evaluations of such policy proposals have hinged primarily on the estimated elasticity values (a measure of price responsiveness). For instance, when making such evaluations the Government Accountability Office (GAO, 2014, p. 22) has used static scoring and hence has assumed no response from farmers in terms of participation and coverage levels. The GAO noted, nevertheless, that the response to the reduction can be small based on the available literature. Meanwhile, the CBO (2017) has used dynamic scoring; and hence allowed some degree of response from farmers. It can be seen that the CBO, upon reviewing the literature, worked with a rather small elasticity value.[3]

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[1] The Federal Crop Insurance Reform Act of 1994 (1994 Act) increased subsidy rates primarily at the lower insurance coverage levels, while the Agricultural Risk Protection Act of 2000 (ARPA) increased rates more at the higher coverage levels. Premium subsidy rates were further increased for enterprise units in 2009 following the authorization under the Food, Conservation, and Energy Act of 2008. Over time, progressive subsidy increases along with the innovations in the product space stimulated higher and more diverse participation, which—combined with better data—improved the program's actuarial performance by reducing adverse selection and enhancing underwriting and ratemaking.

[2] These acts are formally known as Agricultural Act of 2014 and Agriculture Improvement Act of 2018.

[3] In the December 2017 report, the CBO considers a scenario in which the average subsidy rate is reduced from 62% to 47%, that is a drop of 15 percentage points (henceforth, ppts). As noted on p. 21 of the report (footnote 34), the coverage level impacts are downwards: 5 ppts at 85%, 10 ppts at 80%, 15 ppts at 75%, and 10 ppts at 70%. The elasticity is obtained as the ratio of % change in coverage demand to the % change in farmer-paid premium rate. In the numerator, we take the average coverage level as 70% (which is a bit higher than the calculated figure in 2020 in the data section) and the average drop in coverage as 10 ppts, which translates as a 14.3% drop

As noted in the CBO review, a large body of work have found demand elasticity values lower than one, i.e., to be inelastic. These studies typically regressed some measure of crop insurance purchases (coverage levels or liability per acre) on the farmer-paid premium rate. Examples of this approach include Goodwin (1993); Yu, Smith, and Sumner (2018); and Yi, Bryant, and Richardson (2020), all inferring inelastic demand. Goodwin (1993) estimates the value of elasticity in terms of liability per planted acre as -0.73 for corn grown in Iowa over the period 1985-1990. Yi, Bryant, and Richardson (2020) also study corn and find some heterogeneity of demand response across coverage levels and regions. Yu, Smith, and Sumner (2018) find that, based on an acreage response model, a 10% increase in the subsidy per dollar of liability increases the planted acreage by 0.43%. A strand of literature took the discrete choice modeling approach instead. Sherrick et al. (2004) apply the multinomial logit econometric method to a survey of farmers and find, among other factors, that highly leveraged farms, or those with higher perceived exposure to yield risks are more likely to use crop insurance products. Shaik et al. (2008) apply a multinomial logit model to find that crop insurance is inelastic (-0.40) for the yield insurance product, and also that choices between yield and revenue insurance are relatively more elastic (-0.88). Du, Hennessy, and Feng (2017) estimate a mixed logit model based on crop insurance data in 2009 and find inelastic demand. Heerman et al. (2016) does ordered generalized extreme value modeling in comparison with the multinomial logit modeling. This study finds that the market shares of high coverage levels are most elastic, while the market shares of low coverage levels are least elastic—the opposite holds with multinomial logit modeling. In their simulations, the elasticity in terms of subsidy expenditure

in the coverage level. In the denominator, a 15 ppts drop in the average subsidy rate results in nearly 40% increase in the average farmer-paid premium rate. Combining the two, the elasticity values used by the CBO appears to be 0.36 in absolute value.

turns out to be inelastic. In one of the scenarios, for instance, a 5% (proportional) cut in subsidy rates for all buyup coverage levels reduces the subsidy expenditures for corn by $80 million in 2009, a less than 4% reduction as the subsidy expenditures stood at $2.03 billion for the same crop in that year. Nevertheless, their analysis contained a technical error, which raises questions about the reliability of the findings.[4] Finally, some other studies (such as Lusk, 2017, and Maisashvili, Bryant, and Jones 2020) opt for simulation methods to study large changes in subsidy rates, including the scenarios that allow their complete elimination.

The CBO report points to a methodological issue previously raised in Woodard (2016). Woodard noted that prior studies have fallen short of properly accounting for the endogeneity issue arising from the simultaneous choice of insurance quantity and the attendant price. While a few studies have suggested near unitary or elastic crop insurance demand, it appears that these studies did not carry the same weight as others in the CBO review. For instance, Woodard (2016), which has the same results as in Woodard and Yi (2018, see the third panel, p. 20), reports an elasticity coefficient of near 1 once buyup coverage levels (the dependent variable) were adjusted to reflect their differences over catastrophic coverage. Nevertheless, in this case, the interpretation of the elasticity value depends on how the adjustment was made and the text is unclear on that point. The CBO apparently opted for the result when coverage levels were unadjusted, which shows -0.33 and hence suggest inelastic demand (footnote 3). On the other hand, the CBO merely cites Richards (2000) who finds an elastic response in a specialty crops

[4] This is regarding the elasticity matrix as shown in table 6 in p. 21 in their paper. For instance, if the subsidy rate at the 50% coverage level goes up by 1%, the total change in the market shares should vanish, that is, market shares multiplied by the elasticities should add up to zero, but they do not.

context (specifically grapes).[5] Finally, O'Donoghue and Tulman (2016) find elasticity values near one for corn and above one for soybeans, yet this study was not cited in the CBO review.[6]

The elasticity assumptions made in the GAO and CBO reports are central to their conclusion because a small response from farmers to the reduction in premium subsidies translates as potentially large savings for the government.[7] Nevertheless, there is a disconnect between that premise and the statistical association between the rise in participation (both at the extensive and intensive margins) and the legislative interventions in the subsidy space over time (see figures 1a and 1b; footnote 1 and the data section). To account for the observed growth, we employ time-series (dynamic) econometric modeling tools, which have not been done in this literature. Economic dynamics can be important here as relevant on-farm adjustments, such as

[5] Richards (2000) proposes a two-stage model in which the first stage is the coverage level choice and the second stage is the proportion of land allocated to each coverage level. The first stage consideration improves upon earlier studies such as Hojjati and Bockstael (1988) who model the proportion of land under a single coverage. By accounting for a sample-selection correction factor via an ordered probit modeling in the first stage, the author estimates participation (acreage wise) regression models in the second stage and finds, in the context of grapes, demand at 50% coverage is price elastic and warns that further increases in farmer paid premium may reduce participation significantly. The high coverage level (75%) also turns out to be elastic, while the middle option, 65% coverage, is found to be inelastic. Specifically, the own-price elasticities—defined as the percentage change in the probability of choosing a coverage level for a given percentage change in premium—are estimated as -4.92, -0.75, and -3.94 for 50%, 65%, and 75% coverage levels, respectively (table 1, p. 187). The more common form of elasticity, in terms of liability per acre, is also estimated as -1.68, -0.669, and -0.504 for 50%, 65%, and 75% coverage levels, respectively (p.183).

[6] O'Donoghue and Tulman (2016) report -1.6 and -0.92 as elasticity values in terms of liability for soybeans and corn, respectively (pp. 21-22). Consideration of yield controls in their model specification appears to be the main driver of such a qualitatively different finding compared with other studies such as O'Donoghue (2014). In particular, the effects of yield shocks are found to be statistically, but not economically, significant. Some other differences in terms of model specification are also apparent.

[7] In the December 2017 report, the CBO estimated $8.1 Billion savings over the period 2018-2027 as a result of 15 ppts drop in the average subsidy rate, which translates as $810 million per year savings. In addition, the GAO (2014) notes "the federal government would have potentially saved more than $400 million in 2012 by reducing premium subsidies by 5 ppts, and the savings would have been nearly $2 billion by reducing these subsidies by 20 ppts."

entering or exiting operational loans, rental, or other contractual arrangements, may take time.[8]

To elicit farmers' responses, we focus on the policy change on enterprise units that took place in 2009. This is the only relevant policy experiment since the passage of the Agricultural Risk Protection Act (ARPA) of 2000 and yet has been overlooked in the literature (other than Bulut, 2020). With authorization under the 2008 Farm Bill, the USDA's Risk Management Agency (RMA) increased the subsidy on enterprise units so that subsidy dollars remained about the same across different units. Since premium amounts associated with enterprise units were lower, higher subsidy rates resulted for such units.[9] This policy change resulted in economically and statistically significant demand responses across unit choices. Enterprise units have been available to farmers since 1999 but were not popular initially because of the higher level of aggregation required when compared with other unit types. Switching to this product appeared to be motivated by increased subsidy rates (Bulut, 2020).

Accurate measurement and understanding of farmers' coverage demand responses are critically important when making policy assessments. Were the potential downward response of coverage levels and participation in response to subsidy reductions markedly underestimated, then the effectiveness of crop insurance in deterring ad hoc disaster aid would be undermined and the large savings as proposed in GAO (2014) and CBO (2017) may not materialize (Innes, 2003; Bulut, 2017). For instance, while there were no legislative attempts to provide disaster aid

[8] It has been recognized that insurance with sufficient coverage can facilitate credit use (Ifft, Kuethe and Morehart, 2013). As lenders may require crop insurance in loan applications, their preferences for a minimum coverage level may influence observed coverage level choices. In addition, advance rate in loans—the portion of the value of the collateral that is extended as a loan—may be positively associated with coverage levels chosen (Jensen, 2017).
[9] The subsidy rates for individual plans are, as a share of premium, 0.53, 0.68, 0.75, 0.80, 0.80, 0.80, and 0.80 for enterprise units; 0.38, 0.48, 0.55, 0.59 0.59, 0.64, 0.64, 0.67 for basic/optional units at 85, 80, 75, 70, 65, 60, 55, and 50 percent coverage levels, respectively.

during the 2012 drought, which took place in the Midwest (a high coverage region), the 2017 hurricanes in Florida and the Carolinas (part of a low coverage region) triggered significant amounts in disaster aid. To assist in understanding the implications of subsidy reductions, we derive elasticity measures in terms of total crop insurance subsidy expenditures and the average coverage level based on changes in the subsidy rates at buyup coverage levels. These measures are evaluated by using crop insurance data and econometric estimation of market share impacts for crop insurance coverage level options. The estimations are made for corn and soybeans at the countrywide level covering the period 2001-2020.

This article contributes to the literature in several ways. We take a market share approach to the elasticity estimation problem. One advantage of this approach is that since market shares are in essence insured acres when normalized by planted acres (to which prevented acres are added, if any), any effects via the changes in crop prices or price risks are already reflected in the variable's denominator. While Heerman et al. (2016) is the only other study to also take a market shares approach in this context, they only considered market shares within insured acres and buyup coverage. The other studies limiting their analysis to buyup coverage included Yi, Bryant, and Richardson (2020) and Woodard and Yi (2018). Since we also model market shares for catastrophic coverage and no insurance options, we can and do study effects both at the intensive and extensive margin, that is, effects that arise from entry into and exit from insurance, shifts across catastrophic and buyup coverage as well as the shifts within the buyup coverage. We derive elasticity formulations in terms of total crop insurance subsidy expenditures and the average coverage level based on changes in the subsidy rates at buyup coverage levels. This is the first study to look at the relationship between these two elasticity measures. By establishing an auto-regressive structure in the market shares of coverage options, ours is also the first study to consider economic dynamics in this context. We point out that the small elasticity values found in prior studies arise from accounting for mostly the short-run effects rather than the long-term effects of a policy change. Farmers' crop insurance demand over the long term turns out to be quite responsive to price changes.

The remainder of this article is organized as follows. In the next section, we provide analytical derivations of elasticities with respect to additive changes in subsidy rates at buyup coverage levels. Elasticity formulations are further broken down into their static- versus dynamic- scoring components. Our econometric analysis of market share impacts then follows. Elasticity estimates are then presented and discussed. An application illustrating the use of elasticity estimates is also provided. The article concludes with a summary of findings and suggestions for future research avenues.

2. Elasticity Formulations

Schnitkey and Sherrick (2014) analyze the distribution of average coverage levels in corn and soybean growing counties across economic regions. These authors note that, in 2013, average coverage levels in most midwestern counties were at least 75%, while the counties in the Great Plains and the South saw predominantly lower coverage levels (i.e., 70% and below). In line with this pattern, we consider two buyup insurance coverage levels, ϕ_l and ϕ_h with individual plans in which ϕ_l denotes low buyup coverage (at least 50% and less than 75%), and ϕ_h denotes high buyup coverage (at least 75%). The respective market shares for each coverage level are denoted by m_l and m_h. On the other hand, we consider a single buyup coverage level with area plans and denote that by ϕ_a. This is done for three reasons. First is that area plans have a small share of overall premium volume.[10] Second, the bulk of the coverage with area plans concentrates at high levels. [11] Third, we normalize area plan coverage levels by subtracting 15 ppts to make them equivalent to individual plan coverage levels. This is exemplified by the CAT coverage being set at 50% with individual plans while being at 65% with area plans and how subsidy rates were set for area plans before the 2008 Farm Bill (Wang, Hanson and Black, 2003, p. 124). After this adjustment, ϕ_a represents all of $\{0.55, 0.60, 0.65, 0.70, 0.75\}$, the individual plan equivalent coverage levels.[12] The market share for buyup area plans is then denoted by m_a. In addition, catastrophic (CAT) coverage (100% subsidized with a small administrative fee) is considered. The CAT coverage includes acres from both individual and area plans—while the share of the latter was less than 0.5% in 2020 for corn and soybeans. This coverage and its attendant market share are denoted by ϕ_c and m_c. Note that $\phi_h > \phi_l > \phi_c$ and $\phi_a > \phi_c$ holds. Similarly, ϕ_n represents no insurance choice and m_n is the respective market share.

Before proceeding, the following notational convention can be useful. Denote individual and area plans by "i" and "a" in the subscripts. The same notation also refers to the respective buyup coverage levels as the CAT coverage will not be specified in terms of individual or area plans. Only optional and enterprise units are considered with individual plans and these are indicated with "e" and "o" in the subscripts. The optional unit category includes optional units along with basic unit acres. The enterprise unit category includes enterprise units along with

[10] For corn and soybeans, all area-based plans represented less than 4.5% and 3.1% of the entire MPCI liability over buyup coverage levels in 2020.
[11] For corn and soybeans, the most popular coverage level with non-supplemental area plans was at 90% representing 64.8% and 72.1% of acres in 2020. The 90% and 91% of acres under such plans were at least 90% coverage level.
[12] The 65% buyup coverage level with area plans (the equivalent of 50% individual buyup coverage level) was eliminated in the 2008 Farm Bill.

whole-farm unit acres.[13] Whenever "e" and "o" appear in the subscripts, that should be sufficient to infer that the variable of interest belongs to individual plans, and hence the appearance of "i" in the subscript would be redundant. Similarly, "e" and "o" in the subscripts would refer to buyup coverage as the CAT coverage cannot be on enterprise units and will not be specified in terms of units. In referring to buyup coverage levels when individual and area plans are combined, the notation "b" is used in the subscripts. Buyup coverage levels with individual plans are further classified as "low" and "high" and these are indicated with "l" and "h" in the subscripts as used earlier. Since the preceding decomposition is not done with area plans, whenever "l" and "h" appear in the subscripts, that should be sufficient to infer that the variable of interest belongs to buyup coverage levels with individual plans and hence the appearance of "i" in the subscript would be redundant.

Furthermore, we denote the unit structure alternatives by μ so that $\mu \in \{o, e, a\}$ holds. For buyup coverage levels with individual plans, $m_{\phi\mu}$ then denote the market share of coverage level ϕ at the unit structure μ. On the other hand, for area-based plans m_a is sufficient notation to represent both the attendant single coverage and that unit type. Upon combining all these, $\phi\mu \in \{he, ho, le, lo, a, c\}$ is used to collect the coverage and unit structure options considered: high coverage on enterprise or optional units, low coverage on enterprise or optional units, area coverage, and CAT coverage.

[13] Optional and basic units carry the same subsidy schedule even though their premium rates differ. Regarding combining enterprise units along with whole farm unit acres, Olen and Wu (2017) report that 72% for the average subsidy rate with whole farm units and that many farms had at least two commodities. That in turn suggests that the relevant subsidy schedule that is closer to the enterprise unit subsidy schedule. Finally, whole farm units had a very small share of the premium. In 2020, premiums under such policies constituted less than 2% of the entire MPCI premium volume.

Now, $\phi\overline{y}$ is the insurance guarantee, $p_\mu(\phi\overline{y})$ is the premium function at the guarantee on the unit structure μ. It is assumed that the farmer is the representative of the area. The insurance book of business (per planted acre), which is denoted by p_B, can be written as

$$p_B = m_c p(\phi_c\overline{y}) + m_{lo} p_o(\phi_l\overline{y}) + m_{le} p_e(\phi_l\overline{y}) + m_{ho} p_o(\phi_h\overline{y}) + m_{he} p_e(\phi_h\overline{y}) + m_a p_a(\phi_a\overline{y}). \quad (1)$$

Recall that all market shares are with respect to the planted acres, therefore, their summation adds up to 1.

Further distinguishing low and high coverage levels by units, denoted by ϕ_{lo}, ϕ_{le}, ϕ_{ho}, and ϕ_{he}, the average coverage level can be written as

$$\overline{\phi} \equiv m_n\phi_n + m_c\phi_c + m_{lo}\phi_{lo} + m_{le}\phi_{le} + m_{ho}\phi_{ho} + m_{he}\phi_{he} + m_a\phi_a, \quad (2)$$

Now, the notation $s_\mu(\phi)$ represents the subsidy rate at coverage ϕ and unit structure $\mu \in \{o, e, a\}$. Henceforth, we use the shorthand notation $s_{l\mu}$ and $s_{h\mu}$ for $s_\mu(\phi_l)$ and $s_\mu(\phi_h)$, respectively. In addition, S_c, S_i, and S_a are short-hand notations for subsidy dollars for CAT, individual buyup, and area buyup policies. Now, CAT subsidy dollars are obtained as $S_c = m_c p(\phi_c\overline{y})$. The buyup subsidy dollars are denoted by S_b and can be expressed in several ways depending on the levels of aggregation. First, $S_b = S_i + S_a$ holds, that is the sum of subsidy dollars in buyup coverage with individual and area plans. One can write the subsidy expenditure for area plans as $S_a = m_a s_a p(\phi_a\overline{y})$ where s_a is the average subsidy rate for buyup area coverage. Further breaking down the subsidy expenditures for individual plans by coverage, $S_i = S_l + S_h$ holds. The latter is the sum of subsidy dollars at low and high coverage levels. Further breaking down by unit structure yields $S_l = S_{lo} + S_{le}$ and $S_h = S_{ho} + S_{he}$. Finally, $S_{lo} = m_{lo} s_{lo} p_o(\phi_l\overline{y})$, $S_{le} = m_{le} s_{le} p_e(\phi_l\overline{y})$, $S_{ho} = m_{ho} s_{ho} p_o(\phi_h\overline{y})$, and $S_{he} = m_{he} s_{he} p_e(\phi_h\overline{y})$ holds. Bringing all together

$S_b = S_l + S_h + S_a = S_{lo} + S_{le} + S_{ho} + S_{he} + S_a$, one can then obtain

$$S_b = s_b\left(m_{lo}p_o(\phi_l\overline{y}) + m_{le}p_e(\phi_l\overline{y}) + m_{ho}p_o(\phi_h\overline{y}) + m_{he}p_e(\phi_h\overline{y}) + m_a p_a(\phi_a\overline{y})\right), \quad (3)$$

where s_b is the average subsidy rate for the entire buyup coverage as

$$s_b = \frac{m_{lo}s_{lo}p_o(\phi_l\overline{y}) + m_{le}s_{le}p_e(\phi_l\overline{y}) + m_{ho}s_{ho}p_o(\phi_h\overline{y}) + m_{he}s_{he}p_e(\phi_h\overline{y}) + m_a s_a p_a(\phi_a\overline{y})}{m_{lo}p_o(\phi_l\overline{y}) + m_{le}p_e(\phi_l\overline{y}) + m_{ho}p_o(\phi_h\overline{y}) + m_{he}p_e(\phi_h\overline{y}) + m_a p_a(\phi_a\overline{y})}.$$

Note that the preceding expression for s_b will be approximated by a formulation of the average buyup subsidy rate that focuses on the supply (offer) side of subsidies, which in turn does not depend on market shares (more on this momentarily in the Estimation Section).

Only the subsidy rates at the buyup coverage levels are considered in our policy assessments; hence, no changes in the CAT subsidy rate are considered. In what follows, additive changes in the average subsidy rate for the entire buyup coverage will be analyzed, as often considered in the policy proposals (footnote 7).

Now, formulating additive effects via the parameter θ as $s_b(\phi_l, \phi_h, \theta) = s_b + \theta$ and by using equation (3) one writes

$$S_b(\phi_l, \phi_h, \mu, \theta) = S_b\left(1 + \theta/s_b\right), \quad (4)$$

where S_b is as defined in equation (3) above.

One can then write the total subsidy expense for the government as the sum of subsidies under CAT and buyup policies, i.e.,

$$S(\phi_c, \phi_a, \phi_l, \phi_h, \mu, \theta) = S_c + S_b\left(1 + \theta/s_b\right). \quad (5)$$

Differentiating total subsidy dollars with respect to θ and re-expressing in logarithmic form yields

$$\Psi \equiv \frac{d\ln\left(S(\phi_c,\phi_a,\phi_l,\phi_h,\mu,\theta)\right)}{d\theta} = \frac{S_c\Omega_c + S_b\left(\Omega_b\left(1+\theta/s_b\right)+1/s_b\right)}{S_c + S_b\left(1+\theta/s_b\right)}, \tag{6}$$

where $\Omega_c = \left(dS_c/d\theta\right)/S_c$ and $\Omega_b = \left(dS_b/d\theta\right)/S_b$ are the elasticities. These, in turn, involve the terms $dS_c/d\theta = S_c\, d\ln(m_c)/d\theta$, and—upon differentiating $S_b = S_{lo} + S_{le} + S_{ho} + S_{he} + S_a$ — $dS_b/d\theta = S_{lo}\, d\ln(m_{lo})/d\theta + S_{le}\, d\ln(m_{le})/d\theta + S_{ho}\, d\ln(m_{ho})/d\theta + S_{he}\, d\ln(m_{he})/d\theta + S_a\, d\ln(m_a)/d\theta$ where the market share effects, $dm_c/d\theta$, $dm_{ho}/d\theta$, $dm_{he}/d\theta$, $dm_{lo}/d\theta$, $dm_{le}/d\theta$, and $dm_a/d\theta$ will be estimated from an econometric model. Evaluating equation (6) at $\theta = 0$ yields the percent impact of a one-ppt additive change in the average subsidy rate for buyup coverage. The resulting impact can be further broken into a static scoring component and a dynamic scoring component.

Remark 1. *Denote the subsidy expenditures under static scoring by* Ψ^{SS} *and the incremental contribution of dynamic scoring by* Ψ^{DS}. *Evaluate equation* (6) *at* $\theta = 0$. *In line with static scoring, imposing the assumption that the quantity demanded is not responsive to changes in the subsidy rates, that is,* $dm_c/d\theta = dm_l/d\theta = dm_h/d\theta = 0$ *results in* $\Omega_c = \Omega_b = 0$ *in equation* (6). *Combining these with the values of* S_c, S_l, S_h, S_b, *one obtains* $\Psi^{SS} = S_b/\left(s_b(S_c + S_b)\right)$. *In the absence of such a restriction in equation* (6)*, the contribution of dynamic scoring is obtained as* $\Psi^{DS} = \left(S_c\Omega_c + S_b\Omega_b\right)/\left(S_c + S_b\right)$ *so that* $\Psi|_{\theta=0} = \Psi^{SS} + \Psi^{DS}$ *holds.*

So as to better understand the relationship between the dynamic scoring component of the elasticities of subsidy expenditures and the degree of responsiveness of the quantity demanded, we also deploy a more commonly used elasticity in terms of the average coverage level. After differentiating the expression in equation (2), the elasticity of the average coverage level with respect to the average buyup subsidy rate can be obtained as

$$\text{H}_{\theta}^{\bar{\phi}} \equiv \frac{d\bar{\phi}}{d\theta}\frac{1}{\bar{\phi}} \equiv \frac{\phi_n}{\bar{\phi}}\frac{dm_n}{d\theta} + \frac{\phi_c}{\bar{\phi}}\frac{dm_c}{d\theta} + \frac{\phi_{lo}}{\bar{\phi}}\frac{dm_{lo}}{d\theta} + \frac{\phi_{le}}{\bar{\phi}}\frac{dm_{le}}{d\theta} + \frac{\phi_{ho}}{\bar{\phi}}\frac{dm_{ho}}{d\theta} + \frac{\phi_{he}}{\bar{\phi}}\frac{dm_{he}}{d\theta} + \frac{\phi_a}{\bar{\phi}}\frac{dm_a}{d\theta}. \quad (7)$$

The preceding measure shows the percent change in the average coverage level due to a 1 ppt change in the average subsidy rate. Denoting the (average) farmer-paid premium rate by r, then a one ppt change in the average subsidy rate results in $d\ln(r)/d\theta = -1/(1-s_b)$ percent change in the farmer-paid premium rate. Then combine the two to arrive at a version of the elasticity that is more commonly reported in the literature:

$$\text{H}_{r}^{\bar{\phi}} \equiv \frac{d\ln(\bar{\phi})}{d\ln(r)} = -\frac{(1-s_b)}{\bar{\phi}}\left(\phi_n\frac{dm_n}{d\theta} + \phi_c\frac{dm_c}{d\theta} + \phi_{lo}\frac{dm_{lo}}{d\theta} + \phi_{le}\frac{dm_{le}}{d\theta} + \phi_{ho}\frac{dm_{ho}}{d\theta} + \phi_{he}\frac{dm_{he}}{d\theta} + \phi_a\frac{dm_a}{d\theta}\right). (8)$$

The preceding measure shows the percent change in the average coverage level due to a 1 percent change in the farmer-paid premium rate—the latter originating from some ppt change in the average subsidy rate.

Having given the elasticity formulations in terms of subsidy expenditures and the average coverage level, we now look at the data that will be used.

3. Data

Crop insurance summary of business data, available from RMA, are used in carrying out the estimations. For corn and soybeans, the data are aggregated to the countrywide level and the sample period runs from 2001 to 2020.[14] Table 1 provides a snapshot of key variables of interest

[14] Since one observation is lost to the lagged dependent variable in the estimations, the effective sample size begins in 2001. We focus on the post-ARPA period in our analysis and consider 2000 as a transitional year. Recall that the ARPA (2000) provided a permanent increase in subsidies and had passed about the mid-year in 2000. This was in continuation with yet separate from the temporary economic loss assistance that had started in 1999 (Glauber, Collins, and Barry, 2002, p. 89). The subsidy figures (amounts and rates) regarding 2000 that we present here are based on RMA's summary of business tables and do not include additional premium discount provided on an emergency basis through that supplemental legislation (Chite, 2000, tables 1 and 2, p.3 and p. 8).

in 2000 and 2020, which include the market shares for each coverage level and unit structure option and the no insurance option, the average subsidy rates at buyup coverage levels and the average subsidy rate for the entire buyup coverage, the respective subsidy figures in dollars for individual coverage, area coverage, CAT coverage, and the total subsidy dollars. Recall that the individual and area coverage refer to buyup coverage levels, and the low and high coverage distinction belongs to individual coverage.

Some sharp changes between 2000 and 2020 are apparent. For corn, the market shares for no insurance, CAT and area coverage options saw 16.7, 11.5, and 0.8 ppt declines, respectively, while individual coverage share gained 29 ppts. Market share for low coverage level decreased by 22.4 ppts, while market share for high coverage increased by 51.4 ppts. The former was driven by the drop in the use of optional units (29.3 ppts), while the latter was driven by the rise in the use of enterprise units (44.3 ppts). A similar pattern was observed for soybeans, except that the opposing changes in the shares of CAT and individual coverage became a few ppts larger. The average subsidy rates at buyup coverage were 0.226 and 0.275 in 2000; 0.626 and 0.632 in 2020 for corn and soybeans, respectively. As such, this variable increased by 40 ppts and 35.6 ppts for the respective crops. A similar pattern holds when all crops are combined, which can be verified from figure 1a. Note that the latter also includes CAT subsidies. The subsidy rate changes were accompanied by large increases in insured acres (48.8%; 37.8%), base insurance prices (54.5%; 72.4%), and liability (328.9%; 289.0%) for corn and soybeans, respectively over the same period.

In line with the foregoing changes, for corn, subsidy dollars for CAT coverage declined by 87%, whereas subsidy dollars for buyup coverage increased 12.47 times. Subsidy dollars for area coverage increased 10.91 times, while subsidy dollars for low and high coverage increased by 2.37 and 48.01 times. A similar pattern can be verified for soybeans, except that the surges in buyup-related subsidy dollars were a bit pared down. Upon dividing the subsidy expenditures by the liability figures in each year, this ratio stood at 1.9% and 2.3% for corn and soybeans, respectively in 2000. One can further verify that the associated increases in the normalized subsidy expenditures were relatively modest: 159.7% and 108.9% for corn and soybeans, respectively.

Furthermore, the average buyup coverage levels for each crop in 2020 can be calculated from equation (2) as follows. For both crops, $\phi_c = 0.5 \times 0.55 = 0.275$ as catastrophic coverage covers 55% of the base insurance price. For corn, we take $\phi_a = 0.9053 - 0.15 = 0.7553$, $\phi_{le} = 0.654$, $\phi_{lo} = 0.663$, $\phi_{he} = 0.7924$ and $\phi_{ho} = 0.7919$ as the acreage-weighted average of coverage levels within each category. Combining these with the respective market shares from table 1 in equation (2), one obtains $\overline{\phi} = 0.6610$. Similarly, for soybeans, by combining $\phi_c = 0.275$, $\phi_a = 0.95244 - 0.15 = 0.75244$, $\phi_{le} = 0.63683$, $\phi_{lo} = 0.6621$, $\phi_{he} = 0.7881$ and $\phi_{ho} = 0.7911$ with the values of respective market shares, the average coverage level is calculated as $\overline{\phi} = 0.6678$. As for the respective figures in 2000, by applying the same representative coverage levels for each crop, yet using the values of respective market shares in 2000 in table 1, one calculates the average coverage levels for corn and soybeans about the same as 44.1%—the equivalent of CAT coverage with 88.2% price protection, i.e. near minimum buyup coverage level (50%). That in turn would suggest that between 2000 and 2020, the average coverage levels went up by 22.1 and 22.7 ppts for corn and soybeans, respectively.

To better reflect where the program currently is and prospectively evaluate policy changes in the support provided, we use the relevant variable values as of 2020 in equation (6) and the average buyup coverage levels as of 2020 from earlier in equations (7) and (8) to calculate the corresponding elasticity values. The latter requires the estimation of market share impacts to which we now turn.

4. Estimation Results

As noted in Bulut (2020), anecdotal evidence suggests that farmers' coverage choices and expenditures on crop insurance in the preceding year have influenced their current year choices. In line with this possible anchoring effect and rather limited sample size (21 years), we consider first-order vector autoregressive model, VAR(1), with the diagonal structure and write

$$m_{\phi\mu,t} = \alpha_{\phi\mu 0} + \alpha_{\phi\mu j} m_{\phi\mu,t-1} + \beta_{\phi\mu 1} x_{1,t} + \ \dots \ + \beta_{\phi\mu k} x_{K,t} + u_{\phi\mu,t} \ , \qquad (9)$$

where the subscript $t \in \{0,1, \ \dots \ ,T\}$ indexes years, $\phi\mu \in \{he, ho, le, lo, a, c\}$ indexes coverage and unit structure options, and $j \in \{1, \ \dots \ ,6\}$ is the order in which the $\phi\mu$ is listed in the set $\{he, ho, le, lo, a, c\}$. For instance, $\phi\mu = he$ would correspond to $j = 1$. In the same equation, $m_{\phi\mu,t}$ and $m_{\phi\mu,t-1}$ are the respective market shares and their 1-period lagged values, x_k denote the other (forcing) explanatory variables for $k \in \{1, \ \dots \ ,K\}$ which can be in-levels or in-differences, $\alpha_{\phi\mu 0}, \alpha_{\phi\mu j}, \beta_{\phi\mu 1}, \ \dots \ , \beta_{\phi\mu K}$ are parameters to be estimated and $u_{\phi\mu,t}$ are the attendant error terms. Within a given equation, the error terms follow a white noise process in the sense that they satisfy the standard assumptions having zero mean, constant variance, and zero autocovariances. Across equations, however, error terms can be contemporaneously correlated. Since all market shares should sum to 1, the market share for no insurance acres is obtained from the fitted values of other market shares as $\hat{m}_n = 1 - (\hat{m}_{he} + \hat{m}_{ho} + \hat{m}_{le} + \hat{m}_{lo} + \hat{m}_a + \hat{m}_c)$—henceforth, the overstruck "^" indicates the fitted values.

The explanatory variables of interest include the average subsidy rate for buyup coverage level and the percentage changes in premium per acre at each coverage level and unit structure as these variables naturally influence farmers' coverage level choices via their cost and value calculations. From the econometric estimation standpoint, the consideration of such explanatory variables is problematic, however. Even though, being determined by Congress, subsidy rates are exogenous to farmers' coverage choices, the average subsidy rate for buyup coverage is somewhat influenced by farmers' coverage level choices; hence, it is potentially endogenous. For instance, a preferential shift towards high coverage levels (within a given unit structure) would dampen the average subsidy rate because subsidy rates decline as coverage levels increase. The percentage changes in premium per acre at each coverage level and unit structure are endogenous as they clearly depend on farmers' coverage level and unit choice. What this means is that the disturbance terms in the market share equations given in equation (9) are correlated with the explanatory variables in question, which in turn would lead to biased estimates. These explanatory variables need to be instrumented or approximated by their exogenous variants.

For the average subsidy rate for buyup coverage level, we focus on the offer (supply) side of this variable, not the equilibrium outcome that is influenced by farmers' coverage and unit choices. [15] The average subsidy rate (offered), in essence, is the simple average of the average buyup subsidy rates on the three units considered: optional units, enterprise units, and area. As explained in the Elasticity Formulations section, area plan coverage levels (by subtracting 15 ppts) are first matched with individual plan coverage levels. The average subsidy rate at each coverage level across the units considered is then calculated. The resulting values are further

[15] In line with this approach, Yu, Smith and Sumner (2018) used the two legislatively set subsidy rates for given coverage levels (65% and 75%) so that farmers' coverage choices do not influence the total subsidy per dollar of liability variable.

averaged over coverage levels to arrive at the final average buyup subsidy rate figure.[16] The details are relegated to Supplementary Appendix 1 (SA1). Based on this calculation, the average buyup subsidy rate jumped 5.651 ppts from 0.5675 to 0.62361 between the pre-2009 and post-2009 periods. The proposed version allows variation only on the time dimension as the subsidy schedule is generally the same for all farmers. With this formulation, it is then possible to trace out the effects of potential changes in optional unit subsidy rates—as shown in equation (11) and (12) in SA1—while holding the relative subsidy rates between optional and enterprise units as well as the area plan subsidy rates in their current levels. Such a policy change would be commensurate with the policy target of a reduction of equal subsidy dollars across optional and enterprise units.

As for the percentage changes in premium per acre at each coverage and unit structure option, a general indicator is that, for corn and soybeans, up to 90.2% and 92.8% of the variation in the buyup coverage levels can be explained (based on *Adjusted-* R^2 measure) by the percentage changes in base insurance prices and the percentage changes in volatility factor values. This can be verified in the auxiliary regression results provided in table A.2 and figures A.1a and A.1b in Supplementary Appendix 2, SA2). These price-risk-related variables, provided that they are found as significant in market share equations, may provide an indication as to

[16] A more simple-minded approach would first find the average subsidy rate at each unit considered. This would be done by averaging subsidy rates over coverage levels in each unit (after adjusting area plan coverage levels as before). The resulting figures would then be further averaged across the units considered. To illustrate this, denote the resulting average subsidy rate variables for optional units, enterprise units, and area plans by $.s_e$., s_o and s_a, respectively as defined in SA1. The average buyup subsidy rate then would be calculated as $s_b = (s_e + s_o + s_a)/3$. The estimations that are done separately with the alternative approach indicate a more elastic demand than the estimations that are done with proposed version, yet the main conclusions remain the same across both formulations. One drawback of the alternative approach is that it would be muted to any reshuffling of subsidy rate schedule within a given unit structure, while such a change would be reflected (to some extent) in the proposed formulation.

possible budget heuristic effects. Theoretically, an actuarially fair increase in premium—reflecting the change in underlying risk (yield or price)—should not be changing a farmer's optimal choice as to coverage level and unit structure. With the insurance being subsidized, assuming premium rates are actuarially fair (which holds in the aggregate at minimum), risk-averse farmers should be choosing the maximum available coverage. Since this is not consistent with the observed regional differences, one hypothesis raised is that an upper threshold—5% of expected crop value—may be influencing farmers' insurance choices (Bulut, 2018). One implication of such a budget constraint is that the constrained choice would remain the same against the potential changes in base insurance price but not those in volatility factor.

The base insurance prices are used to set the crop insurance guarantees and are obtained from futures markets. The volatility factor values are used to measure the price risk in revenue protection policies and are obtained from option values for the underlying futures contracts (Bulut, Schnapp and Collins, 2011). Since these variables are primarily influenced by market forces, any feedback from the market shares of insurance coverage options back to these variables can be a second-order effect at best. To economize on the number of parameters estimated, we directly include the percentage changes in base insurance prices and the percentage changes in volatility factor values in the market share equations.

With the suggested versions of explanatory variables, we then maintain that the disturbance terms in the market share equations given in equation (9) and the suggested explanatory (forcing) variables are not correlated.

Table 2 lists the explanatory variables considered. All models include 1-period lagged dependent (own market shares) variables. Additional explanatory (forcing) variables then distinguish between these models. Model 1 includes the average subsidy rate (offered) for buyup coverage. Model 2 additionally includes the percentage changes in the base insurance price or volatility factor values. Model 3 appends cross-market share effects (1-period lagged) to Model 2.

As an example, for $t \in \{0,1, \ldots ,T\}$, $\phi\mu \in \{he, ho, le, lo, a, c\}$, and $j \in \{1, 2, 3, 4, 5, 6\}$, Model 1 then can be written as

$$m_{\phi\mu,t} = \alpha_{\phi\mu 0} + \alpha_{\phi\mu j} m_{\phi\mu,t-1} + \beta_{\phi\mu 1} s_{b,t} + \beta_{\phi\mu 2} z_{1,t} + \beta_{\phi\mu 3} z_{2,t} + u_{\phi\mu,t}, \quad (10)$$

where $s_{b,t}$ denotes the value of the average buyup subsidy rate in year t, $z_{1,t}$ and $z_{2,t}$ are the shorthand notation for the variables percentage changes in base insurance prices and the percentage changes in volatility factor values, respectively, in year t, and the remaining notation is as defined earlier. In essence, what equation (10) conveys is that in the absence of outside shocks to subsidy rates for buyup coverage or to the premiums via the price and volatility factor changes, the expected value of market shares of insurance coverage options for the next year is an affine function of the current year's market shares.

Finally, the estimations of Models 1 and 2 are made at the countrywide level over the period 2001-2020. The results are presented in tables 3a and 3b for corn and soybeans, respectively. The latter is deferred to SA3. The fit performances of the models are measured in the form of R^2 as suggested in McElroy (1977). This measure show values of at least 97.8%, which suggest strong fit performance. Consistent with that finding, the actual and predicted values from the regressions line up well. With Model 1, this is verified in figures 2a and 2b for corn and soybeans, respectively. The latter is also deferred to SA3. Similar figures for the remaining models are available upon request. Also consistent is the fact that most explanatory variables are generally found to be significant at the 1% level. The generalization does not hold for the variables distinguishing Model 2 from Model 1: percent changes in the base insurance price and percent change in volatility factor as their significance and admittance into the model of interest are crop and market share equation dependent.[17]

Based on the estimation results, the elasticity values are calculated in two forms of dynamic scoring: the short-term (contemporaneous) effects[18] versus long-term effects. In the case of short-term effects, the market share impacts directly reflect the respective slope coefficients from the regression. In the case of long-term effects, the accumulated effect of the initial shock (change) in the average subsidy rate for buyup coverage on market shares over f forecast periods are traced out via the impulse-response functions. In doing so, the error term values in all models are all set to zero (Enders, p. 293). This is consistent with the conditional

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[17] Likelihood Ratio tests, once adjusted for small sample size, see Enders (2010, p. 316), are conducted. To see how the adjustment is made, denote the natural logarithm of likelihood function values (reported as $\ln(L)$ in tables 3a, 3b, 3c, and 3d) under unrestricted and restricted models by $\ln(L^U)$ and $\ln(L^R)$, respectively, the number of usable observations by T as before, and the number of parameters estimated in each equation of the unrestricted system by c. Then the adjusted likelihood ratio test statistic is $\left((T-c)/T\right)2\left(\ln(L^U)-\ln(L^R)\right)$.

Model 4 in tables 3c and 3d are considered as the unrestricted versions of Model 2 in tables 3a and 3b, while maintaining the diagonal VAR(1) structure. For corn, loglikelihood values are 432.9 in Model 2 and 437.9 in Model 4, which results in the 7.6 test statistic value after setting $c=5$. For soybeans, the respective loglikelihood values are 432.8 and 440.7, which results in 11.8 test statistic value after setting $c=5$. Since Model 2 has 10 parameter restrictions relative to Model 4 for both crops, the χ^2 distribution values are 15.99, 18.31, and 23.21 at respective 10%, 5% and 1% significance levels. Comparing the critical values with the table values leads to the said conclusion for each crop. Note that the Akaike Information Criterion (*AIC*) and Bayesian Information Criterion (*BIC*) values are lower (more negative) in Model 2 versus Model 4 in the respective tables, also favoring the restrictions placed on Model 4. Similarly, Model 2 is selected all nesting alternatives relative Model 4. From the combination formula, this meant 1,023 different ways of lifting the 10 restrictions and testing Model 2 against that many alternative models that are nested within Model 4.

Finally, the selection of Model 2 over Model 1 can be similarly verified. Model 1 has two additional parameter restrictions relative to Model 2, which are placed on the base insurance price or volatility factor related variables. In the case of corn, while these restrictions can be rejected at 5% but not at 1% level of significance, both the *AIC* and *BIC* criteria favor lifting the restrictions. In the case of soybeans, the restrictions can be rejected at 1% level of significance.

[18] An alternative phrase is 'impact effects' as suggested in Enders (2010, p. 275).

expectation of error terms over the forecast periods being all zero. Furthermore, the values of the other explanatory variables in Models 2 and 3, the percentage changes in base insurance price or volatility factor are all set to zero over the forecast horizon. This is consistent with the fact that these variables concentrate around zero as Figures A.2a and A.2b in Supplemental Appendix 2 (SA2) indicate for corn and soybeans, respectively. In addition, the null hypothesis of the mean equals zero for each variable is well supported in a *t*-test. The details are relegated to SA2.

Now, denote the values of market shares by $m^1_{\phi\mu,T+f}$ and $m^0_{\phi\mu,T+f}$ at the end of the forecast period f for $\phi\mu \in \{he, ho, le, lo, a, c\}$ where the superscripts 1 and 0 indicate with and without the subsidy intervention. Meanwhile, the intervention (a given ppt change) in the average subsidy rate for buyup coverage equals $s_{b,t+1} - s_{b,t}$. Under the assumption that $\alpha_{\phi\mu j,1} < 1$ holds, as the forecast horizon extends indefinitely, one obtains market share impacts as

$$\frac{dm_{\phi\mu}}{d\theta} \cong \frac{\lim_{f\to\infty}\left(m^1_{\phi\mu,T+f} - m^0_{\phi\mu,T+f}\right)}{s_{b,T+1} - s_{b,T}} = \frac{\beta_{\phi\mu 1}}{1-\alpha_{\phi\mu j}}. \tag{11}$$

where $j \in \{1, 2, 3, 4, 5, 6\}$ is the respective order of $\phi\mu$ as before. To give a sense of the impulse-response function analysis of the market shares, figures 3a and 3b display the time paths of market shares after reducing the average subsidy rate by 15 ppts based on Model 1 for corn and soybeans, respectively. The latter is deferred to SA3. Note that the charts based on Model 2 are very similar to those based on Model 1 are available upon request. In particular, a change in the negative direction (a cut) in the average subsidy rate by 15 ppts drives down the market share for enterprise units to nil for both crops in less than five years. The same scenario also greatly reduces the market share for high coverage for both crops.

Based on the resulting market share impacts from equation (11), Model 1 and 2 elasticity values are reported in tables 4a and 4b for corn and soybeans, respectively. In particular, the elasticities of subsidy expenditures values are decomposed into contributions from both the static- and dynamic-scoring components. The static-scoring component (indicated by Ψ^{SS}), where the quantity demanded is unresponsive (Remark 1), are evaluated by plugging the variable values from table 1 into the relevant formulations from earlier and the resulting values are reported in the respective second rows of these tables. Furthermore, for each model, the elasticity values based on the short-term effects and long-term effects are reported side by side. The latter are found to be materially larger (in absolute value) than the former for nearly all model-crop combinations.

Even though the models above with the own market share effects achieve R^2 (Mc-Elroy's) values over 97% (see tables 3a and 3b), one could conceivably include the lag of other market shares in addition to the own-market share lag in equation (9). We turn now to the investigation of cross-market share effects as a robustness check to the results that we have obtained so far.

We introduce cross-market share effects in equation (10) as

$$
\begin{aligned}
m_{he,t} &= \alpha_{he0} + \alpha_{he1} m_{he,t-1} + \alpha_{he2} m_{ho,t-1} + \alpha_{he3} m_{le,t-1} + \alpha_{he4} m_{lo,t-1} + \alpha_{he5} m_{a,t-1} + \alpha_{he6} m_{c,t-1} + \beta_{he1} s_{b,t} + \beta_{he2} z_{1,t} + \beta_{he3} z_{2,t} + u_{he,t} \\
m_{ho,t} &= \alpha_{ho0} + \alpha_{ho1} m_{he,t-1} + \alpha_{ho2} m_{ho,t-1} + \alpha_{ho3} m_{le,t-1} + \alpha_{ho4} m_{lo,t-1} + \alpha_{ho5} m_{a,t-1} + \alpha_{ho6} m_{c,t-1} + \beta_{ho1} s_{b,t} + \beta_{ho2} z_{1,t} + \beta_{ho3} z_{2,t} + u_{ho,t} \\
m_{le,t} &= \alpha_{le0} + \alpha_{le1} m_{he,t-1} + \alpha_{le2} m_{ho,t-1} + \alpha_{le3} m_{le,t-1} + \alpha_{le4} m_{lo,t-1} + \alpha_{le5} m_{a,t-1} + \alpha_{le6} m_{c,t-1} + \beta_{le1} s_{b,t} + \beta_{le2} z_{1,t} + \beta_{le3} z_{2,t} + u_{le,t} \\
m_{lo,t} &= \alpha_{lo0} + \alpha_{lo1} m_{he,t-1} + \alpha_{lo2} m_{ho,t-1} + \alpha_{lo3} m_{le,t-1} + \alpha_{le4} m_{lo,t-1} + \alpha_{lo5} m_{a,t-1} + \alpha_{lo6} m_{c,t-1} + \beta_{lo1} s_{b,t} + \beta_{lo2} z_{1,t} + \beta_{lo3} z_{2,t} + u_{lo,t} \\
m_{a,t} &= \alpha_{a0} + \alpha_{a1} m_{he,t-1} + \alpha_{a2} m_{ho,t-1} + \alpha_{a3} m_{le,t-1} + \alpha_{a4} m_{lo,t-1} + \alpha_{a5} m_{a,t-1} + \alpha_{a6} m_{c,t-1} + \beta_{a1} s_{b,t} + \beta_{a2} z_{1,t} + \beta_{a3} z_{2,t} + u_{a,t} \\
m_{c,t} &= \alpha_{c0} + \alpha_{c1} m_{he,t-1} + \alpha_{c2} m_{ho,t-1} + \alpha_{c3} m_{le,t-1} + \alpha_{c4} m_{lo,t-1} + \alpha_{c5} m_{a,t-1} + \alpha_{c6} m_{c,t-1} + \beta_{c1} s_{b,t} + \beta_{c2} z_{1,t} + \beta_{c3} z_{2,t} + u_{c,t}
\end{aligned}
\tag{12}
$$

where $\alpha_{he2}, \alpha_{he3}, \alpha_{he4}, \alpha_{he5}, \alpha_{he6}$; $\alpha_{ho1}, \alpha_{ho3}, \alpha_{ho4}, \alpha_{ho5}, \alpha_{ho6},$; $\alpha_{le1}, \alpha_{le2}, \alpha_{le4}, \alpha_{le5}, \alpha_{le6}$; $\alpha_{lo1}, \alpha_{lo2}, \alpha_{lo3}, \alpha_{lo5}, \alpha_{lo6}$; $\alpha_{a1}, \alpha_{a2}, \alpha_{a3}, \alpha_{a4}, \alpha_{a6}$; and $\alpha_{c1}, \alpha_{c2}, \alpha_{c3}, \alpha_{c4}, \alpha_{c5}$ are the additional parameters (30 in total) to be estimated due to the cross-market share effects. In using the notation $\alpha_{\phi\mu j}$ as before, the first index in the subscript $\phi\mu \in \{he, ho, le, lo, a, c\}$ refers to the rows within the VAR(1) structure, that is, the market share equation of interest, while the second index $j \in \{1,2,3,4,5,6\}$ refers to the columns, that is, the variable of interest. The latter index corresponds to 1-period respective lagged market shares. As an example, α_{le1} represents the cross-effect of 1-period lagged market share for high coverage on enterprise units ($j = 1$) on the market share for low coverage on enterprise units $(\phi\mu = le)$, which can also be verified in equation (12).

The theory provides no guidance on the signs and magnitudes of these parameters. In particular, these effects may not even be symmetric, that is, $\alpha_{he2} = \alpha_{ho1}$, $\alpha_{he3} = \alpha_{le1}$, $\alpha_{he4} = \alpha_{lo1}$, $\alpha_{he5} = \alpha_{a1}$, $\alpha_{he6} = \alpha_{c1}$ for instance, may not hold. Tables 3a and 3b present the results for selected models for corn and soybeans, respectively. The latter is deferred to SA3. Based on the intuition that low buyup coverage would have the most mobility as it sits between CAT and high buyup coverage, cross-market share effects are allowed there first and other alternatives (such as area coverage) are looked at. As a result of this process, the candidate Model 3 in corn and soybeans are identified in tables 3a and 3b, respectively. These models are obtained by imposing the respective parameter restrictions in the unrestricted models. The latter are shown as Model 5 for corn and soybeans in tables 3c and 3d, respectively. The parameter restrictions indicate that the low coverage on optional units provides the greatest number of cross market share effects, while such claim is shared by several other coverage options in the case of soybeans.

Model 3 for each crop is then tested against all nesting alternative models in terms of cross-market share effects: there are 2,097,151 and 32,767 such models for corn and soybeans, respectively. To see this, for corn, Model 3 is obtained, as before, based on 21 restrictions on the parameters of cross share effects that are imposed on Model 5. From the combination formula

$\sum_{\iota=1}^{n}(n!/[\iota!(n-\iota)!])$ for $n=21$, there are then 2,097,151 different ways to remove the preceding restrictions, i.e., add these cross effects on top of Model 3—each of which in turn constitutes a nesting alternative to Model 3. One such nesting alternative, for instance, is Model 5 for which all 21 restrictions are removed from Model 3, i.e., all these additional 21 parameters are estimated as shown in table 3c. For soybeans, Model 3 is, as before, obtained based on 16 restrictions that are imposed on Model 5. Based on the combination formula for $n=15$ this time, one can similarly count 32,767 nesting alternatives to Model 3. One such alternative is Model 5, as shown in the respective column of table 3d. Removing all 15 restrictions from Model 3 yields back Model 5. For both crops, Model 3 is tested against all such nesting alternatives and strongly selected, and Model 3 is selected over Model 2 as well.[19] Finally, diagnostic tests on the residuals of Model 3 provide considerable support on the assumption that residuals from each market share equation follow a white noise process. It should be evident from the fit performance of these models that the magnitudes of residuals are small, which in turn suggests that the

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[19] Since these models constitute nested alternatives to Model 3 in each crop, the Likelihood Ratio test statistic (with the small sample adjustment) is used (as illustrated in footnote 17). For corn, among the 2,097,151 alternatives considered, the minimum *p-value* associated with the likelihood ratio test statistic was 0.1542. For soybeans, among the 32,767 alternatives considered, the minimum *p-value* associated with the likelihood ratio test statistic stood at 0.2326. Both suggest considerable evidence in favor of selecting Model 3 against all nesting alternatives relative to Model 5.

Regarding selecting Model 3 over Model 2, for corn, the adjusted Likelihood Ratio test statistic had the resulting value of 34.4, after setting $c=8$, which exceeded the χ^2 critical value (21.7) at 1% level of significance with 9 cross-market share restrictions (degrees of freedom). For soybeans, the value of the adjusted Likelihood Ratio test statistic became 65.7, after setting $c=8$, which exceeded the χ^2 critical value (30.6) at 1% level of significance with 15 cross-market share restrictions (degrees of freedom).

That Model 3 is selected over Models 2 and 5 for both crops is also supported by the *AIC* and *BIC* criteria. Both the *AIC* and *BIC* criteria show markedly lower values for Model 3 in tables 3a and 3b vis-à-vis those for Model 2 in the same tables as well as for Model 5 in tables 3c and 3d.

proposed models captured a significant portion of the data generating process. Generally, for both crops, any remaining serial correlation or heteroskedasticity does not appear to be materially important. The support for the no heteroskedasticity assumption is stronger in the case of soybeans compared with corn.[20]

The fit performance of Model 3 in terms of actual versus fitted values of market shares is slightly better than the already strong case of Model 2. Recall that the figures for Model 2 are very similar to those for Model 1 and the latter will be referred for both models in what follows. The respective figures for Model 3, figures 2c and 2d, are nearly identical to figures 2a and 2b and relegated to SA3. Nevertheless, the impulse response functions show somewhat different

[20] To test the null hypothesis that any remaining autocorrelations within a market share equation are not significantly different from zero, the Ljung–Box Q-Statistic cannot be used here as the degrees of freedom is exhausted due to the small sample size. To see this, the maximum number of sample autocorrelations and partial autocorrelations considered $(T/4)=(20/4)=5$ (as recommended in Enders, p. 70), while the number of estimated coefficients equals $c=8$ for both crops, the difference (the degrees of freedom) is not positive. This issue can be resolved in the future as more observations become available each passing year. Plots of the sample autocorrelations and partial autocorrelations over the maximum number of lags considered (5 from earlier) indicate their values are generally within the two-standard deviation bounds, which suggests no serious remaining autocorrelation issue.

The Engle test for residual heteroscedasticity (autoregressive conditional heteroscedasticity, ARCH) is performed on the residuals of each of the market share equation. The number of lags is chosen as 2 based on the consideration that the data are annual and the sample size is rather short. For soybeans, the null hypothesis of no residual heteroscedasticity (no ARCH effects) is not rejected (with the minimum p-value of 0.2161) for all market shares. For corn, the same hypothesis is not rejected at 5% and 1% level of significance for the market share for high coverage on enterprise units (with the minimum *p-value* of 0.0620), and it is also not rejected for the remaining marker shares (with the minimum *p-value* of 0.1012). All this is suggesting that the remaining heteroskedasticity is not materially important.

The standardized residuals are plotted in figures A.4a and A.4b in SA3 for corn and soybeans, respectively. It can be seen that the residuals bounce around zero without any obvious pattern, yet with some sharp swings in certain years. Most of them lie within 2 as it should be in a standard normal distribution. For soybeans, all of the residuals are within 3, whereas for corn only one of the residuals slightly exceeds 3. The latter occurs to the market share for area coverage in 2006, just when the share of area plans started to decline, ahead of subsidy changes in the 2008 Farm Bill.

patterns, both as a response to a 15 ppts cut in the average subsidy rate.

For corn, the respective figure for Model 3, figure 3c, is similar to figure 3a in terms of the trends in market shares of low and high coverage on enterprise units and no insurance as these shares decline to zero within five years. Both figures also show similar patterns when it comes to coverage on optional units: the market share of low coverage on optional units monotonically increases to near 57%, while the market share for high coverage on optional units, after an initial rise, declines and settles near 25%. One difference is that, in Model 2, the market shares for area plans and CAT coverage monotonically increase to exceed 11% and 7% respectively over time (figure 3a). In Model 3, on the other hand, the market share for area plans, after an initial rise and followed by a dip, levels off above 15%; and the market share for CAT coverage, after an initial rise, declines to nil within 10 years only to bounce back slightly and remain less than 1% in later years (figure 3c). Thus, in Model 3, the market share for buyup coverage nears 100%.

For soybeans, both Models 2 and 3 predict that the market shares on enterprise units (high or low coverage) will go to nil within five years. This can be verified upon comparing figures 3b and 3d, both of which are deferred to SA3. Model 2 further predicts that the market share for no insurance will also go to nil within five years, while area and CAT coverage will maintain a modest presence exceeding 10% each. The remaining near 78% of acres will go to optional units over time: high and low coverage levels representing near 25% and 53% respectively. In contrast, Model 3 predicts that the market share for CAT coverage would go up as much as 29% and there would be an eventual near 19% market share for no insurance. These expansions would come at the expense of market share for buyup coverage, which would recede down to near 50%. Specifically, the market shares for low coverage on optional units and area plans would bear the brunt of the reduction (the latter going to nil eventually), while the share for high coverage on optional units would remain intact and even see a small expansion.

As similarly done in Model 1, the market share impacts, for $\phi\mu \in \{he, ho, le, lo, a, c\}$, $dm_{\phi\mu} / d\theta$ are elicited from Model 3. The short-term market share impacts directly reflect the respective slope coefficients of the predicted average subsidy rate in each market share equation from the regression. Long-term market share impacts are obtained from a process that is more involved than what is given in equation (11), where details are relegated to Supplemental Appendix 5 (SA5). Tables 4a and 4b also report the short-term and long-term elasticity estimates under Model 3 in the respective columns. The long-term values are estimated to be a bit higher than those found under Model 2 and hence they stand higher than those reported in prior studies as reviewed earlier. Because the short term elasticity values are estimated a bit lower under Model 3, the long-term elasticity values are again markedly higher than the short-term counterparts: more than two-fold higher in the case of subsidy expenditures and nearly six-fold and seven-fold as high as that in the case of average coverage level for corn and soybeans, respectively. As before, the long-term elasticity values of average coverage level and subsidy expenditures are higher for soybeans than corn.

The finding that soybean crop is a bit more price sensitive than corn is consistent with the differences in the predicted long-term trends. While O'Donoghue and Tulman (2016) also report a similar finding (as discussed in footnote 6), most prior studies find the opposite. The latter can be verified in the elasticity figures in terms of liability across crops in tables 4 and 5 in O'Donoghue (2014, p. 14). Compared with the studies reviewed therein, the differences mainly arise with respect to our long-term elasticity estimates. Our estimates for the short-term elasticity of average coverage with respect to farmer-paid premium rate are generally in line with

O'Donoghue (2014, table 5, p.15).[21] Soybeans tend to have lower yield risk as well as price risk (the latter as measured in implied volatilities) relative to corn and hence the safer of the two to plant, which in turn may suggest more room for self-insurance for soybeans (Hungerford and Rosch, 2016). On the other hand, corn is more input (such as fertilizer) intensive than soybeans. Since corn is expected to be more sensitive to input prices, that sensitivity, as part of the same production budget, may carry over into insurance purchases as well. Also, in situations where corn is the main cash crop, rotation effects may play some role as the planting of soybeans in that case would be due to need to give ground a break and provide nutrients.

Finally, the following application illustrates how these elasticity estimates can be put in use.

5. Application

We consider a scenario in which the average subsidy rate for buyup coverage level is reduced by 15 ppts, which is in line with the CBO recommendation. The impact of this reduction on the average coverage level can be calculated by using the elasticity estimates of average coverage

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[21] The author reports 0.23 and 0.19 for corn and soybeans in terms of the countrywide elasticities of liability per acre with respect to a 1% change in subsidy amount per acre variable. The preceding elasticity values can be translated into the values of elasticity of average coverage level with respect to the farmer-paid premium in several steps. First, the elasticity of liability per acre can be shown to be the same as the elasticity of the average buyup coverage level with respect to an exogenous change in subsidy rate. Second, as the author implicitly assumes, 1% change in subsidy dollars is treated to reflect a 1% change in the average buyup subsidy rate. Note that this assumption ignores any resulting coverage effects influencing the subsidy dollars. One begins by converting a 1% change in the average buyup subsidy rate to a 1 ppt change in the average buyup subsidy rate: 1 divided by the level of the latter variable. The resulting figures are further converted into the respective changes in the farmer-paid premium rate as done in equation (8) in the text. Having obtained what 1% change in subsidy dollars means in terms of changes in the farmer-paid premium rate, the initial values of countrywide elasticities of liability per acre can be re-expressed as -0.137 and -0.11 for corn and soybeans in terms of countrywide elasticity of average coverage level with respect to the farmer-paid premium rate. These values are consistent with the corresponding short-term elasticity values (-0.16 and -0.18, respectively) in tables 4a and 4b as claimed.

level with respect to the average subsidy rate for buyup coverage in tables 4a and 4b (the third row) under Model 3. Back in the data section, the average coverage levels are calculated as 66.1% and 66.8% for corn and soybeans in 2020. Based on the respective short-term elasticity values, the resulting coverage would be calculated as $61.7\% = 100 \times 0.661(1 - 0.441 \times 0.15)$ and $61.9\% = 100 \times 0.668 \times (1 - 0.486 \times 0.15)$, for corn and soybeans, respectively. These in turn would suggest 4.4 and 4.9 ppts declines from the initial levels for the same crops. If one replaces the short-term elasticity values (0.441; 0.486) with the long-term counterparts (2.64; 3.38) in the preceding formulas, the resulting average coverage levels would be 40% and 32.9%, which would, in turn, suggest deeper declines from the initial levels: 26.1 ppts for corn, and 33.9 ppts decline for soybeans. Since these average coverage levels are lower than the minimum buyup coverage level, they can be interpreted as CAT coverage levels with price protection factors at 80% and 66%, respectively.

Similarly, the impact of the reduction on the subsidy expenditures can be calculated by using the related elasticity estimates in tables 4a and 4b (the first row) under Model 3. Note that the total subsidy expenditures (CAT plus buyup) are reported as \$2.147 billion and \$1.249 billion for corn and soybeans in 2020 in table 1. Combining these values along with the respective short-term elasticity values, the resulting subsidy expenditure would be calculated as, in billion dollars, $1.463 = 2.147(1 - 2.123 \times 0.15)$ and $0.754 = 1.249 \times (1 - 2.641 \times 0.15)$ for corn and soybeans, respectively. These in turn would suggest a \$684 million and \$495 million declines from the initial levels for the same crops. If one replaces the short-term elasticity values in this case (2.123; 2.641) with the long-term counterparts (4.376; 6.218) in the preceding formulas, the resulting subsidy expenditure levels would be \$738 and \$84 million, which in turn would suggest deeper declines from the initial levels: \$1.41 billion for corn, and \$1.17 billion for soybeans. The total savings from these two crops ($1.18 billion and $2.57 billion based on short-term and long-term elasticity values, respectively) are considerably higher than the figures that CBO or the GAO found (footnote 7) since they also included other major crops.

Other additive changes (in either direction) in the average buyup subsidy rate can be similarly evaluated. Table 5 collects the resulting changes in the average coverage level and subsidy expenditures from policy scenarios of 1, 5, 10, and 15 ppt reductions in the average buyup subsidy rate. All evaluations are made based on Model 3 for each crop. As expected, the impacts are nearly proportional to the size of the reductions. It is noticeable that (second-to-the-last row) even the 10 ppt cut would bring the average coverage levels below the minimum for buyup coverage in both crops.

6. Conclusion

We have estimated elasticity measures in terms of total crop insurance subsidy expenditures and the average coverage level based on the changes in the subsidy rates at buyup coverage levels and explored the relationship between the two measures. By reexpressing the elasticity formula for subsidy expenditures into their static scoring (i.e., assuming zero coverage response) and dynamic scoring (i.e., allowing some coverage response) components, we have observed that the contribution of the dynamic scoring component to the elasticity values move in tandem with the absolute value of the elasticity values in terms of coverage response.

We have evaluated these elasticity measures by using crop insurance data and econometric estimation of the market share impacts of crop insurance coverage level options. The estimations are done for corn and soybeans at the countrywide level covering the period 2001-2020. Econometric findings suggest an auto-regressive structure in the market shares of coverage options. Previous price elasticity studies of crop insurance demand overlooked dynamic adjustments, as captured by an auto-regressive pattern, and typically considered limited categories of coverage options. The small elasticities as often found in these studies arise mostly from accounting for the short-term (contemporaneous) effects rather than the long-term effects of a policy change. Improving in these ways, our findings confirm that the elasticity values based on the long-term effects are materially larger (in absolute value) than those obtained from the short-term effects.

We have demonstrated the importance of these differences in an application involving a policy scenario in which a 15 ppts cut in the average subsidy rate for buyup coverage level is considered (as recommended by the CBO). If one were to use elasticity values based on short-term effects—which would be about half of the CBO's assumed elasticity value (footnote 3)—the impact on the average buyup coverage level would be about up to 5 ppts decline in the average coverage level for corn and soybeans. If one were to use long-term elasticity values instead, the average coverage level would come down to a CAT coverage (with somewhat higher price protection). In particular, such a reduction would reduce, for corn and soybeans, the market shares of enterprise units both high (at least 75%) and low coverage levels to nil within five years, while the market share for high coverage would be markedly reduced. The attendant savings in subsidy expenditure would also be higher than recent CBO calculations but the savings would come at the expense of reversing the progress that has been made in coverage over the last two decades. The promised savings in turn may not materialize as the case for ad hoc disaster aid would grow stronger in the absence of meaningful insurance coverage (Innes, 2003; Bulut, 2017).

Future research can extend this work to state or county-level data and further investigate regional differences (as pointed out in O'Donoghue, 2014; Yi, Bryant and Richardson 2020;

Bulut, 2020) or to differences in type/practice (such as irrigated versus non-irrigated, or organic versus conventional) in the elasticity measures derived. Methodologically, our market shares-based time-series framework may be useful to study the long-term effects of policy interventions in crop insurance program in other areas of interest.

Table 1. Countrywide Data in 2000 and 2020 by Crop [a]

Variables	Corn 2000	Corn 2020	Soybeans 2000	Soybeans 2020
Market Share for No Insurance (m_n)	0.2923	0.1255	0.2643	0.1115
Market Share for CAT Cov. (m_c)	0.1281	0.0131	0.1745	0.0101
Market Share for Area Coverage m_a	0.0165	0.0087	0.0156	0.0085
Market Share for Low Cov. and Enterprise Units (m_{le})	0.0090	0.0783	0.0081	0.0959
Market Share for Low Cov. and Optional Units (m_{lo})	0.4003	0.1070	0.3834	0.1047
Market Share for Low Cov. (m_l)	0.4093	0.1853	0.3915	0.2007
Market Share for High Cov. and Enterprise Units (m_{he})	0.0129	0.4556	0.0101	0.4398
Market Share for High Cov. and Optional Units (m_{ho})	0.1408	0.2117	0.1438	0.2295
Market Share for High Cov. (m_h)	0.1538	0.6674	0.1540	0.6693
Subsidy Rate for Area Cov. (s_a)	0.1972	0.4439	0.1825	0.4453
Subsidy Rate for Low Cov. (s_l)	0.2887	0.6777	0.3477	0.6820
Subsidy Rate for High Cov. (s_h)	0.1295	0.6205	0.1623	0.6241
Subsidy Rate for Buyup Cov. (s_b)	0.2261	0.6260	0.2753	0.6317
Subsidy for CAT Cov. (S_c) in Million $s	33.7	4.4	39.5	2.1
Subsidy for Area Cov. (S_a) in Million $s	3.3	39.3	1.7	12.9
Subsidy for Low Cov. (S_l)	121.2	408.3	87.6	239.1
Subsidy for High Coverage (S_h) in Million $s	34.5	1,695.0	24.9	994.8
Subsidy for Buyup Cov. (S_b)	159.0	2,142.5	114.2	1,246.8
Subsidy in Total (S) in Million $s	192.7	2,146.9	153.7	1,248.9
Insured Acres in Total in Million units	56.5	84.11	54.8	75.55
Base Insurance Price in $/bu	2.51	3.88	5.32	9.17
Volatility Factor	0.21	0.15	0.21	0.12
Premium in Total in Million $s	737.0	3,426.9	454.4	1,975.8
Liability	10,149.5	43,528.8	6,695.1	26,044.2

Note. [a] Source is RMA's summary of business tables. The subsidy figures (amounts and rates) in 2000 do not include additional premium discount provided on an emergency basis through a supplemental legislation (Chite, 2000, tables 1 and 2, p.3 and p. 8).

Table 2. Econometric Models Considered: Dependent Variables in Each Model are the Market Shares

Explanatory Variables	Model 1	Model 2	Model 3
1-Period Lagged Own-Market Share	Yes	Yes	Yes
1-Period Lagged Cross-Market Shares			Yes
Average Subsidy Rate (Offered) at Buyup Coverage	Yes	Yes	Yes
Percentage Changes in Base Insurance Price or Volatility Factor		Yes	Yes

Table 3a. Estimated Models for the Market Shares, Corn [a]

Expl. Variables [b]	Param. [e]	Model 1 [c]			Model 2 [c]			Model 3 [c]		
Intercept	α_{he0}	***	-1.651	(-11.7)	***	-1.657	(-13.1)	***	-1.675	(-11.4)
	α_{ho0}	***	0.280	(3.1)	***	0.309	(3.6)	***	0.705	(5.5)
	α_{le0}	***	-0.150	(-3.6)	***	-0.147	(-3.5)	***	-0.249	(-5.3)
	α_{lo0}	***	1.368	(11.2)	***	1.333	(11.1)	***	1.144	(7.7)
	α_{a0}	*	0.119	(1.9)	*	0.120	(1.9)	***	1.104	(9.0)
	α_{c0}	***	0.111	(5.4)	***	0.105	(5.0)	**	0.047	(2.1)
1-Period Lagged Market Share (Own Effects)	α_{he1}	***	0.579	(16.0)	***	0.593	(17.9)	***	0.598	(14.6)
	α_{ho2}	***	0.627	(15.8)	***	0.630	(13.7)	***	0.484	(8.5)
	α_{le3}	***	0.764	(12.8)	***	0.769	(12.9)	***	0.561	(7.1)
	α_{lo4}	***	0.482	(12.6)	***	0.497	(13.0)	***	0.583	(10.4)
	α_{a5}	***	0.920	(14.3)	***	0.915	(14.7)	***	-0.663	(-4.4)
	α_{c6}	***	0.756	(32.8)	***	0.765	(32.6)	***	1.036	(20.0)
1-Period Lagged Market Share of High Coverage on Enterprise Units (Cross Effects)	α_{ho1}									
	α_{le1}									
	α_{lo1}									
	α_{a1}							***	-0.697	(-7.2)
	α_{c1}									
1-Period Lagged Market Share of High Coverage on Optional Units (Cross Effects)	α_{he2}									
	α_{le2}									
	α_{lo2}									
	α_{a2}							***	-0.890	(-7.9)
	α_{c2}									

Table 3a Continues.

Expl. Variables [b]	Param. [e]	Model 1 [c]	Model 2 [c]	Model 3 [c]
1-Period Lagged Market Share of Low Coverage on Enterprise Units (Cross Effects)	α_{he3}			
	α_{ho3}			
	α_{lo3}			
	α_{a3}			*** -1.377 (-7.0)
	α_{c3}			
1-Period Lagged Market Share of Low Coverage on Optional Units (Cross Effects)	α_{he4}			
	α_{ho4}			*** -0.153 (-3.4)
	α_{le4}			
	α_{a4}			*** -0.519 (-4.3)
	α_{c4}			*** -0.067 (-4.1)
1-Period Lagged Market Share of Area Coverage (Cross Effects)	α_{he5}			** 0.226 (2.2)
	α_{ho5}			
	α_{le5}			
	α_{lo5}			
	α_{c5}			*** 0.163 (4.6)
1-Period Lagged Market Share of CAT Coverage (Cross Effects)	α_{he6}			
	α_{ho6}			
	α_{le6}			
	α_{lo6}			
	α_{a6}			*** -3.183 (-11.4)

Table 3a Continues.

Expl. Variables [b]	Param. [e]	Model 1 [c]			Model 2 [c]			Model 3 [c]		
Average Subsidy Rate (Offered) at Buyup Coverage	β_{he1}	***	2.936	(12.0)	***	2.940	(13.4)	***	2.956	(11.5)
	β_{ho1}	**	-0.327	(-2.2)	***	-0.377	(-2.7)	***	-0.921	(-4.8)
	β_{le1}	***	0.272	(3.8)	***	0.267	(3.7)	***	0.451	(5.4)
	β_{lo1}	***	-2.085	(-10.9)	***	-2.034	(-10.7)	***	-1.754	(-7.7)
	β_{a1}	*	-0.195	(-1.9)	*	-0.196	(-1.9)	***	-0.576	(-3.9)
	β_{c1}	***	-0.171	(-5.2)	***	-0.162	(-4.9)	**	-0.071	(-2.1)
Percentage Change (year-over-year) in Base Insurance Price	β_{he2}									
	β_{ho2}									
	β_{le2}									
	β_{lo2}									
	β_{a2}									
	β_{c2}									
Percentage Change (year-over-year) in Volatility Factor	β_{he3}				***	0.053	(3.5)	***	0.040	(3.1)
	β_{ho3}				***	-0.032	(-2.3)	**	-0.024	(-2.1)
	β_{le3}									
	β_{lo3}									
	β_{a3}									
	β_{c3}									

Table 3a Continues.

Measures of Fit	Model 1	Model 2	Model 3
R^2 *(McElroy's)*	97.78%	98.03%	98.79%
$\ln(L)$ [d]	428.0	432.9	461.6
T [d]	20	20	20
N [d]	18	20	29
AIC [d]	-820.0	-825.7	-865.1
BIC [d]	-802.1	-805.8	-836.2

Notes. [a] Based on the econometric estimations using countrywide data over the period 2001-2020.

[b] See table 2 notes for details on the explanatory variables. See equation (10) or (12) in the text for an example of the estimated models.

[c] Estimated parameters are listed in the same order with the market shares for high coverage on enterprise and optional units, low coverage on enterprise and optional units, area coverage, and CAT coverage levels as also shown in the Parameters column. The superscripts *** , * , * indicate significance at 1%, 5%, and 10%, respectively, based on the *t*- test statistic values reported inside the parentheses.

[d] The notation $\ln(.)$ represents the natural logarithm operator, L is the maximized value of the multivariate likelihood function, T is the number of usable observations per market share equation, and N is the total number of estimated parameters (across all equations). By combining the information on these, the A*IC* and *BIC* criteria values are calculated from $AIC = -2\ln(L) + 2N$; $BIC = -2\ln(L) + \ln(T)N$. Both criteria take the goodness of fit and parsimony into account; while, given the sample size here, the *BIC* penalizes the model complexity more so than the *AIC*.

[e] In using the notation $\alpha_{\phi\mu j}$, the first index in the subscript $\phi\mu \in \{he, ho, le, lo, a, c\}$ refers to the rows within the VAR(1) structure, that is, the market share equation of interest, while the second index $j \in \{1,2,3,4,5,6\}$ refers to the columns, that is, the variable of interest. The latter index, in that order, corresponds to 1-period lagged market shares for high coverage on enterprise and optional units, low coverage on enterprise and optional units, area coverage, and CAT coverage levels, respectively. As an example, α_{a1} represents the cross effect of 1-period lagged market share for high coverage on enterprise units ($j = 1$) on the market share for area coverage $(\phi\mu = a)$, which can also be verified in equation (12).

Table 3c. Additional Estimated Models for the Market Shares, Corn [a]

Expl. Variables [b]	Param. [e]	Model 4 [c]			Model 5 [c]		
Intercept	α_{he0}	***	-1.579	(-12.7)	***	-3.038	(-7.2)
	α_{ho0}	***	0.328	(3.6)		0.580	(1.2)
	α_{le0}	***	-0.154	(-3.5)	*	-0.363	(-1.8)
	α_{lo0}	***	1.225	(10.9)	***	1.998	(3.8)
	α_{a0}	**	0.135	(2.1)	***	1.352	(4.6)
	α_{c0}	***	0.094	(4.5)		0.100	(1.2)
1-Period Lagged Market Share (Own Effects)	α_{he1}	***	0.609	(19.0)	***	1.809	(4.2)
	α_{ho2}	***	0.657	(13.5)		0.595	(1.0)
	α_{le3}	***	0.772	(12.6)	**	0.902	(2.2)
	α_{lo4}	***	0.523	(14.7)		-0.766	(-1.2)
	α_{a5}	***	0.904	(12.2)	***	-1.066	(-2.9)
	α_{c6}	***	0.775	(33.6)	***	0.903	(3.8)
1-Period Lagged Market Share of High Coverage on Enterprise Units (Cross Effects)	α_{ho1}					0.314	(0.6)
	α_{le1}					-0.029	(-0.1)
	α_{lo1}				**	-1.082	(-2.0)
	α_{a1}				**	-0.639	(-2.2)
	α_{c1}					-0.080	(-1.0)
1-Period Lagged Market Share of High Coverage on Optional Units (Cross Effects)	α_{he2}				***	1.769	(3.6)
	α_{le2}					0.134	(0.6)
	α_{lo2}				*	-1.120	(-1.8)
	α_{a2}				***	-1.160	(-3.4)
	α_{c2}					-0.068	(-0.7)

Table 3c Continues.

Expl. Variables [b]	Param. [e]	Model 4 [c]	Model 5 [c]		
1-Period Lagged Market Share of Low Coverage on Enterprise Units (Cross Effects)	α_{he3}		***	2.843	(3.4)
	α_{ho3}			-0.206	(-0.2)
	α_{lo3}			-1.151	(-1.1)
	α_{a3}		***	-2.279	(-3.9)
	α_{c3}			-0.042	(-0.3)
1-Period Lagged Market Share of Low Coverage on Optional Units (Cross Effects)	α_{he4}		***	1.513	(3.0)
	α_{ho4}			0.254	(0.4)
	α_{le4}			-0.073	(-0.3)
	α_{a4}			-0.434	(-1.2)
	α_{c4}			-0.162	(-1.7)
1-Period Lagged Market Share of Area Coverage (Cross Effects)	α_{he5}		***	1.380	(2.6)
	α_{ho5}			-0.212	(-0.3)
	α_{le5}			0.220	(0.9)
	α_{lo5}			-0.400	(-0.6)
	α_{c5}			0.145	(1.4)
1-Period Lagged Market Share of CAT Coverage (Cross Effects)	α_{he6}		***	3.573	(2.9)
	α_{ho6}			0.193	(0.1)
	α_{le6}			0.385	(0.7)
	α_{lo6}			-2.086	(-1.4)
	α_{a6}		***	-3.952	(-4.7)

Table 3c Continues.

Expl. Variables [b]	Param. [e]	Model 4 [c]			Model 5 [c]		
Average Subsidy Rate (Offered) at Buyup Coverage	β_{he1}	***	2.807	(13.0)	***	2.943	(8.8)
	β_{ho1}	***	-0.418	(-2.8)	***	-1.027	(-2.6)
	β_{le1}	***	0.277	(3.6)	***	0.561	(3.5)
	β_{lo1}	***	-1.868	(-10.6)	***	-1.535	(-3.7)
	β_{a1}	**	-0.219	(-2.0)	***	-0.792	(-3.4)
	β_{c1}	***	-0.145	(-4.4)		-0.052	(-0.8)
Percentage Change (year-over-year) in Base Insurance Price	β_{he2}	*	-0.032	(-1.9)			
	β_{ho2}		-0.011	(-0.5)			
	β_{le2}		0.001	(0.1)			
	β_{lo2}	**	0.044	(2.4)			
	β_{a2}		-0.016	(-1.0)			
	β_{c2}	**	0.007	(2.4)			
Percentage Change (year-over-year) in Volatility Factor	β_{he3}	***	0.075	(3.1)	***	0.034	(2.8)
	β_{ho3}		-0.047	(-1.6)	*	-0.019	(-1.7)
	β_{le3}		0.007	(0.6)			
	β_{lo3}		-0.016	(-0.6)			
	β_{a3}		0.012	(0.5)			
	β_{c3}		-0.007	(-1.5)			

Table 3c Continues.

Measures of Fit	Model 4	Model 5
R^2 *(McElroy's)*	98.39%	99.17
$\ln(L)$ [d]	437.9	473.9
T [d]	20	20
N [d]	30	50
AIC [d]	-815.8	-847.8
BIC [d]	-785.9	-798.0

Notes. [a] Based on the econometric estimations using countrywide data over the period 2001-2020.

[b] See table 2 notes for details on the explanatory variables. See equation (10) or (12) in the text for an example of the estimated models.

[c] Estimated parameters are listed in the same order with the market shares for high coverage on enterprise and optional units, low coverage on enterprise and optional units, area coverage, and CAT coverage levels as also shown in the Parameters column. The superscripts *** , * , * indicate significance at 1%, 5%, and 10%, respectively, based on the *t*- test statistic values reported inside the parentheses.

[d] The notation $\ln(.)$ represents the natural logarithm operator, L is the maximized value of the multivariate likelihood function, T is the number of usable observations per market share equation, and N is the total number of estimated parameters (across all equations). By combining the information on these, the A*IC* and *BIC* criteria values are calculated from $AIC = -2\ln(L) + 2N$; $BIC = -2\ln(L) + \ln(T)N$. Both criteria take the goodness of fit and parsimony into account; while, given the sample size here, the *BIC* penalizes the model complexity more so than the *AIC*.

[e] The respective notes in table 3a apply here as well.

Table 4a. Elasticity Values; and Coverage Level and Subsidy Expenditure Impacts for Corn[a]

	Model 1		Model 2		Model 3	
	Short-Term Effects	Long-Term Effects	Short-Term Effects	Long-Term Effects	Short-Term Effects	Long-Term Effects
Elasticities of subsidy expenditures	2.938	1.968	2.937	2.390	2.123	4.376
Elasticity of subsidy expenditures under static scoring	1.600	1.600	1.600	1.600	1.600	1.600
Elasticity of average coverage Level w.r.t. subsidy rate	1.012	1.342	1.007	1.600	0.441	2.636
Elasticity of average coverage Level w.r.t. the farmer-paid premium rate	-0.379	-0.502	-0.376	-0.598	-0.165	-0.986
Current average coverage level	66.1	66.1	66.1	66.1	66.1	66.1
Predicted average coverage level after a cut of 15 ppts in the average subsidy rate	56.1	52.8	56.1	50.2	61.7	40.0
Resulting change in the average coverage level (in ppts)	-10.0	-13.3	-10.0	-15.9	-4.4	-26.1
Current subsidy expenditures (in billion $s)	2.147	2.147	2.147	2.147	2.147	2.147
Predicted subsidy expenditures (in billion $s) after a cut of 15 ppts in the average subsidy rate	1.201	1.513	1.201	1.377	1.463	0.738
Resulting change in the subsidy expenditures (in billion $s)	-0.946	-0.634	-0.946	-0.770	-0.684	-1.409

Notes: [a] Based on the econometric estimations using countrywide data over the period 2001-2020.
Elasticity formulas are based on additive changes in the average buyup subsidy rate.

Table 4b. Elasticity Values and Coverage Level and Subsidy Expenditure Impacts for Soybeans [a]

	Model 1		Model 2		Model 3	
	Short-Term Effects	Long-Term Effects	Short-Term Effects	Long-Term Effects	Short-Term Effects	Long-Term Effects
Elasticities of subsidy expenditures	3.041	5.519	3.169	4.440	2.641	6.218
Elasticity of subsidy expenditures under static scoring	1.601	1.601	1.601	1.601	1.601	1.601
Elasticity of average coverage level w.r.t. subsidy rate	0.904	2.731	1.014	1.729	0.486	3.380
Elasticity of average coverage level w.r.t. the farmer-paid premium rate	-0.333	-1.006	-0.374	-0.637	-0.179	-1.245
Current average coverage level	66.8	66.8	66.8	66.8	66.8	66.8
Predicted average coverage level after a cut of 15 ppts in the average subsidy rate	57.7	39.4	56.6	49.5	61.9	32.9
Resulting change in the average coverage level (in ppts)	-9.1	-27.4	-10.2	-17.3	-4.9	-33.9
Current subsidy expenditures (in billion $s)	1.249	1.249	1.249	1.249	1.249	1.249
Predicted subsidy expenditures (in billion $s) after a cut of 15 ppts in the average subsidy rate	0.679	0.215	0.655	0.417	0.754	0.084
Resulting change in the subsidy expenditures (in billion $s)	-0.570	-1.034	-0.594	-0.832	-0.495	-1.165

Notes: [a] Based on the econometric estimations using countrywide data over the period 2001-2020.
Elasticity formulas are based on additive changes in the average buyup subsidy rate.

Table 5. Coverage Level and Subsidy Expenditure Impacts of Various Cut Options in the Average Buyup Subsidy Rate [a]

	Corn				Soybeans			
Options to Reduce the Average Buyup Subsidy Rate (in ppts)	Resulting change in the average coverage level (in ppts) [b]		Resulting change in the subsidy expenditures (in billion $s) [b]		Resulting change in the average coverage level (in ppts) [c]		Resulting change in the subsidy expenditures (in billion $s) [c]	
	Short-Term Effects	Long-Term Effects	Short-Term Effects	Long-Term Effects	Short-Term Effects	Long-Term Effects	Short-Term Effects	Long-Term Effects
1	-0.3	-1.7	-0.046	-0.094	-0.3	-2.3	-0.033	-0.078
5	-1.5	-8.7	-0.228	-0.470	-1.6	-11.3	-0.165	-0.388
10	-2.9	-17.4	-0.456	-0.940	-3.2	-22.6	-0.330	-0.777
15 [d]	-4.4	-26.1	-0.684	-1.409	-4.9	-33.9	-0.495	-1.165

Notes: [a] Based on the estimated Model 3 from tables 3a and 3b for corn and soybeans, respectively.
[b] See Model 4a for the current average coverage level, subsidy expenditures, and the respective elasticity values used.
[c] See Model 4b for the current average coverage level, subsidy expenditures, and the respective elasticity values used.
[d] Same results are also reported in tables 4a and 4b for the respective crop.

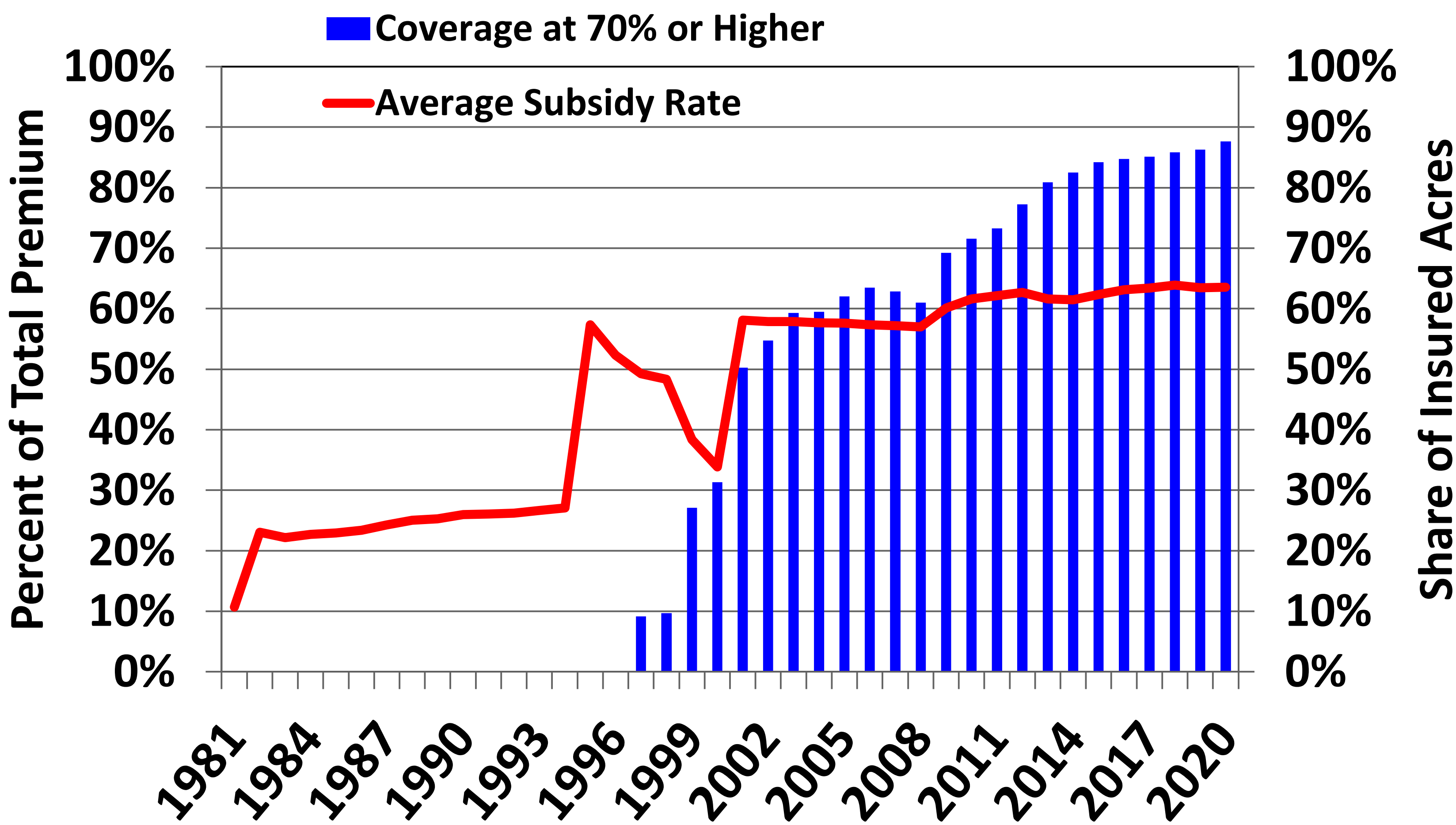

Figure 1a: Average Premium Subsidy Rate Across All Policies for Major Crops (LHS) and Growth in Share of Acres Covered at 70% or Higher (RHS). Insured acres are for major crops: barley, corn, cotton, grain sorghum, peanuts, potatoes, sweet potatoes, rice, soybeans, tobacco, and wheat and obtained from the RMA's Summary of Business.

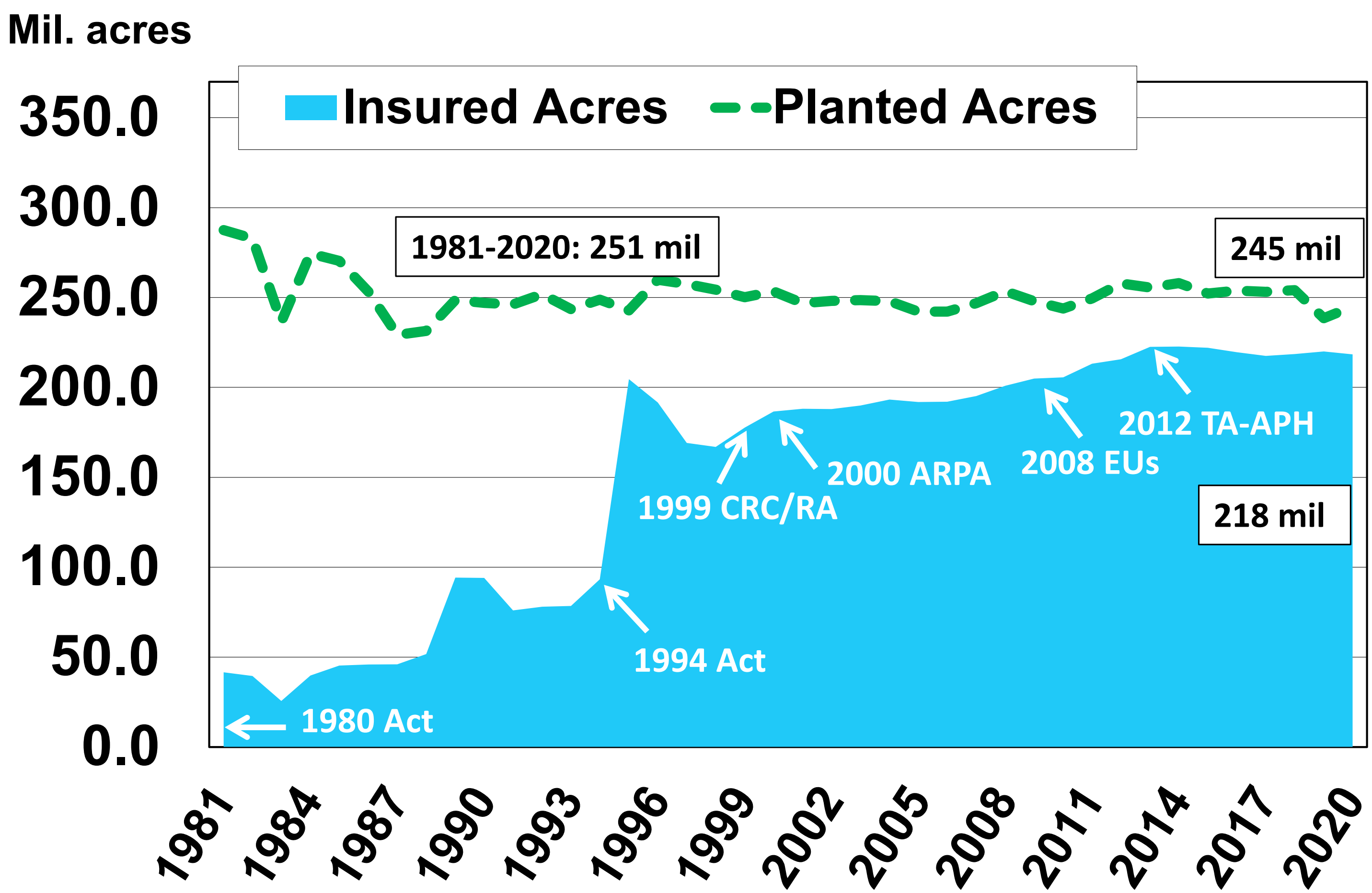

Figure 1b. Planted Acres for Major Crops Under Crop Insurance, 1981-2020. '1999 CRC/RA' refers to the introduction of the Crop Revenue Coverage and Revenue Assurance plans of insurance. '2008 EUs' refers to the Enterprise Units authorization in the 2008 Farm Bill. '2012 TA-APH' refers to the introduction of the Trend-Adjusted Actual Production History yield endorsement. Planted acres include the following major crops as detailed in figure 1a. Data are from the NASS databases. Insured acres are from the RMA's Summary of Business. The 2020 figures, which are shown in the far-right edge of the chart, indicate 89.1% participation rate.

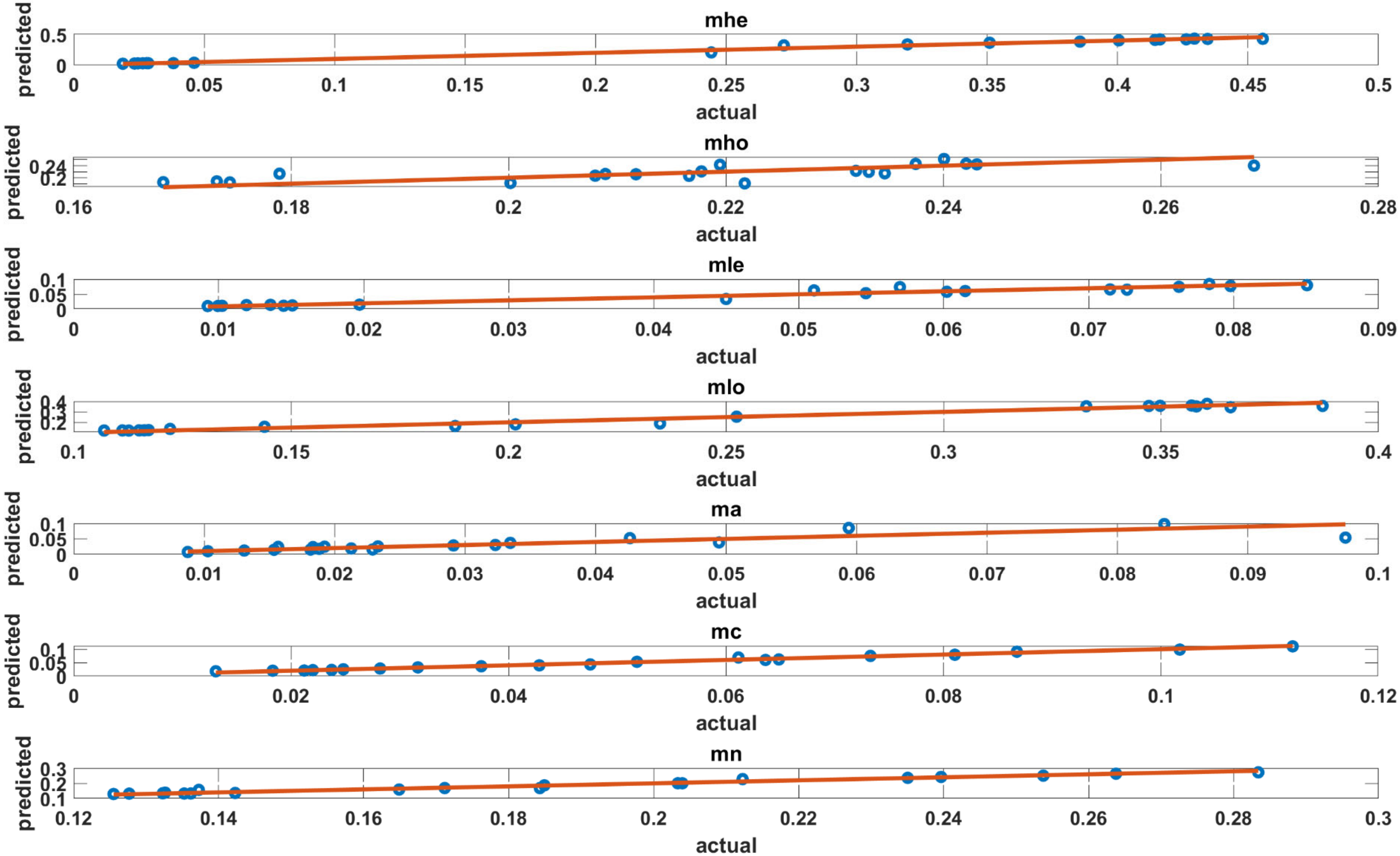

Figure 2a: Corn, Fit Performance of Model 1. Predicted values of market shares over 2001-2020 are on the y-axis, the actual values are on the x-axis. The notation (mn, mc, ma, mlo, mle, mho, and mhe) on top of the charts indicate the market shares for no insurance, CAT coverage, area coverage, low coverage on optional and enterprise units, and high coverage on optional and enterprise units, respectively.

Figure 3a: Corn, Model 1, Impulse Response Function, 30-Period, 15 ppts Cut. The average subsidy rate for buyup coverage was decreased by 15 ppts. The notation (mn, mc, ma, mlo, mle, mho, and mhe) on top of the charts are as defined in figure 2a. Market share predicted values are on the y-axis, periods are on the x-axis.

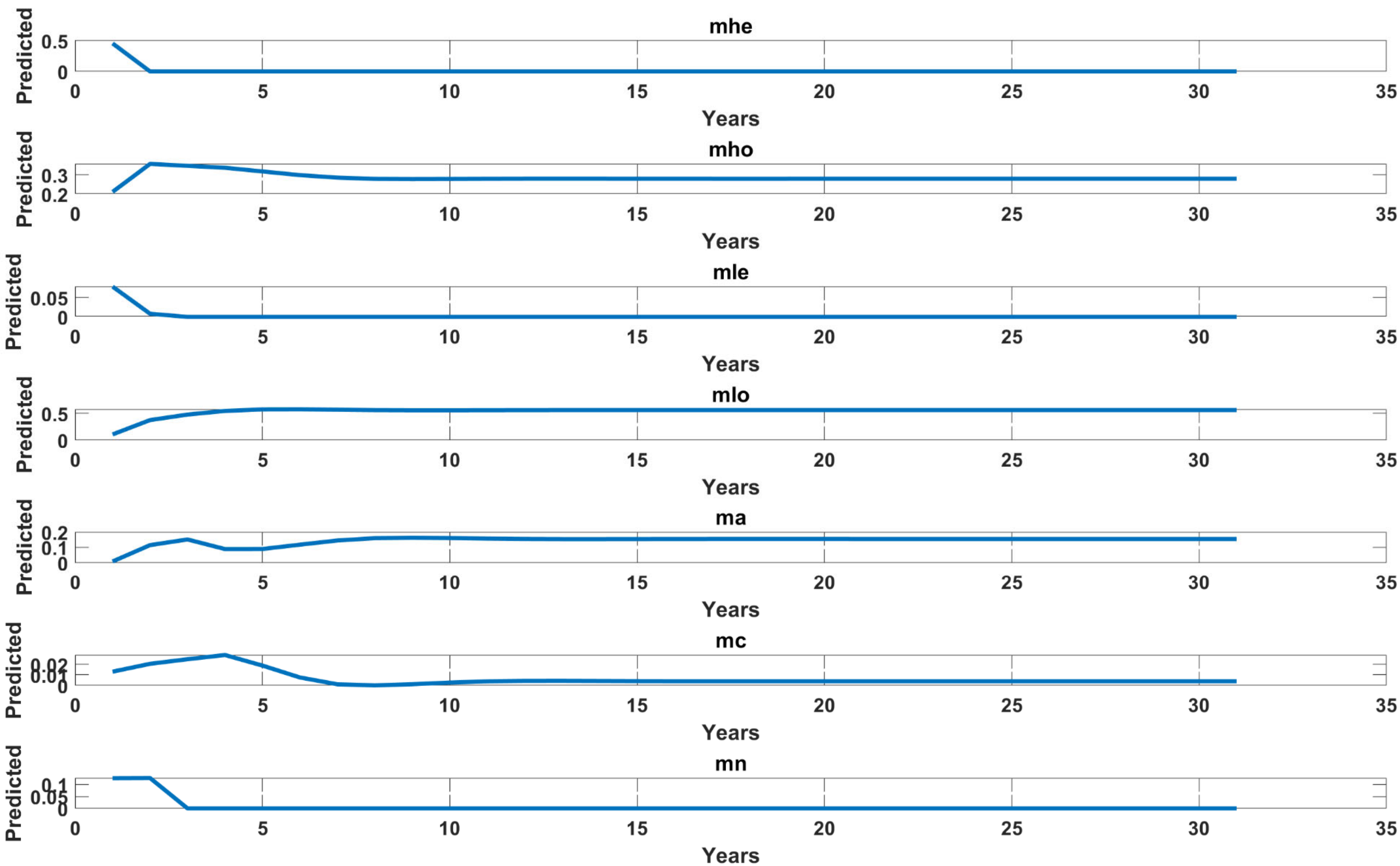

Figure 3c: Corn, Model 3, Impulse Response Function, 30-Period, 15 ppts Cut. The average subsidy rate for buyup coverage was decreased by 15 ppts. The notation mn, mc, ma, mlo, mle, mho, and mhe are as defined in figure 2a. Market share predicted values are on the y-axis, periods are on the x-axis.

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Supplemental Appendix 1 (SA1).

In this appendix, the details on the proposed formulation of the average subsidy rate are provided. Unless noted otherwise, notations defined in the text apply here as well. Also equation numbers are restarted in this section as they are intended to be self-contained and distinct from those in the text.

Note that the premium rate, subsidy rate, and hence premium and subsidy dollars all depend on coverage level as well as on the type of unit structure at a given coverage level. As explained in the text, for simplicity, only optional and enterprise units are considered with individual plans.

We define the average subsidy variable over individual buyup coverage levels as

$$s_i \equiv (1/8)\sum_{\phi=0.5}^{0.85}\left(\frac{s_e(\phi)+s_o(\phi)}{2}\right). \tag{1}$$

The same approach can be used to define the average subsidy rates for low and high buyup coverage levels as follows

$$s_l \equiv (1/5)\sum_{\phi=0.5}^{0.70}\left(\frac{s_e(\phi)+s_o(\phi)}{2}\right), \tag{2}$$
$$s_h \equiv (1/3)\sum_{\phi=0.75}^{0.85}\left(\frac{s_e(\phi)+s_o(\phi)}{2}\right).$$

Define the average subsidy rates for optional and enterprise units as

$$s_o \equiv (1/8)\sum_{\phi=0.5}^{0.85} s_o(\phi) \text{ and } s_e \equiv (1/8)\sum_{\phi=0.5}^{0.85} s_e(\phi). \tag{3}$$

Using the preceding expressions, one can then reexpress equation (1) as

$$s_i = \frac{s_o + s_e}{2}. \tag{4}$$

The relative subsidy rate between enterprise and optional units can be written as

$$\frac{s_e(\phi)}{s_o(\phi)} = 1+\lambda(\phi),$$

where $\lambda(\phi) > 0$ is the additional subsidy rate that is offered via enterprise units. One can verify that the relative subsidy rate is increasing up to 80% coverage level (see the last column in table A.1).

Now, using $\lambda(\phi)$, one can reexpress s_e as follows

$$s_e \equiv (1/8)\sum_{\phi=0.5}^{0.85} s_o(\phi)\big(1+\lambda(\phi)\big), \tag{5}$$

which in turn can be written as $s_e = s_o + (1/8)\sum_{\phi=0.5}^{0.85} s_o(\phi)\lambda(\phi)$. Now, there exists a λ_i such that the average subsidy rate at buyup coverage can be re-expressed as

$$s_e = s_o(1+\lambda_i), \tag{6}$$

To get a sense of λ_i, it is approximately equal to $(1/8)\sum_{\phi=0.5}^{0.85} \lambda(\phi)$ as they are calculated as 0.317 and 0.327, respectively. Similarly, one can define the average subsidy rates for optional and enterprise units at low and high coverage levels.

Plugging the preceding expression back in equation (4), one arrives at

$$s_i = s_o(1+\lambda_i/2). \tag{7}$$

In addition to individual plans, we consider area plans including the Area Risk Protection Insurance (ARPI) plans and the stand-alone versions of the Margin Protection (MP) products.[23] For ARPI, buyup coverage levels with area plans vary from 70% to 90% with five percentage

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[23] ARPI plans consist of Area Yield Protection (AYP), Area Revenue Protection (ARP), and Area Revenue Protection with Harvest Price Exclusion (ARP-HPE). These plans trigger at the county level, while farmers have the option of scaling the county level liability up or down in line with their individual situations. Since we consider a representative farmer, no scaling is necessary.

We leave out the 2014 Farm Bill's supplemental (toward protecting the deductible) area-based products SCO-YP, SCO-RP, SCO-RPHPE as well as more recent products including HIP-WI, MP, MP-HPO. In particular, SCO plans carry higher subsidy rate 65%, which exceed the subsidy rates of ARPI plans at high coverage levels. The effect of these products on individual coverage is downwards at best. For buyup acres in 2020, the share of liability under supplemental area-based products stood less than 1% for corn and soybeans. On the other hand, the share of liability under non-supplemental area products were 3.6% and 2.6%, respectively. Contributing to the latter to a large degree were the stand-alone MP products (MP or MPHPO). These products protect against profit margin losses and got started in 2017 for corn and in 2018 for soybeans.

As it stands, RMA's Summary of Business data shows zero acres for the supplemental area-based products, because those acres are already accounted via the underlying policy that are being supplemented. One can impute acres for the supplemental portion of those policies by assigning acres in proportion to their liability relative to the liability on high individual coverage. Even with these additional imputed acres, market share for area coverage have been on the decline since 2006.

point increments. Even though the coverage can further go up to 95% with the MP plans, we focus on coverage levels with the ARPI plans as the MP was introduced starting in 2017 for corn and 2018 for soybeans. Note that MP plans have the same subsidy schedule as the ARP plan.

As explained in the text, we normalize area plan coverage levels by subtracting 15 ppts to make them equivalent to individual plan coverage levels.[24]

The average subsidy variable for area plans is calculated over all coverage levels in ARPI plans—without breaking further into low or high buyup coverage levels. This is because the combined premium volume for ARPI and stand-alone MP plans still constitute a small portion of the overall premium volume (see footnote 10).

Denoting the average subsidy for area plans variable by s_a, one can calculate it as

$$s_a \equiv (1/5) \sum_{\phi=0.70-0.15}^{0.90-0.15} s_a(\phi) . \tag{8}$$

where $s_a(\phi) = \dfrac{s_{AYP}(\phi) + s_{ARP}(\phi) + s_{ARPHPE}(\phi)}{3}$. This is in line with the fact that, before 2008, all area plans saw a single subsidy schedule. In calculating s_a before 2011, the same formula is used after replacing the insurance plan names with their earlier versions: GRP, GRIP, and GRIPHRO. As part of the Combo policy changes back in 2011, ARPI plans of insurance replaced the prior set of area plans (see Bulut and Collins, 2014, p. 415, footnote 1 in their paper).[25] One important change to the s_a variable occurred in the 2008 Farm Bill as it was reduced by 7 ppts.

Finally, the s_b variable—which represents the average subsidy rate for the entire buyup coverage (individual and area plans combined)—is approximated as follows. Recall that area plan coverage levels are normalized in line with individual plans as shown in equation (8). At each coverage level, we first average the subsidy rates across units—while treating area plans as another unit—and then average again over coverage levels.

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[24] Note that, prior to the 2008 Farm Bill, a buyup coverage at 65% was offered with area plans, which would be the 50% equivalent of individual plans, and that coverage level carried the subsidy rate of 59%. Since this was eliminated in the 2008 Farm Bill, the average subsidy rate for area plan calculations accounted 70% and above with area plans as these coverage levels prevailed over both periods.
[25] Bulut, H. and K.J. Collins. 2014. Designing Farm Supplemental Revenue Coverage Options on Top of Crop Insurance Coverage. *Agricultural Finance Review*. 74(3): 397-426.

$$
s_b(\phi) = \begin{cases} \dfrac{s_o(\phi) + s_e(\phi)}{2} & if \quad \phi = 0.5 \\ \dfrac{s_o(\phi) + s_e(\phi) + s_a(\phi)}{3} & if \quad 0.55 \le \phi \le 0.75 \\ \dfrac{s_o(\phi) + s_e(\phi)}{2} & if \quad \phi > 0.75 \end{cases} . \tag{9}
$$

In the preceding formulation, the middle case arises when individual and adjusted-area coverage levels overlap, while the top and bottom cases hold otherwise. Further averaging $s_b(\phi)$ over coverage levels yield the desired variable

$$
s_b \equiv (1/8) \sum_{\phi=0.5}^{0.85} s_b(\phi) . \tag{10}
$$

To show how the forgoing formulation of the average subsidy rate can work with additive effects, express the latter via the parameter θ as $s_b(\phi_l, \phi_h, \phi_a, \theta) = s_b + \theta$, where θ originates from an additive effect on s_o, which in turn is denoted by the parameter τ. From equation (6), the relationship between s_e and s_o is governed by the parameter λ_i. It can be shown that keeping λ_i as the same as part of a future policy change is commensurate with the policy of a reduction of equal subsidy dollars across units. Substituting for s_e in line with equation (6) and plugging τ in equation (9), one obtains

$$
s_b(\phi) + \theta = \begin{cases} \left(s_o(\phi) + \tau\right) \dfrac{(2+\lambda_i)}{2} & if \quad \phi = 0.5 \\ \left(s_o(\phi) + \tau\right) \dfrac{(2+\lambda_i)}{3} + \dfrac{s_a(\phi)}{3} & if \quad 0.55 \le \phi \le 0.75 \\ \left(s_o(\phi) + \tau\right) \dfrac{(2+\lambda_i)}{2} & if \quad \phi > 0.75 \end{cases} . \tag{11}
$$

Notice in the preceding equation that the term $\frac{(2+\lambda_i)}{3}$ appears five times, while the term $\frac{(2+\lambda_i)}{2}$ appears three times per relevant coverage level. Since the policy change of interest leaves λ_i and $s_a(\phi)$ unchanged, one can then infer via equation (10) that

$$
d\theta \cong \frac{1}{8}\left(5\frac{(2+\lambda_b)}{3} + 3\frac{(2+\lambda_b)}{2}\right) d\tau = (1+\lambda_b/2)\frac{1}{4}\left(\frac{5}{3}+\frac{3}{2}\right) d\tau = (1+\lambda_b/2)\frac{19}{24} d\tau . \tag{12}
$$

That in turn traces out the effects of potential changes in optional unit subsidy rates. One can verify that the multiplicative effects workout similarly.

In a policy scenario, $s_o(\phi)$ is reduced by 16 ppts by reducing the subsidy rates at all coverage levels for optional units. Since the relative subsidy rates between enterprise and optional units ($\lambda(\phi)$ values at each coverage level from earlier) are held the same as in table A.1, this leads to $s_e(\phi)$ is being reduced by 21 ppts. Reflecting these changes, the average subsidy rate for buyup coverage levels with both individual and area plans s_b is being reduced by 14.75 ppts—approximately 15 ppts as targeted by the CBO. In this example, the exact $\lambda(\phi)$ values at each coverage level, as formulated in equation (5), are used; whereas the average value λ_i from equation (6) is used in equation (12). One can verify that this does not make a material difference. Plugging $\lambda_i = 0.317$ and $d\tau = -0.16$ in equation (12) results in $d\theta \cong (1+0.317/2)\frac{19}{24}\times(-0.16) = -0.1468$, which is again approximately a cut of 15 ppts.

Table A.1. Subsidy Rates for Units of Individual Plans

Coverage Level (ϕ)	Subsidy Rates for Optional Units ($s_o(\phi)$)	Subsidy Rates for Enterprise Units ($s_e(\phi)$)	Relative Subsidy Rates ($s_e(\phi)/s_o(\phi)$)
85%	0.38	0.53	1.395
80%	0.48	0.68	1.417
75%	0.55	0.77	1.400
70%	0.59	0.80	1.356
65%	0.59	0.80	1.356
60%	0.64	0.80	1.250
55%	0.64	0.80	1.250
50%	0.67	0.80	1.194

Supplemental Appendix 2 (SA2).

This appendix provides the following

(i). table A.2 showing the estimation results from the auxiliary regressions of percent changes in per acre premium at buyup coverage on percent changes in base insurance price and volatility factor for corn and soybeans.

(ii). Figures A.1a and A.1b plotting of actual and fitted values of the percentage changes in premium per acre at buyup coverage level from the preceding estimated models for each crop.

(iii). Figures A.2a and A.2b plotting the fitted normal and kernel densities (and the histogram) of year-over-year (YoY) percentage changes in base insurance prices and volatility factor for each crop.

(iv). *t*-test results for the zero mean hypothesis for percentage changes in base insurance prices and volatility factor for each crop.

Table A.2. Estimated Models for Percent Changes in Per Acre Premium at Buyup Coverage, Corn and Soybeans

	Corn	Soybeans
Dependent Variable (across)/ Explanatory Variables (below)	*Percentage Change in Premium Per Insured Acre at Buyup Cov.*	*Percentage Change in Premium Per Insured Acre at Buyup Cov.*
Intercept	0.036^{**} (2.26)	0.030 (1.64)
Percentage Change in the Base Insurance Price	0.951^{***} (11.4)	1.019^{***} (10.8)
Percentage Change in the Volatility Factor	0.324^{**} (2.70)	0.356^{***} (4.2)
Adjusted- R^2	90.2%	92.8%

Notes. [a] Based on the econometric estimations using countrywide data over the period 2001-2020. [b] The superscripts ***, **, * indicate significance at 1%, 5%, and 10%, respectively, based on the *t*- test statistic values reported inside the parentheses.

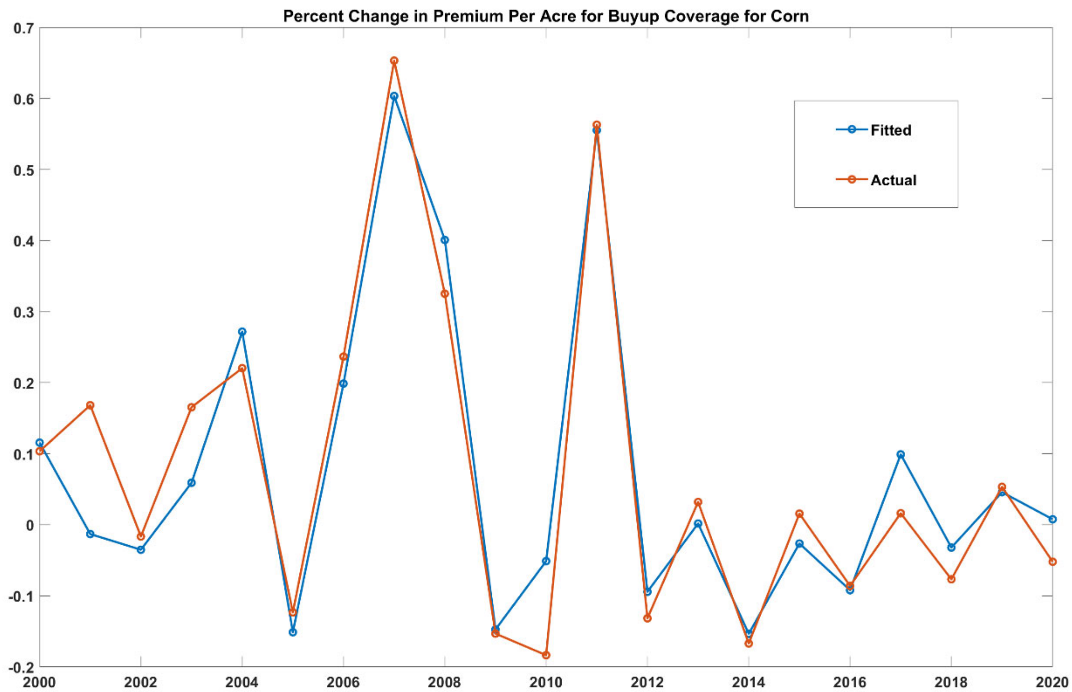

Figure A.1a for Corn in 2000-2020: Actual and fitted values of the percentage changes in premium per acre at buyup coverage level. The fitted values are from the estimated model for corn in table A.2.

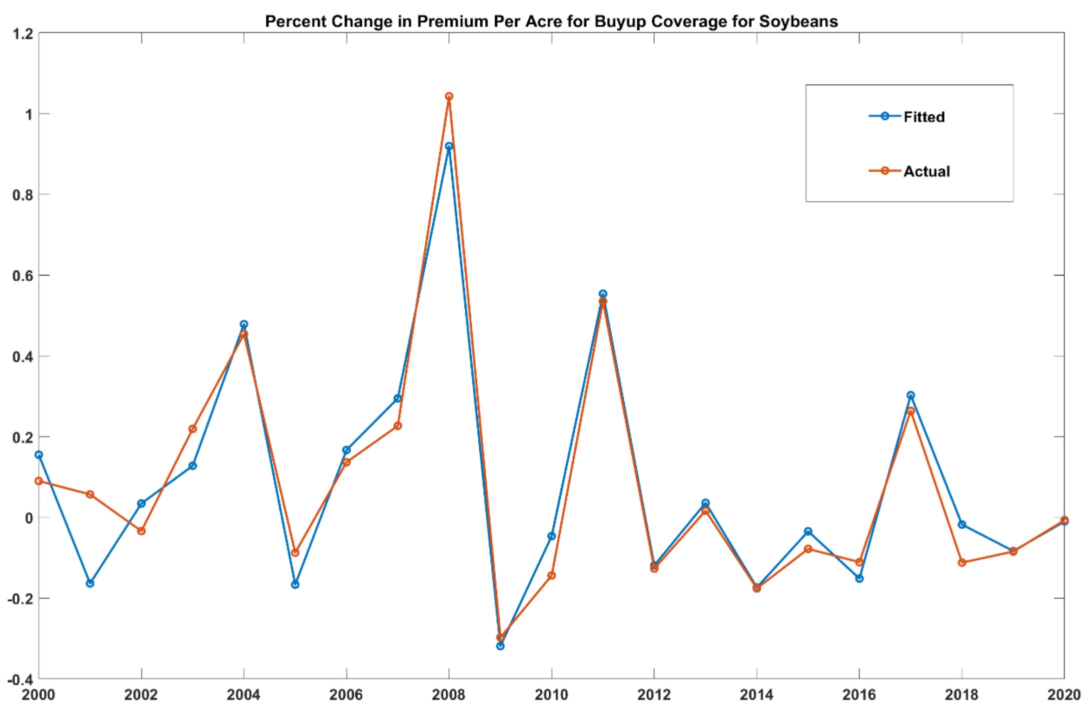

Figure A.1b for Soybeans in 2000-2020: Actual and fitted values of the percentage changes in premium per acre at buyup coverage level. The fitted values are from the estimated model for soybeans in table A.2.

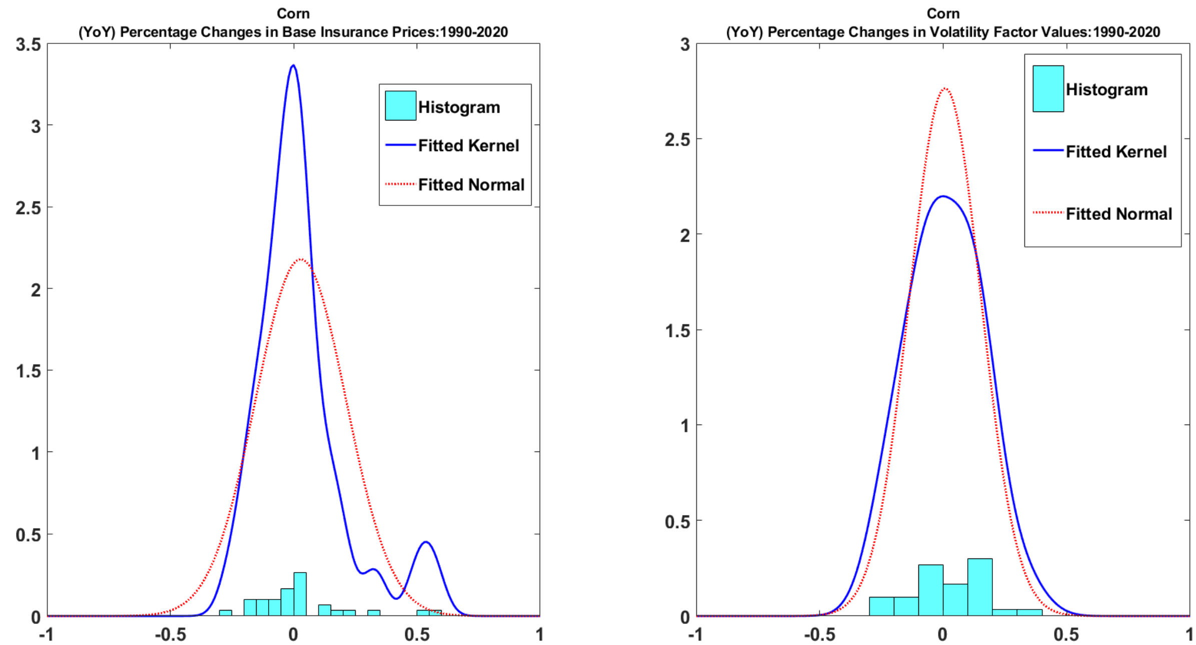

Figure A.2a for Corn in 1990-2020: Fitted normal and kernel densities (and the histogram) of year-over-year (YoY) percentage changes in **base insurance prices (LHS) and volatility factor (RHS). Notes.** In the histogram, frequencies are reexpressed as probabilities. In the Kernel density estimation, the standard Normal kernel function is used.

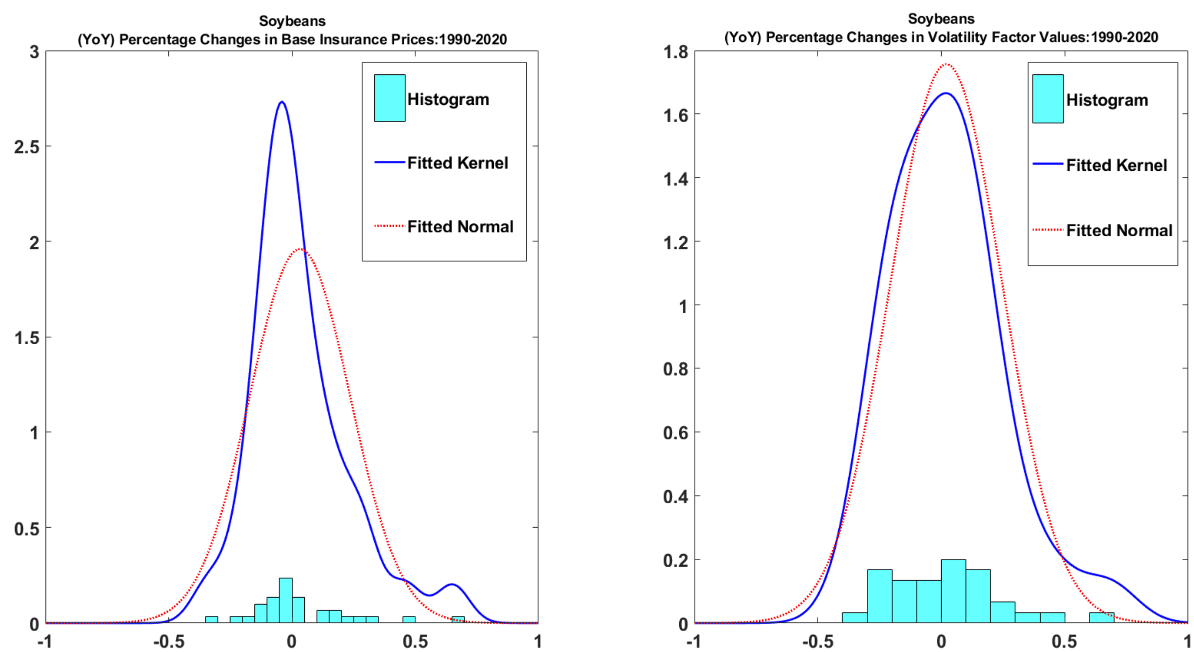

Figure A.2b for Soybeans in 1990-2020: The same figure title as in figure A.2a otherwise. **Notes.** The same notes in figure A.2a apply here.

Figures A.2a and A.2b above display the percentage changes in both base insurance price and volatility factor values over the 1990-2020 period for corn and soybeans, respectively. It is apparent the values of these variables concentrate around zero. Since any potential non-normality does not appear to be excessive, one can carry out *t*-tests to test the null hypothesis of zero mean for each variable (Keller, p. 453).[26] Upon conducting *t*-tests, the null hypothesis of the mean equals zero for each variable is well-supported in this case as well. The *p-values* associated with the *t*-test statistic stood at (0.379; 0.327) and (0.9744; 0.834) for the percentage changes in base insurance price and volatility factor variables, respectively. Note that the figures inside the preceding parentheses (in that order) belong to corn and soybean cases.

[26] Keller, G. 2008. Statistics for Management and Economics. Eight Edition. South-Western, Cengage Learning. Mason, Ohio.

Supplemental Appendix 3 (SA3). Additional Estimation Results (Primarily for Soybeans)

This appendix provides figures 2b, 3b, and 3d for soybeans. The corresponding figures 2a, 3a, and 3c for corn are provided in the text. Also, figures 2c; A.4a and 2d; A.4b for corn and soybeans, respectively, are both provided here.

Table 3b. Estimated Models for the Market Shares, Soybeans [a]

Expl. Variables [b]	Param. [e]	Model 1 [c]			Model 2 [c]			Model 3 [c]		
Intercept	α_{he0}	***	-1.588	-11.4	***	-1.636	-13.8	***	-1.588	-14.4
	α_{ho0}	***	0.392	4.9	***	0.388	4.8	***	0.594	5.7
	α_{le0}	***	-0.205	-6.8	***	-0.207	-6.9	***	-0.252	-7.0
	α_{lo0}	***	1.255	9.3	***	1.264	9.4	***	2.220	17.4
	α_{a0}	***	0.129	3.5	***	0.115	3.0		0.022	0.5
	α_{c0}	***	0.203	5.9	***	0.221	6.4	**	0.098	2.3
1-Period Lagged Market Share (Own Effects)	α_{he1}	***	0.588	15.5	***	0.578	18.3	***	0.259	4.3
	α_{ho2}	***	0.431	8.7	***	0.439	8.9	***	0.651	6.3
	α_{le3}	***	0.759	21.6	***	0.755	21.7	***	0.684	14.3
	α_{lo4}	***	0.494	10.4	***	0.490	10.4	***	-1.483	-6.7
	α_{a5}	***	0.863	13.1	***	0.923	15.0	***	0.353	5.2
	α_{c6}	***	0.700	23.4	***	0.678	23.3	***	0.957	9.8
1-Period Lagged Market Share of High Coverage on Enterprise Units (Cross Effects)	α_{ho1}							***	0.386	3.0
	α_{le1}									
	α_{lo1}							***	-1.307	-8.7
	α_{a1}							***	0.453	8.0
	α_{c1}									
1-Period Lagged Market Share of High Coverage on Optional Units (Cross Effects)	α_{he2}							**	0.217	2.6
	α_{le2}									
	α_{lo2}							***	-1.750	-11.9
	α_{a2}							***	0.406	8.0
	α_{c2}									

Table 3b Continues.

Expl. Variables [b]	Param. [e]	Model 1 [c]	Model 2 [c]	Model 3 [c]		
1-Period Lagged Market Share of Low Coverage on Enterprise Units (Cross Effects)	α_{he3}			***	1.770	6.5
	α_{ho3}					
	α_{lo3}			***	-3.275	-14.0
	α_{a3}					
	α_{a3}					
1-Period Lagged Market Share of Low Coverage on Optional Units (Cross Effects)	α_{he4}					
	α_{ho4}			***	0.511	2.6
	α_{le4}					
	α_{a4}			***	0.710	8.0
	α_{c4}			**	-0.100	-2.1
1-Period Lagged Market Share of Area Coverage (Cross Effects)	α_{he5}					
	α_{ho5}			***	-0.590	-4.2
	α_{le5}					
	α_{lo5}			***	-0.592	-2.6
	α_{c5}			***	0.351	2.7
1-Period Lagged Market Share of CAT Coverage (Cross Effects)	α_{he6}					
	α_{ho6}					
	α_{le6}					
	α_{lo6}			***	-2.421	-12.1
	α_{a6}					

Table 3b Continues.

Expl. Variables [b]	Param. [e]	Model 1 [c]			Model 2 [c]			Model 3 [c]		
Average Subsidy Rate (Offered) at Buyup Coverage	β_{he1}	***	2.816	11.6	***	2.901	14.1	***	2.712	15.2
	β_{ho1}	***	-0.438	-3.4	**	-0.434	-3.4	***	-1.168	-5.9
	β_{le1}	***	0.367	7.0	***	0.371	7.2	***	0.452	7.2
	β_{lo1}	***	-1.901	-9.0	***	-1.913	-9.1	***	-1.034	-5.4
	β_{a1}	**	-0.209	-3.4	**	-0.188	-3.0	***	-0.601	-7.6
	β_{c1}	***	-0.316	-5.7	***	-0.344	-6.2	**	-0.148	-2.2
Percentage Change (year-over-year) in Base Insurance Price	β_{he2}				***	-0.023	-2.8	***	-0.033	-4.1
	β_{ho2}									
	β_{le2}									
	β_{lo2}									
	β_{a2}									
	β_{c2}									
Percentage Change (year-over-year) in Volatility Factor	β_{he3}				***	0.039	5.3	***	0.030	4.9
	β_{ho3}									
	β_{le3}									
	β_{lo3}									
	β_{a3}									
	β_{c3}									

Table 3b Continues.

Measures of Fit	Model 1	Model 2	Model 3
R^2 *(McElroy's)*	98.05%	98.25%	99.33
$\ln(L)$ [d]	425.8	432.8	487.6
T [d]	20	20	20
N [d]	18	20	35
AIC [d]	-815.6	-825.6	-905.1
BIC [d]	-797.7	-805.6	-870.3

Notes. [a] Based on the econometric estimations using countrywide data over the period 2001-2020.

[b] See table 2 notes for details on the explanatory variables. See equation (10) or (12) in the text for an example of the estimated models

[c] Estimated parameters are listed in the same order with the market shares for high coverage on enterprise and optional units, low coverage on enterprise and optional units, area coverage, and CAT coverage levels as also shown in the Parameters column. The superscripts *** , * , * indicate significance at 1%, 5%, and 10%, respectively, based on the *t*- test statistic values reported inside the parentheses.

[d] The notation $\ln(.)$ represents the natural logarithm operator, L is the maximized value of the multivariate likelihood function, T is the number of usable observations per market share equation, and N is the total number of estimated parameters (across all equations). By combining the information on these, the A*IC* and *BIC* criteria values are calculated from $AIC = -2\ln(L) + 2N$; $BIC = -2\ln(L) + \ln(T)N$. Both criteria take the goodness of fit and parsimony into account; while, given the sample size here, the *BIC* penalizes the model complexity more so than the *AIC*.

[e] In using the notation $\alpha_{\phi\mu j}$, the first index in the subscript $\phi\mu \in \{he, ho, le, lo, a, c\}$ refers to the rows within the VAR(1) structure, that is, the market share equation of interest, while the second index $j \in \{1,2,3,4,5,6\}$ refers to the columns, that is, the variable of interest. The latter index, in that order, corresponds to 1-period lagged market shares for high coverage on enterprise and optional units, low coverage on enterprise and optional units, area coverage, and CAT coverage levels, respectively. As an example, α_{lo1} represents the cross effect of 1-period lagged market share for high coverage on enterprise units ($j = 1$) on the market share for low coverage on optional units $(\phi\mu = lo)$, which can also be verified in equation (12).

Table 3d. Additional Estimated Models for the Market Shares, Soybeans [a]

Expl. Variables [b]	Param. [e]		Model 4 [c]			Model 5 [c]	
Intercept	α_{he0}	***	-1.426	(-12.4)	***	-2.329	(-8.8)
	α_{ho0}	***	0.435	(5.8)		0.328	(1.3)
	α_{le0}	***	-0.215	(-7.1)	**	-0.231	(-2.3)
	α_{lo0}	***	0.993	(9.0)	***	2.471	(11.4)
	α_{a0}	***	0.133	(3.6)		0.151	(1.6)
	α_{c0}	***	0.191	(5.1)	**	0.249	(2.4)
1-Period Lagged Market Share (Own Effects)	α_{he1}	***	0.632	(21.3)	***	0.961	(3.5)
	α_{ho2}	***	0.488	(9.2)	***	1.018	(3.4)
	α_{le3}	***	0.764	(22.3)	**	0.594	(2.3)
	α_{lo4}	***	0.576	(14.3)	***	-1.658	(-5.3)
	α_{a5}	***	0.931	(15.4)		0.094	(0.6)
	α_{c6}	***	0.698	(23.0)	***	0.627	(2.8)
1-Period Lagged Market Share of High Coverage on Enterprise Units (Cross Effects)	α_{ho1}				***	0.834	(3.1)
	α_{le1}					-0.085	(-0.8)
	α_{lo1}				***	-1.531	(-6.7)
	α_{a1}				**	0.363	(3.7)
	α_{c1}				*	-0.222	(-2.0)
1-Period Lagged Market Share of High Coverage on Optional Units (Cross Effects)	α_{he2}				***	1.071	(3.4)
	α_{le2}					-0.045	(-0.4)
	α_{lo2}				***	-2.012	(-7.8)
	α_{a2}				**	0.277	(2.5)
	α_{c2}				*	-0.218	(-1.7)

Table 3d Continues.

Expl. Variables [b]	Param. [e]	Model 4 [c]	Model 5 [c]		
1-Period Lagged Market Share of Low Coverage on Enterprise Units (Cross Effects)	α_{he3}		***	2.904	(4.6)
	α_{ho3}			0.374	(0.6)
	α_{lo3}		***	-3.544	(-6.2)
	α_{a3}			-0.166	(-0.7)
	α_{c3}			-0.219	(-0.8)
1-Period Lagged Market Share of Low Coverage on Optional Units (Cross Effects)	α_{he4}		**	0.748	(2.0)
	α_{ho4}		***	1.117	(3.1)
	α_{le4}			-0.171	(-1.2)
	α_{a4}		***	0.656	(4.9)
	α_{c4}		**	-0.371	(-2.5)
1-Period Lagged Market Share of Area Coverage (Cross Effects)	α_{he5}		***	1.061	(2.6)
	α_{ho5}			-0.507	(-1.2)
	α_{le5}			0.135	(0.8)
	α_{lo5}		***	-1.032	(-2.8)
	α_{c5}			0.185	(1.0)
1-Period Lagged Market Share of CAT Coverage (Cross Effects)	α_{he6}		***	1.660	(3.2)
	α_{ho6}			0.541	(1.0)
	α_{le6}			-0.009	(0.0)
	α_{lo6}		***	-3.030	(-6.7)
	α_{a6}			-0.320	(-1.6)

Table 3d Continues.

Expl. Variables [b]	Param. [e]	Model 4 [c]			Model 5 [c]		
Average Subsidy Rate (Offered) at Buyup Coverage	β_{he1}	***	2.535	(12.8)	***	2.747	(12.5)
	β_{ho1}	***	-0.527	(-4.4)	***	-1.358	(-5.6)
	β_{le1}	***	0.383	(7.3)	***	0.534	(5.6)
	β_{lo1}	***	-1.504	(-8.8)	***	-1.094	(-5.2)
	β_{a1}	***	-0.217	(-3.6)	***	-0.651	(-7.2)
	β_{c1}	***	-0.296	(-5.0)		-0.069	(-0.7)
Percentage Change (year-over-year) in Base Insurance Price	β_{he2}	***	-0.045	(-3.0)	***	-0.028	(-3.0)
	β_{ho2}	*	-0.031	(-1.9)			
	β_{le2}		0.003	(0.7)			
	β_{lo2}	***	0.057	(3.5)			
	β_{a2}	**	-0.017	(-2.1)			
	β_{c2}		0.007	(1.3)			
Percentage Change (year-over-year) in Volatility Factor	β_{he3}	***	0.036	(2.8)	***	0.033	(5.3)
	β_{ho3}		-0.011	(-0.8)			
	β_{le3}		0.005	(1.2)			
	β_{lo3}		-0.004	(-0.3)			
	β_{a3}		0.007	(1.0)			
	β_{c3}		0.000	(0.1)			

Table 3d Continues.

Measures of Fit	Model 4	Model 5
R^2 *(McElroy's)*	98.48%	99.44%
$\ln(L)$ [d]	440.7	496.4
T [d]	20	20
N [d]	30	50
AIC [d]	-821.4	-892.8
BIC [d]	-791.5	-843.0

Notes. [a] Based on the econometric estimations using countrywide data over the period 2001-2020.

[b] See table 2 notes for details on the explanatory variables. See equation (10) or (12) in the text for an example of the estimated models.

[c] Estimated parameters are listed in the same order with the market shares for high coverage on enterprise and optional units, low coverage on enterprise and optional units, area coverage, and CAT coverage levels as also shown in the Parameters column. The superscripts *** , * , * indicate significance at 1%, 5%, and 10%, respectively, based on the *t*- test statistic values reported inside the parentheses.

[d] The notation $\ln(.)$ represents the natural logarithm operator, L is the maximized value of the multivariate likelihood function, T is the number of usable observations per market share equation, and N is the total number of estimated parameters (across all equations). By combining the information on these, the A*IC* and *BIC* criteria values are calculated from $AIC = -2\ln(L) + 2N$; $BIC = -2\ln(L) + \ln(T)N$. Both criteria take the goodness of fit and parsimony into account; while, given the sample size here, the *BIC* penalizes the model complexity more so than the *AIC*.

[e] The respective notes in table 3b apply here as well.

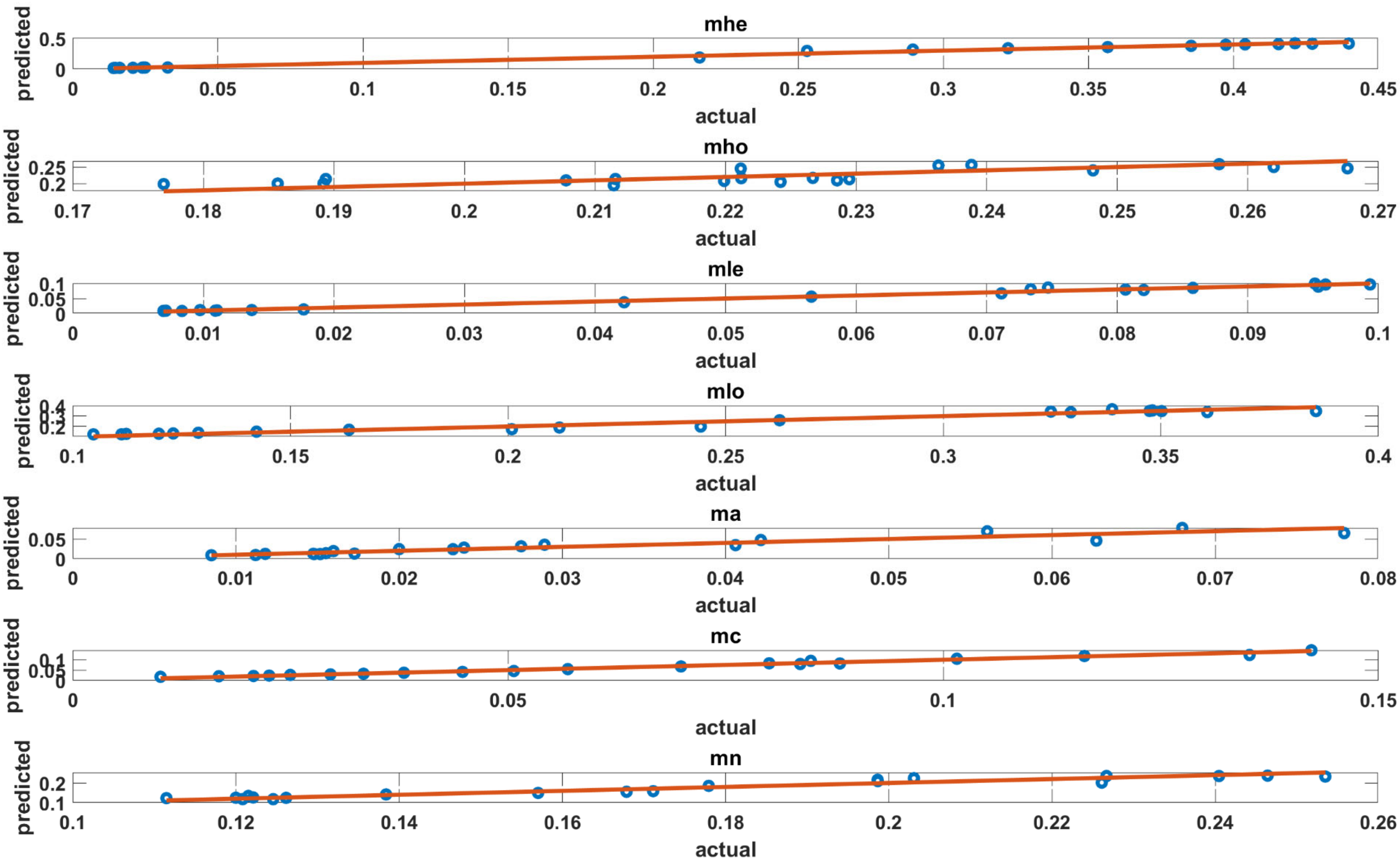

Figure 2b: Soybeans, Fit Performance of Model 1. Predicted values of market shares over 2001-2020 are on the y-axis, the actual values are on the x-axis. The notation (mn, mc, ma, mlo, mle, mho, and mhe) on top of the charts are as described in figure 2a.

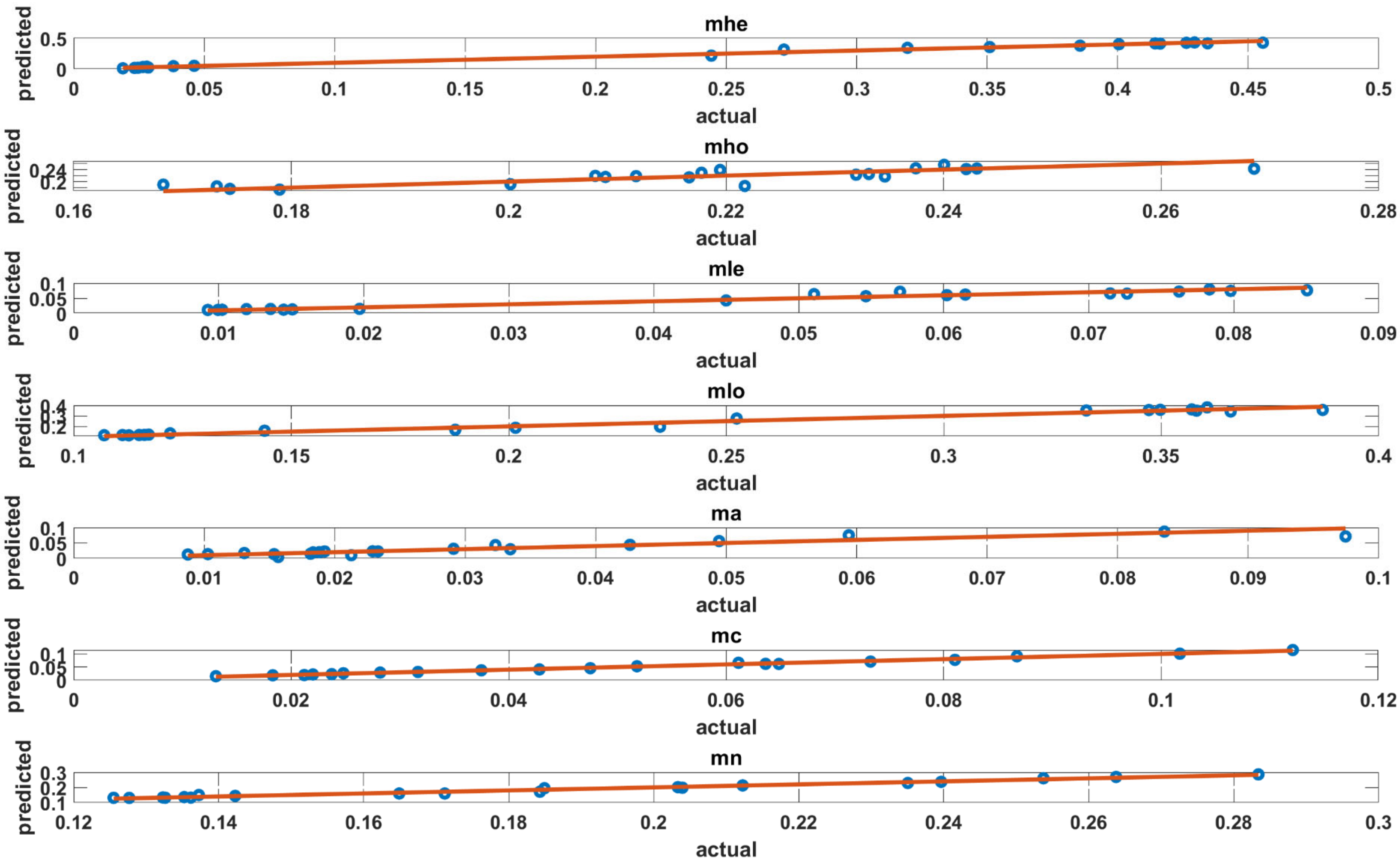

Figure 2c: Corn, Fit Performance of Model 3. Predicted values of market shares over 2001-2020 are on the y-axis, the actual values are on the x-axis. The notation (mn, mc, ma, mlo, mle, mho, and mhe) on top of the charts are as described in figure 2a.

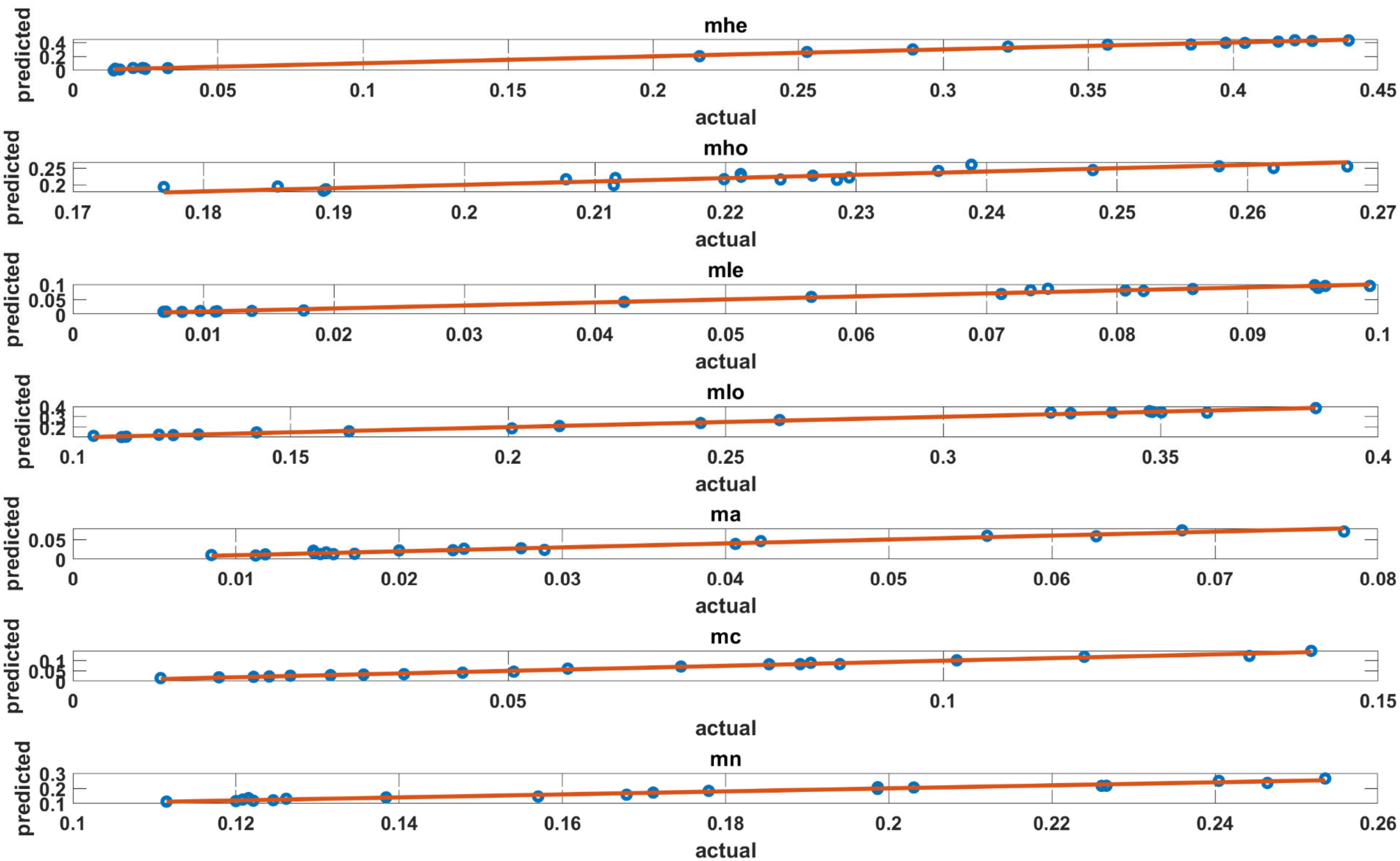

Figure 2d: Soybeans, Fit Performance of Model 3. Predicted values of market shares over 2001-2020 are on the y-axis, the actual values are on the x-axis. The notation (mn, mc, ma, mlo, mle, mho and mhe) on top of the charts indicate the market shares for no insurance, CAT coverage, low buyup, and high buyup coverage levels, respectively.

Figure 3b: Soybeans, Model 1, Impulse Response Function, 30-Period, 15 ppts Cut. The average subsidy rate for buyup coverage was decreased by 15 ppts. The notation (mn, mc, ma, mlo, mle, mho, and mhe) on top of the charts are as described in figure 2a. Market share predicted values are on the y-axis, periods are on the x-axis.

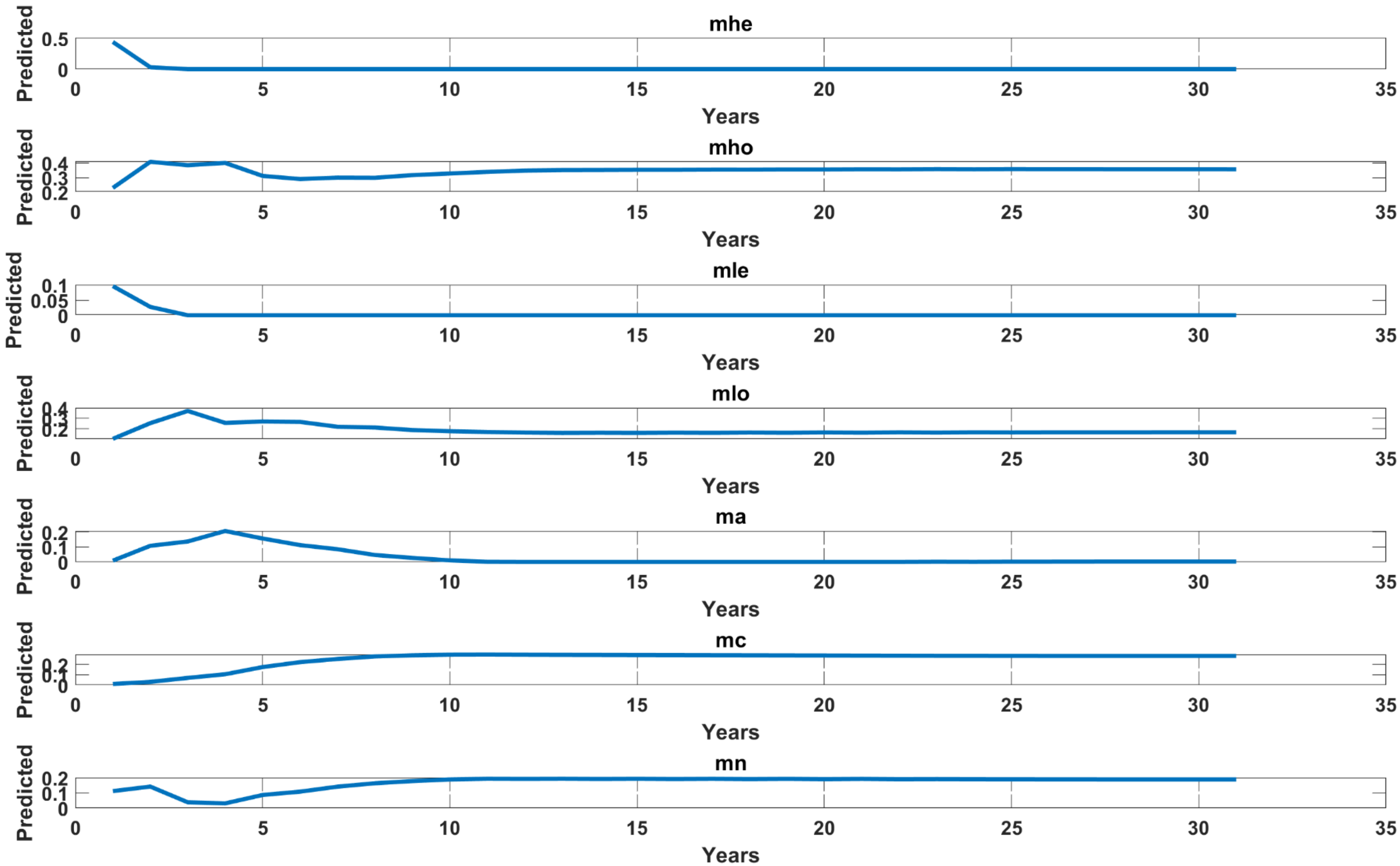

Figure 3d: Soybeans, Model 3, Impulse Response Function, 30-Period, 15 ppts Cut. The average subsidy rate for buyup coverage was decreased by 15 ppts. The notation (mn, mc, ma, mlo, mle, mho, and mhe) on top of the charts are as described in figure 2a. Market share predicted values are on the y-axis, periods are on the x-axis.

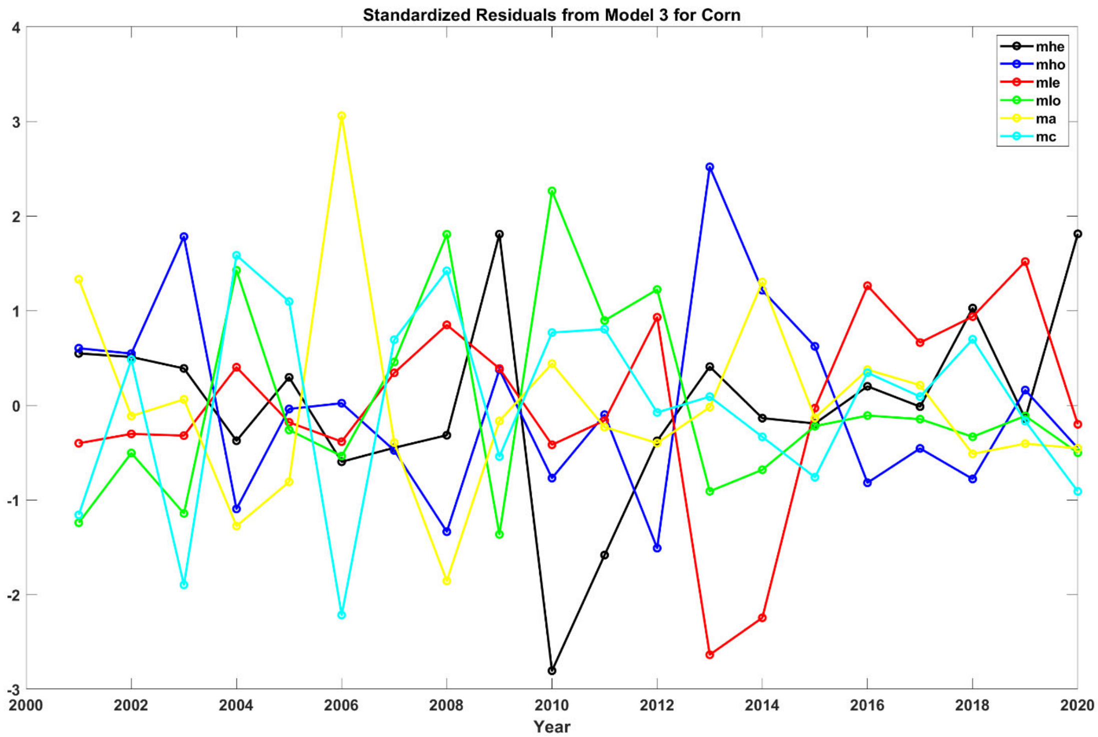

Figure A.4a for Corn. Standardized residuals from Model 3 for corn. The notation (mn, mc, ma, mlo, mle, mho, and mhe) on the legends are as described in figure 2a.

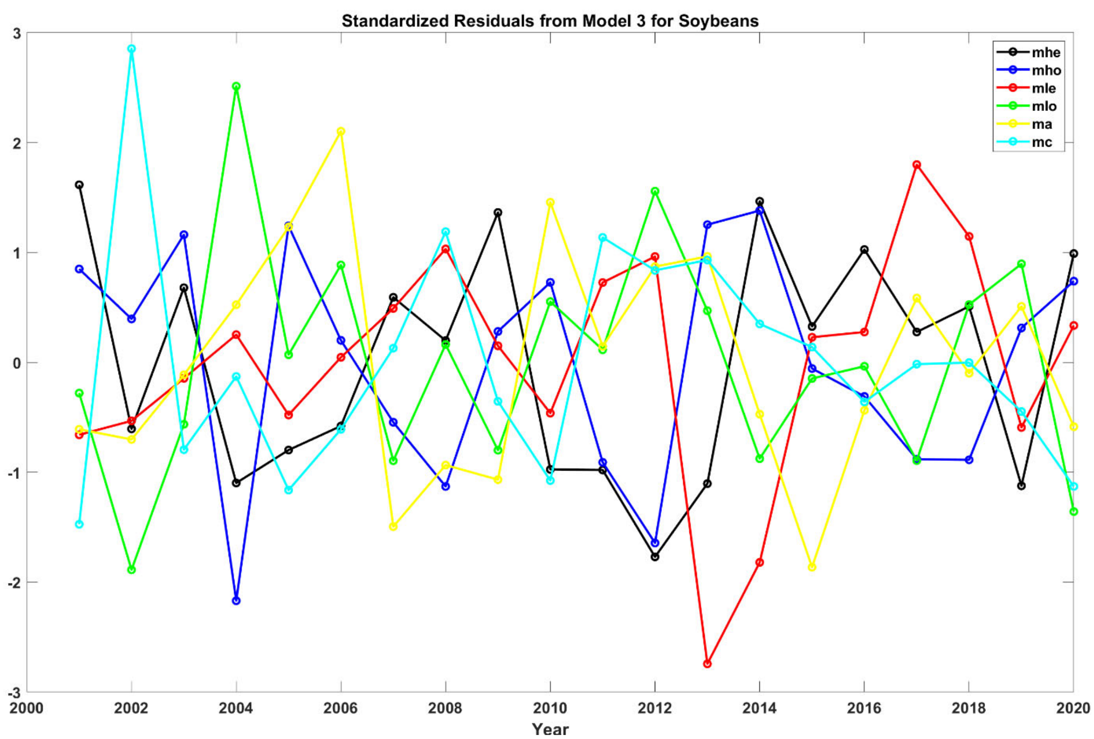

Figure A.4b for Soybeans Standardized residuals from Model 3 for soybeans. The notation (mn, mc, ma, mlo, mle, mho, and mhe) on the legends are as described in figure 2a.

Supplemental Appendix 4 (SA4). Obtaining Long-Term Market Share Impacts for Models with Own Market Share Effects

This appendix shows the steps taken in obtaining the long-term market share effects for Model 2 as given in equation (10) in the text. Similar analyses apply for Model 1 as given in equation (9).

Even though equation (10) in the text is a multi-equation system, since the off-diagonal market share effects are set to zero, each market share equation can be treated individually for an impulse response function. Without loss of generality, focus on the high coverage on enterprise units market share equation at time T, right before the forecast period,

$$m_{he,T} = \alpha_{he0} + \alpha_{he1} m_{he,T-1} + \beta_{he1} s_{b,T} + \beta_{he2} z_{1,T} + \beta_{he3} z_{2,T} + u_{he,T} \,,$$

where the notation as defined in the text. Iterating one period forward yields

$$m_{he,T+1} = \alpha_{he0} + \alpha_{he1} m_{he,T} + \beta_{he1} s_{b,T+1} + \beta_{he2} z_{1,T+1} + \beta_{he3} z_{2,T+1} + u_{he,T+1} \,.$$

Similarly, further iterating one more period and plugging in the preceding equation yields

$$\begin{aligned} m_{he,T+2} &= \alpha_{he0} + \alpha_{he1} m_{he,T+1} + \beta_{he1} s_{b,T+2} + \beta_{he2} z_{1,T+2} + \beta_{he3} z_{2,T+2} + u_{he,T+2} \\ &= \alpha_{he0} + \alpha_{he1} \left(\alpha_{he0} + \alpha_{he1} m_{he,T} + \beta_{he1} s_{b,T+1} + \beta_{he2} z_{1,T+1} + \beta_{he3} z_{2,T+1} + u_{he,T+1} \right) \\ &\qquad + \beta_{he1} s_{b,T+2} + \beta_{he2} z_{1,T+2} + \beta_{he3} z_{2,T+2} + u_{he,T+2} \\ &= \alpha_{he0}(1+\alpha_{he1}) + \alpha_{he1}{}^{2} m_{he,T} + \beta_{he1}\alpha_{he1} s_{b,T+1} + \beta_{he1} s_{b,T+2} \\ &\qquad + \beta_{he2}\alpha_{he1} z_{1,T+1} + \beta_{he2} z_{1,T+2} + \beta_{he3}\alpha_{h1} z_{2,T+1} + \beta_{he3} z_{2,T+2} + \alpha_{he1} u_{he,T+1} + u_{he,T+2} \,. \end{aligned}$$

A pattern then emerges. Noting that

$$s_{b,T+j} = s_{b,T} + d\theta \text{ for all } j \in \{1, 2, \ \dots \ , f\} \,, \tag{13}$$

where $d\theta$ is the additive change in the average subsidy rate.

One can then write

$$\begin{aligned} m_{he,T+f} &= \alpha_{he0}(1+\alpha_{he1}+\ldots+\alpha_{he1}{}^{f-1}) + \alpha_{he1}{}^{f} m_{he,T} + \beta_{he1}\left(s_{b,T}+d\theta\right)\left(1+\alpha_{he1}+\ \dots\ +\alpha_{he1}{}^{f-1}\right) \\ &\quad + \beta_{he2}\sum_{j=1}^{f}\alpha_{he1}{}^{f-j} z_{1,T+j} + \beta_{he3}\sum_{j=1}^{f}\alpha_{he1}{}^{f-j} z_{2,T+j} + \sum_{j=1}^{f}\alpha_{he1}{}^{f-j} u_{he,T+j} \,. \end{aligned} \tag{14}$$

In the impulse-response function calculations over the forecast period, we implicitly work with the conditional expectations of the market shares at time T. To that end, denoting the conditional expectation operator by $E_T\left[.\right]$, we use the implication that the conditional expectation of error terms over the forecast periods being zero, that is, $E_T\left[u_{he,T+j}\right] = 0$ for $j \in \{1, 2, \ \dots \ , f\}$. We also interpret the conditional expectations of the other explanatory variables as being zero that is, $E_T\left[z_{1,T+j}\right] = 0$, and $E_T\left[z_{2,T+j}\right] = 0$ for $j \in \{1, 2, \ \dots \ , f\}$. As for the justification for this interpretation, recall that these variables are the percentage changes in base insurance price and volatility factor. Based on the testing of the zero mean hypothesis for each variable as carried out in SA2, one can set the percentage changes in base insurance price and volatility factor (whenever applicable) at all zero over the forecast horizon.

Taking the conditional expectation of the market share for high coverage that at time T in equation (14) one obtains

$$E_T\left[m_{he,T+f}\right]=\alpha_{he0}(1+\alpha_{he1}+...+\alpha_{he1}{}^{f-1})+\alpha_{he1}{}^{f}m_{he,T}+\beta_{he1}\left(s_{b,T}+d\theta\right)\left(1+\alpha_{he1}+\ ...\ +\alpha_{he1}{}^{f-1}\right)$$
$$+\underbrace{\beta_{he2}\sum_{j=1}^{f}\alpha_{he1}{}^{f-j}E_T\left[z_{1,T+j}\right]}_{=0}+\underbrace{\beta_{he3}\sum_{j=1}^{f}\alpha_{he1}{}^{f-j}E_T\left[z_{2,T+j}\right]}_{=0}+\underbrace{\sum_{j=1}^{f}\alpha_{he1}{}^{f-j}E_T\left[u_{he,T+j}\right]}_{=0}.$$

Based on the foregoing interpretation, one can then directly set the value of the error terms (as done in Enders, p. 293) as well as the values of the other explanatory variables to zero in equation (14) and obtain

$$m_{he,T+f}=\alpha_{he0}(1+\alpha_{he1}+...+\alpha_{he1}{}^{f-1})+\alpha_{he1}{}^{f}m_{he,T}+\beta_{he1}\left(s_{b,T}+d\theta\right)\left(1+\alpha_{he1}+\ ...\ +\alpha_{he1}{}^{f-1}\right)$$
$$+\underbrace{\beta_{he2}\sum_{j=1}^{f}\alpha_{he1}{}^{f-j}z_{1,T+j}}_{=0}+\underbrace{\beta_{he3}\sum_{j=1}^{f}\alpha_{he1}{}^{f-j}z_{2,T+j}}_{=0}+\underbrace{\sum_{j=1}^{f}\alpha_{he1}{}^{f-j}u_{he,T+j}}_{=0}, \qquad (15)$$

which should be understood as the conditional expectation of market share, henceforth.

Now, as f gets large, that is, sending $f\rightarrow\infty$ results in $\lim_{f\rightarrow\infty}\alpha_{he1}{}^{f}=0$ and $\lim_{f\rightarrow\infty}\left(1+\alpha_{he1}+\ ...\ +\alpha_{he1}{}^{f-1}\right)=\frac{1}{1-\alpha_{he1}}$ as $\left|\alpha_{\phi\mu1}\right|<1$ for $\phi\mu\in\{he,ho,le,lo,a,c\}$. Using these results in equation (15), one arrives at

$$\lim_{f\rightarrow\infty}m^{1}_{he,T+f}=\frac{\alpha_{he0}}{1-\alpha_{he1}}+\frac{\beta_{he1}s_{b,T}}{1-\alpha_{he1}}+d\theta\frac{\beta_{he1}}{1-\alpha_{he1}}, \qquad (16)$$

where superscript 1 indicates the presence of subsidy intervention. In the absence of subsidy intervention, which is indicated with the superscript 0, one similarly obtains

$$\lim_{f\rightarrow\infty}m^{0}_{he,T+f}=\frac{\alpha_{he0}}{1-\alpha_{he1}}+\frac{\beta_{he1}s_{b,T}}{1-\alpha_{he1}}. \qquad (17)$$

Combining the two, the market share impact can then be written as

$$\lim_{f\rightarrow\infty}\frac{m^{1}_{he,T+f}-m^{0}_{he,T+f}}{d\theta}=\frac{\beta_{he1}}{1-\alpha_{he1}} \qquad (18)$$

Supplemental Appendix 5 (SA5). Obtaining Long-Term Market Share Impacts for Models with Own-and Cross- Share Effects

This appendix shows the steps taken in obtaining the long-term market share effects for Model 3. Reexpress this model, as given in equation (12) in the text, in the matrix form at the end of sample period as follows:

$$m_T = \alpha_0 + A m_{T-1} + \beta x_T + u_T , \qquad (19)$$

where $m_T = \begin{bmatrix} m_{he,T} \\ m_{ho,T} \\ m_{le,T} \\ m_{lo,T} \\ m_{a,T} \\ m_{c,T} \end{bmatrix}$, $m_{T-1} = \begin{bmatrix} m_{he,T-1} \\ m_{ho,T-1} \\ m_{le,T-1} \\ m_{lo,T-1} \\ m_{a,T-1} \\ m_{c,T-1} \end{bmatrix}$, $\alpha_0 = \begin{bmatrix} \alpha_{he0} \\ \alpha_{ho0} \\ \alpha_{le0} \\ \alpha_{lo0} \\ \alpha_{a0} \\ \alpha_{c0} \end{bmatrix}$, $A = \begin{bmatrix} \alpha_{he1} & \alpha_{he2} & \alpha_{he3} & \alpha_{he4} & \alpha_{he5} & \alpha_{he6} \\ \alpha_{ho1} & \alpha_{ho2} & \alpha_{ho3} & \alpha_{ho4} & \alpha_{ho5} & \alpha_{ho6} \\ \alpha_{le1} & \alpha_{le3} & \alpha_{le3} & \alpha_{le4} & \alpha_{le5} & \alpha_{le6} \\ \alpha_{lo1} & \alpha_{lo2} & \alpha_{lo3} & \alpha_{lo4} & \alpha_{lo5} & \alpha_{lo6} \\ \alpha_{a1} & \alpha_{a2} & \alpha_{a3} & \alpha_{a4} & \alpha_{a5} & \alpha_{a6} \\ \alpha_{c1} & \alpha_{c2} & \alpha_{c3} & \alpha_{c4} & \alpha_{c5} & \alpha_{c6} \end{bmatrix}$,

$\beta = [\beta_1 \quad \beta_2 \quad \beta_3] \equiv \begin{bmatrix} \beta_{he1} & \beta_{he2} & \beta_{he3} \\ \beta_{ho1} & \beta_{ho2} & \beta_{ho3} \\ \beta_{le1} & \beta_{le2} & \beta_{le3} \\ \beta_{lo1} & \beta_{lo2} & \beta_{lo3} \\ \beta_{a1} & \beta_{a2} & \beta_{a3} \\ \beta_{c1} & \beta_{c2} & \beta_{c3} \end{bmatrix}$, $x_T = \begin{bmatrix} s_{b,T} \\ z_{1,T} \\ z_{2,T} \end{bmatrix}$, and $u_T = \begin{bmatrix} u_{he,T} \\ u_{ho,T} \\ u_{le,T} \\ u_{lo,T} \\ u_{a,T} \\ u_{c,T} \end{bmatrix}$.

Iterate the preceding system forward f periods over the forecast horizon—similar to how it is done in SA4 in arriving at equation (14)—and obtain

$$m_{T+f} = \alpha_0(1 + A + ... + A^{f-1}) + A^f m_T + \beta \sum_{j=1}^{f} A^{f-j} x_{T+j} + \sum_{j=1}^{f} A^{f-j} u_{T+j}. \qquad (20)$$

As explained in SA4, for impulse-response function calculations over the forecast horizon $T+f$ when $f \geq 1$, the value of the error terms u_{T+f} and the values of $z_{1,T+f}$ and $z_{2,T+f}$ are all set to zero. Meanwhile, $s_{b,T+j} = s_{b,T} + d\theta$ for all $j \in \{1, 2, \ ... \ , f\}$ from equation (13). The expression in equation (20) then reduces to

$$m_{T+f} = \alpha_0(1 + A + ... + A^{f-1}) + A^f m_T + \beta_1 \sum_{j=1}^{f} A^{f-j} s_{b,T} + \beta_1 \sum_{j=1}^{f} A^{f-j} d\theta , \qquad (21)$$

where β_1 is as defined earlier and $d\theta$ is the additive change in the average subsidy rate for buyup coverage as before.

Assume that the system given in equation (19) is stable, which implies that all characteristic roots (eigenvalues) of the matrix A lie within the unit circle. Recall that A is not necessarily symmetric, which suggests that eigenvalues may have both real and imaginary parts. Based on the eigenvalues and the attendant eigenvectors, A is diagonalizable. Denoting the eigenvalues by λ_i for $i \in \{1,2,3,4,5,6\}$, the diagonal matrix with the eigenvalues by D, and the matrix consisting of the attendant eigenvectors by C. Then, it can be written that $A = CDC^{-1}$. Note that for an identity matrix I, $I = CIC^{-1}$ trivially holds. It can be shown that

$$A^f = CD^f C^{-1} = C\begin{bmatrix} \lambda_1^f & 0 & 0 & 0 & 0 & 0 \\ 0 & \lambda_2^f & 0 & 0 & 0 & 0 \\ 0 & 0 & \lambda_3^f & 0 & 0 & 0 \\ 0 & 0 & 0 & \lambda_4^f & 0 & 0 \\ 0 & 0 & 0 & 0 & \lambda_5^f & 0 \\ 0 & 0 & 0 & 0 & 0 & \lambda_6^f \end{bmatrix} C^{-1} \tag{22}$$

and

$$\sum_{j=1}^{f} A^{f-j} = C\begin{bmatrix} \sum_{j=1}^{f}\lambda_1^{f-j} & 0 & 0 & 0 & 0 & 0 \\ 0 & \sum_{j=1}^{f}\lambda_2^{f-j} & 0 & 0 & 0 & 0 \\ 0 & 0 & \sum_{j=1}^{f}\lambda_3^{f-j} & 0 & 0 & 0 \\ 0 & 0 & 0 & \sum_{j=1}^{f}\lambda_4^{f-j} & 0 & 0 \\ 0 & 0 & 0 & 0 & \sum_{j=1}^{f}\lambda_5^{f-j} & 0 \\ 0 & 0 & 0 & 0 & 0 & \sum_{j=1}^{f}\lambda_6^{f-j} \end{bmatrix} C^{-1} \tag{23}$$

Now, as f gets large, that is, sending $f \to \infty$ results in $\lim_{f\to\infty} A^f = 0$ as $\lim_{f\to\infty} \lambda_i^f = 0$ and $\lim_{f\to\infty} = \sum_{j=1}^{f} \lambda_i^{f-j} = \frac{1}{1-\lambda_i}$ for $i \in \{1,2,3,4,5,6\}$ as the eigenvalues lie within the unit-circle per stability of the system. Use A^* as short-hand for $\lim_{f\to\infty} \sum_{j=1}^{f} A^{f-j}$ and obtain

$$\lim_{f \to \infty} \sum_{j=1}^{f} A^{f-j} \equiv A^* = C \begin{bmatrix} \frac{1}{1-\lambda_1} & 0 & 0 & 0 & 0 & 0 \\ 0 & \frac{1}{1-\lambda_2} & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{1}{1-\lambda_3} & 0 & 0 & 0 \\ 0 & 0 & 0 & \frac{1}{1-\lambda_4} & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{1}{1-\lambda_5} & 0 \\ 0 & 0 & 0 & 0 & 0 & \frac{1}{1-\lambda_6} \end{bmatrix} C^{-1}. \quad (24)$$

Using these results in equation (21), one arrives at

$$\lim_{f \to \infty} m^1_{T+f} = \alpha_0 A^* + \beta_1 s_{b,T} A^* + d\theta \beta_1 A^*, \quad (25)$$

where superscript 1 indicates the presence of subsidy intervention. In the absence of subsidy intervention, which is indicated with the superscript 0, one similarly obtains

$$\lim_{f \to \infty} m^0_{T+f} = \alpha_0 A^* + \beta_1 s_{b,T} A^*. \quad (26)$$

Combining the two, the market share impact can then be written as

$$\lim_{f \to \infty} \frac{m^1_{T+f} - m^0_{T+f}}{d\theta} = \beta_1 A^* = C \begin{bmatrix} \frac{\beta_{he1}}{1-\lambda_1} & 0 & 0 & 0 & 0 & 0 \\ 0 & \frac{\beta_{ho1}}{1-\lambda_2} & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{\beta_{le1}}{1-\lambda_3} & 0 & 0 & 0 \\ 0 & 0 & 0 & \frac{\beta_{lo1}}{1-\lambda_4} & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{\beta_{a1}}{1-\lambda_5} & 0 \\ 0 & 0 & 0 & 0 & 0 & \frac{\beta_{c1}}{1-\lambda_6} \end{bmatrix} C^{-1} \quad (27)$$

The right-hand side expression is calculated and used to estimate the market share impacts as follows. Recall that the estimated parameters of Model 3 are reported in tables 3a and 3b for corn and soybeans, respectively. Based on the estimated parameters of matrix A, the eigenvalues are obtained. These values along with the corresponding eigenvectors are combined with $\hat{\beta}_{he1}$, $\hat{\beta}_{ho1}$

$\hat{\beta}_{le1}$, $\hat{\beta}_{lo1}$, $\hat{\beta}_{a1}$, and $\hat{\beta}_{c1}$, the estimated coefficients of the average subsidy rate for buyup coverage.

Note that if the matrix A were diagonal (which would be the case of own market share effects only as shown in SA4), then the eigenvalues would be equal to the diagonal elements of A, that is, $\lambda_1 = \alpha_{he1}$, $\lambda_2 = \alpha_{ho2}$, $\lambda_3 = \alpha_{le3}$, $\lambda_4 = \alpha_{lo4}$, $\lambda_5 = \alpha_{lo5}$, and $\lambda_6 = \alpha_{lo6}$. The matrix C i turn would reduce to the identity matrix (considering the unit normed eigenvectors). The solution in equation (27) would then coincide with that in equation (18) in SA4. ■