A Text-Based Measure of Farm Bill Uncertainty and Its Effects on Agricultural Credit

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August 4, 2026

Abstract

We develop a text-based measure of Farm Bill uncertainty and study its effects on U.S. agricultural credit supply. Applying a two-stage Bidirectional Encoder Representations from Transformers (BERT) classifier to newspaper articles, we construct a Farm Bill Uncertainty Index (FBUI) that isolates language reflecting legislative delay, disagreement, and procedural impasse. The index tracks negotiation cycles closely, spiking during legislative conflict and declining sharply after enactment. Merging the FBUI with institution-level data for commercial banks, credit unions, and Farm Credit System institutions, we show that higher uncertainty reduces agricultural lending, most clearly for commercial banks: a 0.10 increase in FBUI is associated with about a 0.37% decline in lending. In exposure-weighted specifications, banks in more exposed markets reduce farmland and aggregate loan amounts and average loan sizes rather than uniformly cutting loan counts. Stacked difference-in-differences estimates around the 2008, 2014, and 2018 Farm Bills show that banks experiencing larger uncertainty declines expand lending more rapidly after enactment. Farm Bill uncertainty is thus a distinct supply-side driver of agricultural credit conditions.

Keywords: Agricultural lending, Farm Bill programs, natural language processing, policy uncertainty, text analysis.

JEL Classification: G21, Q14, D81.

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1 Introduction

U.S. agricultural policy is centered on the Farm Bill, a multi-year legislative package governing commodity programs, crop insurance, conservation incentives, and nutrition assistance. While these bills follow a four-to-five-year authorization cycle, their enactment frequently deviates from schedule. Table 1 documents Farm Bills since 1981, highlighting a pattern of delayed reauthorizations and reliance on temporary extensions. Even when Congress meets nominal deadlines, the legislative process involves protracted negotiations over funding levels and program design, leaving key policy parameters unsettled well before enactment.

These recurring cycles are a primary source of policy uncertainty. Until a Farm Bill is finalized and implemented, the structural components of the agricultural safety net remain unsettled. Producers, lenders, and other stakeholders face ambiguity regarding future income support, risk-management tools, and compliance requirements throughout the reauthorization process, rather than only during formal delays.

Despite its importance, Farm Bill uncertainty is poorly captured by existing measures. Broad economic or agricultural policy uncertainty indices aggregate agricultural debate with unrelated macroeconomic, geopolitical, and regulatory shocks. Standard keyword-based approaches further struggle to distinguish genuine legislative conflict from routine reporting or historical mentions of the "Farm Bill" that carry little information regarding forward-looking policy risk.

To address these limitations, we construct the first uncertainty index tailored specifically to Farm Bill legislation. We utilize a two-stage Bidirectional Encoder Representations from Transformers (BERT) classifier applied to a corpus of 156,420 newspaper articles to identify Farm Bill coverage and isolate language reflecting legislative delay, disagreement, or procedural impasse. Unlike traditional keyword counts, our classifier utilizes semantic context and narrative structure. This reduces the misclassification of routine institutional coverage while capturing uncertainty even when canonical terms like "delay" or "uncertainty" are absent. The resulting Farm Bill Uncertainty Index (FBUI) tracks negotiation cycles, spikes during periods of impasse, and declines sharply upon enactment, providing a focused measure of the policy risk faced by producers and lenders. Appendix A details the construction and validation of the index.

Farm Bill uncertainty has direct implications for agricultural credit. Lenders form expectations of farm cash flows, repayment risk, and collateral values based on the anticipated structure of safety-net programs. When these programs are unsettled, lenders may perceive higher default risk, incur greater monitoring costs, or place more weight on collateral-based lending. We hypothesize that these mechanisms have stronger effects on production and operating credit, which depends heavily on short-run income prospects, and that responses vary across lender types. Commercial banks, credit unions, and Farm Credit System (FCS) institutions differ in their mandates, funding structures, and portfolio concentrations, implying different margins of adjustment to policy risk.

We test these channels by merging the FBUI with more than three decades of institution-level data for commercial banks, credit unions, and the FCS. We present four main findings. First, increases in Farm Bill uncertainty are associated with economically meaningful contractions in agricultural lending, with the strongest and most systematic effects for commercial banks. Second, for commercial banks, these contractions are broad across production, farmland, and total agricultural lending outcomes, and are especially clear in loan amounts and loan counts. Appendix robustness checks address broad agricultural-news volume, source composition, and moving-average timing choices, and they support the core commercial-bank adjustment margins.

Third, we document spatial heterogeneity using the exposure measure EXPO defined in Section 4. This measure summarizes persistent geographic dependence on Farm Bill-related support and operating-cost pressure. We find that exposure amplifies the lending response most clearly for commercial banks, but the adjustment is not a uniform contraction across all margins. In high-exposure markets, commercial banks reduce farmland and aggregate agricultural loan amounts and average loan sizes, while loan-count effects are flat or positive.

This pattern suggests credit resizing and risk management rather than a simple withdrawal from agricultural borrowers.

Finally, treating the 2008, 2014, and 2018 Farm Bills as discrete episodes, we use stacked difference-in-differences and event-study designs to show that commercial banks experiencing larger declines in exposure-weighted uncertainty expand lending more rapidly after enactment, with effects persisting for several quarters.

The paper contributes to three strands of literature. First, we extend the economic policy uncertainty literature following Baker et al. (2016) by developing a domain-specific measure tied to legislative dynamics. Related work has constructed uncertainty measures for monetary policy (Husted et al., 2020), trade policy (Fajgelbaum et al., 2020; Handley, 2014; Handley and Limão, 2017; Steinberg, 2019), and geopolitical risk (Caldara and Iacoviello, 2022). Within agriculture, prior studies link policy uncertainty to quota markets (Wilson and Sumner, 2004; Wossink and Gardebroek, 2006), farm employment and investment (Gopinath, 2021), and commodity futures markets (Du and Dong, 2023). Our language-model approach improves upon these keyword methods by incorporating context to isolate sectoral risk.

Second, we contribute to the literature on policy uncertainty and financial intermediation (Bordo et al., 2016; Danisman et al., 2020; Hu and Gong, 2019; Ozili, 2021). Existing work shows that elevated uncertainty reduces credit supply, raises loan pricing, and induces precautionary behavior among financial intermediaries (Bordo et al., 2016; Danisman et al., 2020; Hu and Gong, 2019; Ozili, 2021). We extend this evidence to a highly policy-dependent credit market and show that legislative risk affects not only the volume of credit but also its composition. By showing that uncertainty affects loan categories and adjustment margins differently, we provide a more granular view of how intermediaries manage policy shocks through loan quantities, loan counts, average loan sizes, and collateralized credit.

Third, we add to the agricultural finance literature by providing evidence that the Farm Bill cycle is a distinct driver of rural credit supply. By linking continuous variation in the FBUI to cross-state exposure and discrete enactments, our analysis clarifies how legislative timing translates into persistent changes in rural credit conditions. Unlike transitory demand-side fluctuations, the supply-side responses documented here suggest that the institutional structure of the Farm Bill itself generates systemic risk for agricultural lenders.

The paper proceeds as follows. Section 2 reviews agricultural lending institutions. Section 3 develops conceptual links between policy risk and lending decisions. Section 4 presents the data architecture and FBUI construction, including the text corpus, lender panels, and exposure mapping. Sections 5 and 6 present the baseline and exposure-weighted results. Section 7 provides the event-study analysis of Farm Bill enactments, and Section 8 concludes.

2 Institutional Background

This section reviews the structure of agricultural lending institutions in the United States, the main categories of agricultural loan products, and the channels through which Farm Bill programs shape lenders' incentives and credit decisions.

2.1 Agricultural Lending Institutions

External finance is essential for U.S. agriculture, supporting seasonal production, land acquisition, and long-term capital investment. Total farm-sector debt is projected to reach $624.7 billion in 2026, with a sector-wide debt-to-asset ratio of 13.75 percent (U.S. Department of Agriculture, Economic Research Service, 2026). This credit is supplied by a diverse set of lenders with distinct mandates and funding structures.

The Farm Credit System (FCS) is the largest provider, holding 45.9 percent of total farm debt in 2024 (U.S. Department of Agriculture, Economic Research Service, 2026). Although privately owned, the FCS operates as a government-sponsored enterprise (GSE) and benefits from preferential tax treatment and direct access to capital markets (Congressional Research Service, 2022). The system is organized as a nationwide network of borrower-owned lending associations funded by four regional Farm Credit Banks, which supply funds to local associations that originate loans directly to farm and rural borrowers.

Commercial banks represent the second-largest source of agricultural credit, holding 33.9 percent of total farm debt in 2024. They are particularly influential in non-real-estate lending, accounting for approximately 40 percent of production and operating loans. Unlike the FCS, commercial banks offer a broader range of financial products and are more exposed to fluctuations in market funding costs and general regulatory capital requirements.

Finally, credit unions have expanded their presence in rural areas recently, though they remain a smaller portion of the market (Congressional Research Service, 2025). Regulated by the National Credit Union Administration (NCUA), these nonprofit cooperatives operate with narrower margins and a more localized, retail orientation. Because other entities, such as the Farm Service Agency and equipment dealers, operate under unique policy mandates and offer limited data, we focus the analysis on the FCS, commercial banks, and credit unions.

2.2 Loan Products and Maturity Structures

Agricultural loans are classified into two broad categories that differ in their sensitivity to policy-induced income shocks. Farmland (real-estate) loans finance the purchase of farmland and long-term fixed investments. These loans typically carry maturities of 15 to 30 years and are secured by real property. Because repayment depends on long-run land values and structural profitability, real estate debt is generally less sensitive to the short-term legislative delays associated with Farm Bill reauthorizations. Farm-sector real estate debt has grown steadily since 2000, driven by rising land values and a period of historically low interest rates (U.S. Department of Agriculture, Economic Research Service, 2026).

In contrast, farm production (non-real-estate) loans support annual activities such as seed, fertilizer, and labor expenditure. These loans are short-term, highly seasonal, and closely tied to near-term cash flow. Collateral for production credit often consists of crops or livestock, exposing lenders to immediate yield and price risk. This direct link to annual income makes production credit particularly sensitive to the stability of the agricultural safety net. When the policy parameters governing income support are in transition, the perceived risk of these short-term instruments increases.

2.3 Farm Bill Programs and the Information Environment

Programs authorized through the Farm Bill constitute a risk-management framework that alters the distribution of farm returns, but the relevant mechanisms differ across program components. Federal crop insurance subsidies reduce the cost of yield and revenue protection and are most closely tied to annual production risk, making them especially relevant for operating credit and short-term repayment capacity. Commodity programs such as Agriculture Risk Coverage (ARC) and Price Loss Coverage (PLC) provide crop-specific revenue or price support, with effects concentrated in program-crop regions and with payment timing that may lag the production season. Conservation programs, including land retirement and working-land incentives, can affect longer-run cash flows, land use, and compliance requirements rather than only current-year liquidity. Direct payments, which were predictable and decoupled from production before being eliminated in the 2014 Farm Bill, historically provided a different form of income collateral than the more state-contingent ARC/PLC structure that replaced them.

These components can all act as credit enhancements, but not in identical ways. Crop insurance and commodity support more directly truncate the lower tail of annual income and therefore matter for production-loan repayment risk. Conservation and land-use provisions may matter more through collateral values, acreage allocation, and longer-run profitability. Lenders' information problem during a reauthorization is therefore not simply whether a Farm Bill will pass, but which parts of the safety net will continue, how generous they will be, and which borrowers or regions will be most affected.

The efficacy of this safety net as a credit-stabilizing mechanism depends on the stability of the policy parameters themselves. Because the Farm Bill is subject to periodic reauthorizations and frequent structural revisions, it introduces a unique form of legislative risk. For example, the 2014 Farm Bill significantly altered the agricultural landscape by eliminating "direct payments," which were decoupled from production and prices, in favor of "shallow loss" programs like ARC. Such transitions represent discrete shifts in the policy component of expected farm revenue.

Legislative uncertainty regarding these reauthorizations acts as a shock to the precision of a lender's information. When the future of safety-net parameters, such as subsidy rates, eligibility requirements, or funding levels, remains unsettled, the variance of a borrower's expected future cash flow increases from the perspective of the financial intermediary. For risk-averse lenders, this rise in idiosyncratic and sector-wide risk may induce more conservative credit provision. This effect can manifest through three distinct margins: (i) lower loan volumes; (ii) higher risk premia, tighter screening, or collateral requirements that are not directly observed in our regulatory data; and (iii) changes in loan composition or average loan size. Borrower demand may also move at the same time if producers delay input purchases, land transactions, or investment while policy terms are unresolved. The empirical analysis therefore interprets loan outcomes as reduced-form credit-market responses and uses portfolio-share evidence, state-level demand controls, and post-enactment reversals to assess whether the patterns are consistent with a lender-side policy-risk interpretation rather than a purely demand-driven account.

3 Conceptual Framework

Agricultural lending decisions depend on lenders' expectations regarding borrower repayment capacity, collateral values, and the distribution of future risks. Farm Bill programs influence all three components by shaping expected farm income, the generosity of crop insurance subsidies, and the overall stability of agricultural markets. To formalize these channels, we consider a standard model of lender behavior in which institutions choose the scale and composition of lending to maximize expected profits, subject to default risk and funding costs (Freixas and Rochet, 2008). A more formal derivation of this model is provided in Appendix B.

A representative lender chooses loan supply L to maximize:

$$\max_{L} \Pi = (1+r)L - C(L) - \mathbb{E}[\text{Default Loss}(L; \tilde{S})], \tag{1}$$

where r denotes the loan interest rate, $C(L)$ represents the cost of origination and funding, and expected default losses depend on the borrower's future cash flows.

In this context, the Farm Bill acts as a state-contingent support system. Let S denote the level of policy-related income support and $\tilde{S}$ represent uncertainty regarding its future realization. By providing price floors and revenue guarantees, these programs truncate the lower tail of the farm income distribution, effectively serving as a credit enhancement. Consequently, the variance of farm income, $\text{Var}(Y)$, can be decomposed into market-based revenue volatility and policy-induced uncertainty:

$$\text{Var}(Y) = \text{Var}(\text{Market Revenue}) + \text{Var}(\tilde{S}). \tag{2}$$

This decomposition abstracts from the covariance between market revenue and policy support. Because many support payments are countercyclical, this covariance is typically negative, so Equation (2) should be read as isolating the direct contribution of policy uncertainty to income risk rather than as a complete variance accounting; allowing for a negative covariance would not change the comparative static that greater uncertainty about $\tilde{S}$ raises the policy component of income risk.

Elevated Farm Bill uncertainty increases the variance of expected farm income, raises default risk, and lowers the expected return to agricultural lending. This response may manifest through reduced loan quantities, tighter screening, or changes in the composition of lending.

Importantly, the magnitude of this response depends not only on a lender's exposure to agricultural risk, but also on its ability to adjust lending in response to changing risk conditions. Let $\theta_i \in [0,1]$ denote the share of lender i's portfolio concentrated in agricultural lending, and let $\phi_i \in [0,1]$ capture the lender's effective flexibility in adjusting credit supply, reflecting factors such as balance-sheet substitutability, regulatory constraints, and institutional mandate. We can then write the sensitivity of lending to policy uncertainty as

$$\left|\frac{\partial L_i}{\partial \tilde{S}}\right| = g(\theta_i, \phi_i), \qquad \frac{\partial g}{\partial \theta_i} > 0, \qquad \frac{\partial g}{\partial \phi_i} > 0. \tag{3}$$

This formulation implies that exposure alone does not determine lending responses. While lenders with greater agricultural concentration face larger direct effects of policy uncertainty, their observed response also depends on how easily they can reallocate portfolios or adjust lending standards. Commercial banks, although less specialized than the Farm Credit System (FCS), typically have greater flexibility in tightening standards, shifting portfolios across sectors, and adjusting loan terms. As a result, they may respond more strongly to Farm Bill uncertainty. By contrast, the FCS operates under a specialized institutional mandate and maintains a high structural commitment to agricultural lending, which may limit its short-run adjustment in loan volumes despite high exposure. Credit unions may also face balance-sheet and organizational constraints that make their responses less systematic.

Sensitivity to policy risk is also moderated by loan maturity, collateral structure, and the horizon over which policy uncertainty affects borrower fundamentals. Production and operating loans depend heavily on current-year cash flows and are therefore naturally exposed to short-term uncertainty regarding program payments, crop-insurance support, and farm income. As a result, aggregate increases in Farm Bill uncertainty are expected to reduce production lending.

However, policy uncertainty can also affect expectations of the long-run value of agricultural support programs. Because farmland values capitalize expected future net returns from agricultural production, unresolved policy negotiations may affect land values and real-estate collateral, particularly in regions that are historically more dependent on Farm Bill support. In such settings, uncertainty may be transmitted through collateral values rather than only through current-year cash-flow risk.

Consequently, the relative sensitivity of production and farmland lending is an empirical question. Aggregate uncertainty shocks are expected to affect production credit most directly, while exposure-weighted uncertainty may generate stronger responses in farmland lending if lenders revise expectations about the future value of land-secured collateral.

Finally, policy uncertainty may generate uneven geographic effects because the economic salience of the Farm Bill varies across states. Let E_s denote state-level exposure to Farm Bill programs based on historical dependence on government support and operating-cost intensity. The framework predicts that the credit response to a national uncertainty shock depends on local exposure:

$$\frac{\partial L_s}{\partial \tilde{S}} < 0, \qquad \text{with} \qquad \left| \frac{\partial L_s}{\partial \tilde{S}} \right| = f(E_s). \tag{4}$$

Lending contractions should be larger in places where farm income is more dependent on Farm Bill support, especially for lenders whose portfolios and lending practices are more responsive to local risk conditions. This mechanism also implies a symmetric recovery: when uncertainty is resolved upon enactment, the resulting information gain should generate a stronger lending rebound in more exposed markets.

Together, this framework yields several testable hypotheses: (i) higher Farm Bill uncertainty reduces aggregate agricultural lending; (ii) the contraction is stronger for lenders with greater effective adjustment flexibility, particularly commercial banks; (iii) loan categories respond through different channels, with production lending exposed mainly through short-run cash-flow risk and farmland lending exposed through longer-run profitability and collateral-value risk; and (iv) lending contractions and post-enactment recoveries are larger in high-exposure regions.

4 Data and FBUI Construction

This section consolidates the core data architecture and the construction of the Farm Bill Uncertainty Index (FBUI). We integrate three data blocks: a newspaper corpus for measuring legislative uncertainty, institution-level agricultural lending panels, and a state-level exposure measure used to study heterogeneity in policy transmission.

4.1 Data Architecture and Timing

The empirical design combines text and financial data at different frequencies and levels of aggregation. Newspaper articles are observed daily and aggregated to monthly and then quarterly uncertainty measures. Lending outcomes are measured at the institution-quarter level for commercial banks, credit unions, and Farm Credit System (FCS) associations. Geographic exposure is first defined at the state-year level and then mapped to institutions using lender-specific geographic footprints. This architecture allows us to pair national uncertainty shocks with cross-sectional differences in lender exposure.

4.2 Newspaper Corpus and Filtering

The text data used to construct FBUI are drawn from ProQuest's TDM Studio, which provides digitized historical content from national and regional newspapers, wire services, and trade publications. Working with full-text content, rather than simple keyword counts, allows us to distinguish genuine legislative uncertainty from routine reporting or historical references.

We retrieve 208,293 articles by searching for the phrase "farm bill" across the ProQuest databases listed in Table A2, covering 1980–2025. We then apply two filters: (i) remove 8,663 non-U.S. or non-English articles; and (ii) exclude 43,210 non-news items (for example, blogs, theses, and scholarly journals). The final corpus contains 156,420 articles from 1,861 publishers in 427 cities.

We also audit duplicate publication directly. Using the ProQuest GOID as the article identifier, the cleaned English news corpus contains 156,420 unique GOIDs and no exact GOID duplicates. A more conservative title–date–publication key identifies 151,752 unique article records, implying 4,668 repeated title–date–publication entries, or about 3.0% of the corpus. These repeated title–date–publication entries are collapsed before the monthly and quarterly FBUI aggregation, so they do not enter the numerator or denominator of the constructed index more than once. For the `farmbill_label = LABEL_1` article-volume series used in the robustness checks, the corresponding counts are 41,478 unique GOIDs and 40,204 title–date–publication records, or 1,274 repeated entries, about 3.1%; these repeated records are likewise removed before constructing the quarterly article-volume controls. These diagnostics indicate that duplicate publication is not a material feature of the index data.

The corpus still reflects changes in newspaper digitization, wire-service syndication, and publisher coverage over time. The FBUI construction addresses this concern partly by deduplicating repeated title–date–publication records, by using the share of uncertainty-related Farm Bill coverage rather than the raw number of articles, and by validating the classifier against a keyword alternative in Appendix A. This design reduces the influence of general Farm Bill attention cycles and duplicate article records, but it does not eliminate all measurement concerns from syndicated reporting or changing archive coverage. We therefore interpret FBUI as a media-based measure of perceived legislative uncertainty rather than a direct count of legislative actions. Appendix Section C.1 formalizes additional robustness checks that control for article volume, source composition, publisher counts, publisher-city counts, and wire-service intensity.

4.3 FBUI Construction (Main Specification)

We construct FBUI using a two-stage supervised BERT pipeline designed to separate topic relevance from uncertainty content. Stage 1 identifies whether an article is substantively about U.S. Farm Bill legislation; Stage 2, conditional on Stage-1 relevance, classifies whether the article reflects forward-looking legislative uncertainty (for example, delay, deadlock, temporary extension, or unresolved bargaining). The Stage-2 training labels are credit-relevance constrained. In the manually labeled training set, an article is coded as uncertainty-related only when the unresolved Farm Bill issue concerns program rules, payment levels, crop-insurance provisions, conservation compliance or costs, or another agricultural-policy channel that could affect farm cash flow, collateral values, repayment risk, or lender monitoring. Articles that describe political bargaining without a plausible agricultural-credit link are not treated as uncertainty-related for the FBUI. Thus, rather than estimating separate component-specific indices, the FBUI pools credit-relevant uncertainty across the Farm Bill components discussed in Section 2. This sequential design reduces false positives that arise when articles mention the Farm Bill in historical or descriptive contexts without conveying credit-relevant uncertainty. Applied to the cleaned corpus, Stage 1 identifies 26,509 Farm-Bill-relevant articles, and Stage 2 classifies 22,709 of those as uncertainty-related. Both classifiers achieve out-of-sample accuracy close to 90% in held-out validation samples. The high uncertainty share within relevant coverage (about 86%) reflects the fact that newspapers cover the Farm Bill most intensively when reauthorization is contested; substantive Farm Bill reporting during quiet periods is comparatively rare. The index therefore varies mainly through the time-series volume and share of uncertainty-related coverage rather than through a stable split between certain and uncertain articles, and the robustness checks in Appendix C.1 confirm that the lending results are not driven by general agricultural-news attention.

Let n_t denote the number of articles in month t that contain "farm bill," and let m_t denote the subset classified as both relevant and uncertainty-conveying. We define the raw monthly uncertainty signal as the share of uncertainty articles within Farm-Bill coverage and then apply a small-sample stabilization:

$$\tilde{u}_t = \frac{m_t}{n_t + 4},$$

where the pseudo-count 4 dampens mechanical volatility when article volume is thin. This adjustment is especially relevant in early years, where small changes in m_t could otherwise generate disproportionate swings in raw ratios. We then linearly rescale $\tilde{u}_t$ to $[0, 100]$ to obtain the monthly FBUI, so that the series is interpretable as a normalized measure of Farm Bill legislative uncertainty over time. Figure 1 plots the monthly and weekly FBUI over 1980–2025: the index rises during contested reauthorization periods, spikes around episodes of delay and impasse, and declines sharply after each Farm Bill is enacted.

For institution-level regressions, we aggregate monthly FBUI to quarter-level means and rescale the quarterly series to $[0, 1]$. This scaling makes coefficients directly interpretable as semi-elasticities for a full-range change in the quarterly regression index; a 0.10 increase is a one-tenth-range change in the quarterly FBUI. Because newspaper coverage in the early 1980s is relatively sparse, the main lending analysis starts in 1990 to ensure stable measurement. Appendix A provides full implementation details on annotation, model architecture, confusion matrices, and comparisons with keyword-based alternatives.

4.4 Agricultural Lending Panels

Institution-level agricultural loan data are obtained from quarterly regulatory filings of commercial banks, FCS institutions, and credit unions. These filings report balance-sheet information, loan composition, and loan performance indicators.

Commercial bank: Data are drawn from Call Reports. We use quarterly balances for production and farmland loans from 1990 onward. Loan counts in Schedule RC-C Part II are annual before 2010 and quarterly thereafter.[1]

Credit union: Agricultural data begin in 1994, with semiannual reporting through 2005 and quarterly reporting thereafter. Until 2011, agricultural lending is reported as an aggregate of production and farmland loans; later filings disaggregate these categories.

Farm Credit System: We observe quarterly balance sheets, loan amounts, and delinquency measures from 2005 onward. Category-specific loan counts are unavailable, but aggregate agricultural loan counts are observed.

Table 2 reports institution-level summary statistics by lender type, with means and

[1]Reporting was generally annual through 2009 (typically in the June Call Report), and became quarterly in 2010. Since adoption of FFIEC 051 in 2017, frequency depends on form type: banks filing 031/041 report quarterly, while eligible small banks filing 051 report semiannually (June and December). RC-C Part II also covers small farm loans under $500,000 rather than total agricultural loans.

standard deviations in parentheses. FCS institutions operate at a substantially larger scale, with mean agricultural loan balances around \$2.49 billion, compared with approximately \$37 million for commercial banks and \$43 million for credit unions.

The large standard deviations in Table 2 reflect the highly skewed size distribution of agricultural lenders, especially among commercial banks and FCS associations. The regression analysis addresses this skewness by using log outcomes for loan amounts, counts, and average loan sizes; by including institution fixed effects, which absorb persistent scale differences; and by applying minimum-panel and agricultural-share restrictions so that estimates are not driven by occasional very small agricultural positions. Portfolio-share outcomes provide an additional scale-normalized check for commercial banks and credit unions.

4.5 Geographic Exposure Measure (EXPO)

To measure cross-sectional heterogeneity in dependence on Farm Bill support, we construct a state-level exposure index using USDA ERS farm-income statistics, USDA RMA subsidy records, and a cleaned state-level farm financial-ratio panel. For each state s and year y, we first compute

$$GP_{sy} = \frac{\text{Government Payments}_{sy} + \text{Crop Insurance Subsidies}_{sy}}{\text{Value of Agricultural Production}_{sy}}. \tag{5}$$

We then define

$$GR_{sy} = \frac{\text{Cash Operating Expense}_{sy}}{\text{Gross Cash Farm Income}_{sy}}. \tag{6}$$

Our baseline state exposure measure is

$$\text{EXPO}_s^{state} = \frac{1}{T}\sum_{y=1989}^{2003}(GP_{sy} \times GR_{sy}). \tag{7}$$

Averaging over the fixed 1989–2003 pre-period helps limit simultaneity with the main lending sample and smooth short-run fluctuations in farm-sector conditions. The product form is intended to capture two distinct dimensions of exposure: the importance of Farm Bill-related support in state farm income and the extent to which farms operate with high cash-cost pressure. A state with large program acreage but little payment intensity or low working-capital pressure may not face the same lending-risk channel as a state where government payments and subsidized insurance represent a larger cash-flow backstop. For this reason, program acres alone would be an incomplete proxy for the credit relevance of Farm Bill uncertainty. Appendix Table D1 reports the distribution of the raw and scaled EXPO measures.

We map EXPO_s^{state} to institutions by lender type. For commercial banks, we use annual state deposit shares from Summary of Deposits:

$$\text{EXPO}_{iy}^{bank} = \sum_s \omega_{isy}\, \text{EXPO}_s^{state}, \qquad \omega_{isy} = \frac{D_{isy}}{\sum_{s'} D_{is'y}}. \tag{8}$$

For FCS institutions, we average across statutory service states:

$$\text{EXPO}_i^{fcs} = \frac{1}{|\mathcal{S}_i|} \sum_{s \in \mathcal{S}_i} \text{EXPO}_s^{state}. \tag{9}$$

For credit unions, we average over branch-state coverage in quarter t, with headquarters-state fallback when branch coverage is unavailable:

$$\text{EXPO}_{it}^{cu} = \begin{cases} \frac{1}{|\mathcal{B}_{it}|} \sum_{s \in \mathcal{B}_{it}} \text{EXPO}_s^{state}, & \text{if } |\mathcal{B}_{it}| > 0, \\ \text{EXPO}_{s(i)}^{state}, & \text{if } |\mathcal{B}_{it}| = 0. \end{cases} \tag{10}$$

4.6 Estimation Sample and Variable Definitions

Monetary variables are deflated to 2025 dollars (CPI-U) before constructing ratios and log outcomes. Appendix Table D2 maps each estimation design to its sample period, filters, and fixed-effect and clustering conventions. Baseline FBUI regressions use institution-quarter observations with agricultural (or category-specific) loan share above 10% for commercial banks and credit unions. For FCS institutions, where agricultural concentration is near-universal and specialization differs by loan type, we apply outcome-specific lower-tail share cutoffs in the estimation files. Across institution-level regressions, we require at least 20 quarterly observations per institution. The main outcomes are loan amount, portfolio share, loan count, and average loan size; controls include lagged log total assets, lagged equity-to-assets, lagged delinquent loan ratio, and lagged allowance-to-loans.

5 Farm Bill Uncertainty and Credit Supply

This section examines how Farm Bill uncertainty affects agricultural lending in panel data that, depending on lender type and outcome, span 1990:Q1–2025:Q4. To align frequencies, we aggregate the monthly Farm Bill Uncertainty Index to the quarterly level using within-quarter averages and then rescale the series to the $[0, 1]$ interval. We estimate the following specification:

$$y_{ist} = \beta \, \mathrm{FBUI}_t \, + \mathbf{X}'_{ist}\boldsymbol{\theta} + \mu_i + \lambda_q + \lambda_y + \varepsilon_{ist}, \tag{11}$$

where y_{ist} denotes the lending outcome for institution i in state s and quarter t. For amount, count, and average-size outcomes, y_{ist} is in logs; for portfolio-share outcomes, y_{ist} is in percentage points. The vector $\mathbf{X}_{ist}$ includes institution-level balance-sheet controls, all lagged by one quarter: log total assets, the equity-to-assets ratio, the delinquent loan ratio, and the allowance-to-loans ratio. We also include the VIX index to control for broad financial-market uncertainty. Institution fixed effects μ_i absorb time-invariant differences across lenders, while quarter-of-year fixed effects λ_q and year fixed effects λ_y capture seasonal and annual shocks. The coefficient β captures how changes in national Farm Bill uncertainty affect agricultural lending.

Because FBUI is a national shock, the baseline specification primarily captures average lender responses to aggregate Farm Bill uncertainty. As a result, the estimates may reflect both supply-side adjustments and changes in credit demand driven by local farm conditions. To address this, the exposure-weighted specification in Section 6 exploits cross-sectional differences in predetermined local exposure to Farm Bill programs. By interacting a common national shock with institution-specific exposure, this design sharpens identification and helps isolate supply-side responses to policy uncertainty from local demand variation, which may differ across states.

Standard errors are two-way clustered by state and year–quarter. Sample filters and panel-inclusion rules follow the definitions in Section 4. We estimate the specification for four main outcomes: loan amount, portfolio share, loan count, and average loan size. Because data availability differs across lender types, we do not pool commercial banks, credit unions, and FCS institutions in a single regression. Instead, we estimate the model separately by lender type, allowing each set of regressions to use the longest feasible sample period supported by the underlying data.

Table 3 reports the baseline estimates of the effect of Farm Bill uncertainty on agricultural lending. Overall, higher uncertainty is associated with a contraction in credit supply, although the magnitude and composition of the response vary across lender types. For Farm Credit System institutions, the estimated coefficient is negative and statistically significant for production-loan amounts; the farmland amount estimate is small and statistically insignificant; and the total-agricultural amount estimate is statistically significant but economically small in magnitude. Commercial banks exhibit negative and statistically significant semi-elasticities across all three amount outcomes. For commercial banks, the coefficient on log(total agricultural loan amount) is -0.037, implying that a 0.10 increase in FBUI is associated with about a 0.37% decline in agricultural loan amount. Credit unions also show sizable and statistically significant declines in production, farmland, and total agricultural loan amounts. Appendix C.2 shows that these baseline patterns remain very similar after adding annual state-level demand controls for net farm income, crop cash receipts, and government payments.

This heterogeneity across lender types also helps distinguish supply from demand. A purely demand-driven explanation would predict broadly similar responses across lenders operating in the same local agricultural markets. Instead, we find substantially stronger responses for commercial banks than for the Farm Credit System, with credit-union responses less systematic. This pattern is more consistent with a supply-side channel, in which lender-specific mandates, funding structures, and adjustment frictions shape the response to Farm Bill uncertainty.

Appendix Section C.1 reports additional commercial-bank checks for broad agricultural-news volume, source composition, and moving-average timing windows. The article-volume and source-composition checks strongly support the central national finding: higher FBUI is associated with lower commercial-bank agricultural lending across loan amounts, loan counts, and average loan sizes, with production and aggregate loan shares also declining. The moving-average checks are more selective but still informative: the 2-quarter moving-average amount estimates are negative in all three categories and statistically significant for farmland and aggregate agricultural lending, while count estimates remain negative for production and aggregate lending across both 2-quarter and 4-quarter windows. The article-volume control is especially demanding because it absorbs general agricultural-news attention rather than only Farm Bill coverage, yet the commercial-bank loan-amount coefficients remain negative and statistically significant across production, farmland, and aggregate agricultural lending.

Panel B of Table 3 further clarifies these responses for commercial banks and credit unions by examining loan shares. For commercial banks, production and total agricultural loan shares decline significantly as FBUI rises, while the farmland-share estimate is close to zero and statistically insignificant. For credit unions, production and total agricultural shares also fall significantly, but the farmland-share estimate is imprecise. Taken together, these results suggest that outside the FCS, uncertainty reduces both lending volumes and, in key categories, portfolio exposure to agriculture.[2]

To distinguish between extensive- and intensive-margin adjustments, Table 4 examines the effects of Farm Bill uncertainty on loan counts and average loan sizes. For FCS institutions, higher uncertainty is associated with a statistically significant decline in the number of total agricultural loans and a significant increase in average loan size, suggesting contraction primarily on the extensive margin. Commercial banks also show strong extensive-margin adjustment: production, farmland, and total agricultural loan counts all decline significantly. Average loan-size effects for banks are also negative and statistically

[2]For FCS institutions, agricultural lending accounts for nearly all lending activity, and individual institutions often specialize in either production or farmland lending. As a result, portfolio-share regressions provide limited additional variation and are therefore omitted.

significant across production, farmland, and total agricultural categories; for farmland and total agricultural lending these effects are considerably smaller in magnitude than the corresponding count effects, while for production loans the two margins are of comparable size. This pattern indicates that, for banks, the contraction operates on both margins, with the extensive margin dominating outside of production lending.

Credit unions display the strongest extensive-margin response. A higher FBUI is associated with a large and highly significant decline in the number of production loans and total agricultural loans, while the estimated decline in farmland loan counts is negative but imprecisely estimated. At the same time, average loan sizes for credit unions do not respond significantly to uncertainty in any loan category. Taken together, these results indicate that credit unions respond to Farm Bill uncertainty primarily by extending fewer loans, rather than by changing the size of the loans that remain outstanding.

Additional evidence from commercial bank lending by loan-size bucket (Table D3) provides a more granular view of how uncertainty reshapes agricultural credit. For production loans, higher uncertainty is associated with significant declines in loan amounts and loan counts across all three size buckets, with a negative average-size effect concentrated in the $250,000–$500,000 bucket. For farmland loans, the pattern is weaker in amounts but still contractionary: amount effects are insignificant in the smallest bucket and negative in the middle and largest buckets, while counts decline significantly across all three buckets. Average farmland loan size moves only modestly (slightly positive in the smallest bucket and slightly negative in the largest bucket). Overall, these results point to broad extensive-margin tightening, especially for production lending.

Finally, we compare the BERT-based FBUI with a traditional keyword-based measure. As shown in Table A6, the keyword-based index produces mixed and difficult-to-interpret results across lender types. For the FCS, the production and farmland coefficients are positive but statistically insignificant, while the total-agricultural coefficient is positive and statistically significant. For commercial banks, only farmland lending is significantly negative. For credit unions, the keyword index implies a positive and significant production-loan coefficient but a negative and significant total-agricultural coefficient. These mixed signs contrast with the more coherent contractionary pattern from the BERT-based FBUI.

By contrast, the BERT-based FBUI delivers more consistent and economically interpretable contractionary effects, especially for commercial banks. This comparison illustrates the limitations of keyword-based approaches, which can conflate general Farm Bill coverage with genuine legislative uncertainty, and highlights the value of a context-sensitive measure for isolating policy uncertainty shocks. These lender-level results motivate the next section, which examines whether the effects of Farm Bill uncertainty are amplified in areas with greater exposure to Farm Bill-related support programs.

6 Geographic Exposure and the Transmission of Policy Uncertainty

To examine geographic heterogeneity in the transmission of Farm Bill uncertainty, we use the institution-level exposure measure constructed in Section 4, which captures persistent local dependence on Farm Bill-related support.

Let i index institutions and t quarters, and let EXPO_{it} denote the resulting institution-level exposure measure. We construct the interaction term

$$\mathrm{FBEP}_{it} = \mathrm{EXPO}_{it} \times \mathrm{FBUI}_t.$$

For each lender type, we estimate

$$y_{it} = \beta\, \mathrm{FBEP}_{it} + \mathbf{X}_{it}'\boldsymbol{\theta} + \mu_i + \lambda_t + \varepsilon_{it}, \tag{12}$$

where y_{it} denotes the lending outcome for institution i in quarter t. For loan amount, loan count, and average loan size, y_{it} is in logs. For portfolio-share, it is measured in percentage points. The vector $\mathbf{X}_{it}$ contains institution-level controls, while μ_i and λ_t denote institution and year-quarter fixed effects. Because FBUI_t is common across institutions, its main effect is absorbed by the year-quarter fixed effects. The coefficient β therefore captures whether institutions with greater exposure respond more strongly when national Farm Bill uncertainty rises.

Identification in Equation (12) comes from differential responses across institutions with different exposure to a common national policy shock. This design helps distinguish supply-side responses to Farm Bill uncertainty from local demand shocks. Although farm income, liquidity, and solvency may vary across states and affect credit demand, these factors would need to be systematically correlated with both national Farm Bill uncertainty and our institution-level exposure measure to bias the interaction estimates. This is less likely because FBUI captures national legislative uncertainty, whereas EXPO_{it} is based on pre-period measures of state dependence on Farm Bill support and then mapped to lenders through their geographic footprint. As shown below, the response also differs substantially across lender types, which is harder to reconcile with a purely demand-driven explanation.

We estimate this specification separately for loan amounts, portfolio shares, loan counts, and average loan size. In the preferred specification, we exclude North Dakota credit unions as a sample-homogeneity restriction because that state has a distinct policy-credit environment that can generate outlier credit-union dynamics. The full-sample estimates (including North Dakota) are reported in Appendix C.3.

The results in Table 5 show that the transmission of Farm Bill uncertainty varies systematically with lender exposure, although the pattern differs across institution types. In Panel A, the interaction terms for the FCS are small and mostly statistically insignificant, with only a marginally positive farmland-loan estimate, suggesting limited within-FCS heterogeneity in loan amounts across high- and low-exposure areas once institution and year–quarter fixed effects are included. Commercial banks, by contrast, exhibit significantly stronger contractions in more exposed markets, especially for farmland loans and total agricultural lending. The interaction coefficient is -0.173 for farmland loans, statistically significant at the 1% level, and -0.068 for aggregate agricultural lending, significant at the 10% level, while the estimate for production loans is small and insignificant. For commercial banks, the coefficient on log(total agricultural loan amount) implies that a 0.10 increase in exposure-weighted uncertainty is associated with about a 0.68% decline in agricultural loan amount. Credit unions no longer display a negative pattern: all interaction terms are statistically insignificant, indicating no clear heterogeneity in loan amounts by exposure. Appendix C.2 and Appendix Section C.1 report demand-control, source-composition, and regional checks for the exposure specifications.

The appendix checks reinforce this commercial-bank exposure pattern. The exposure-weighted average-size results remain negative after source-composition controls, and the farmland and aggregate effects remain negative for the main share and average-size margins after adding state-year farm-income demand controls or pre-period regional principal-component interactions. We therefore view the exposure-weighted results as strong reduced-form evidence that Farm Bill uncertainty is transmitted most clearly through commercial-bank lending decisions in more Farm-Bill-exposed markets.

Panel B shows that these heterogeneous responses are also reflected in portfolio composition. For commercial banks, the interaction terms are significantly negative for farmland and total agricultural loan shares, while the production-share estimate is negative but not statistically significant. For credit unions, all loan-share coefficients are imprecisely estimated and statistically insignificant, providing no evidence of systematic heterogeneity in portfolio composition across more and less exposed markets. Taken together, these results suggest that geographic exposure amplifies retrenchment among commercial banks, while generating comparatively little cross-sectional heterogeneity within either the FCS or the credit union sector.

An interesting feature of Table 5 is that the strongest exposure-weighted effects appear for farmland lending rather than production lending. This pattern differs from the baseline FBUI results in Section 5, where production credit exhibits a clear contraction in response to aggregate uncertainty. One interpretation is that the exposure measure captures a different transmission mechanism. Because EXPO reflects long-run dependence on Farm Bill support, the interaction term may proxy for uncertainty regarding future policy-supported profitability that is capitalized into farmland values. Commercial banks operating in highly exposed regions may therefore respond by tightening land-secured lending, even when short-run production-credit effects are less heterogeneous across regions. In this interpretation, aggregate uncertainty primarily affects operating cash-flow risk, whereas exposure-weighted uncertainty amplifies collateral-value concerns.

The exposure-weighted results in Table 6 show that the adjustment does not operate as a uniform contraction across all margins. In Panel A, the interaction term for the Farm Credit System is statistically insignificant, providing little evidence that exposure-weighted Farm Bill uncertainty affects the number of agricultural loans in the FCS. Credit unions also show no systematic extensive-margin response, with statistically insignificant coefficients across loan categories. Commercial banks, however, display a different pattern: production-loan counts increase modestly in more exposed markets, and total agricultural loan counts are also positive and marginally significant, while farmland loan counts are small and imprecisely estimated.

Panel B shows that the more pronounced adjustment for commercial banks occurs along the intensive margin. Exposure-weighted uncertainty is associated with significantly smaller farmland and total agricultural loans, while the effect on production-loan size is statistically insignificant. In contrast, the FCS and credit-union estimates for average loan size are imprecisely estimated across categories.

Taken together, these results suggest that commercial banks in more exposed markets respond to Farm Bill uncertainty by resizing and restructuring agricultural credit rather than simply reducing the number of loans. Banks may limit exposure per borrower, tighten loan-size limits, or divide credit into smaller commitments while maintaining lending relationships with agricultural clients. The strongest intensive-margin effects appear in farmland and total agricultural lending, consistent with the collateral-value channel discussed in Section 3. Thus, the exposure-weighted evidence is best interpreted as a reallocation of credit structure in high-exposure markets, rather than as a uniform lending contraction. Appendix Section C.1 further reports source-composition, demand-control, and regional-characteristic checks for these exposure-weighted margins. The next section examines whether these lending responses reverse following Farm Bill enactment using event-study and stacked difference-in-differences designs.

7 Credit Responses to Farm Bill Enactment

This section examines how agricultural credit responds when Farm Bill uncertainty is resolved. We focus on the 2008, 2014, and 2018 Farm Bill episodes and track lending dynamics around each episode-specific resolution quarter. Because these episodes occurred under distinct macro-financial conditions, we treat them as repeated policy episodes and then pool them in a stacked design to improve precision and comparability.

To keep the empirical design aligned with our strongest institutional results and comparable loan definitions, we restrict this section to commercial banks. The key identifying variation is whether banks with larger exposure-weighted declines in Farm Bill uncertainty expand lending more after policy resolution.

The identifying comparison is between higher- and lower-ΔFBEP banks within the stacked bank-episode design, after absorbing bank-episode stack effects and calendar-quarter shocks. This design uses repeated Farm Bill resolutions to test whether banks facing larger effective uncertainty declines expand lending more after enactment.

Inference is aligned with the level of identifying variation in each design. In Sections 5 and 6, we use multi-way clustering that matches common national shocks and panel dependence. In this stacked design, treatment variation is episode-specific and repeated within bank-episode cohorts, so the baseline stacked specification clusters by stack ID, where a stack ID denotes a bank's appearance in a specific Farm Bill episode window rather than one of the three aggregate Farm Bill episodes. Single-episode models cluster by institution ID because no stack dimension is present.

7.1 Empirical Design and Stacked DID Specification

We construct event windows around each Farm Bill episode, indexing time relative to the episode-specific resolution quarter using a relative-quarter indicator relative $\text{quarter}_t^{(b)}$. Stacking the three episodes yields a panel in which a bank may appear up to three times, once for each Farm Bill episode, with each appearance tied to a distinct bank-episode stack and event-time position. The dependent variable is log(agricultural loan amount).

Figure 2 shows that the stacked event windows capture a sharp uncertainty-resolution pattern: average FBUI is elevated before resolution, drops at relative quarter 0, and remains lower in post-resolution quarters.

In the stacked design, we measure the resolution of uncertainty in episode b by the decline in FBUI between the pre- and post-resolution portions of the event window:

$$\Delta\text{FBUI}^{(b)} = \overline{\text{FBUI}}^{(b)}_{\text{pre}} - \overline{\text{FBUI}}^{(b)}_{\text{post}}.$$

$$\Delta\text{FBEP}^{(b)}_{it} = \text{EXPO}_{it} \times \Delta\text{FBUI}^{(b)}.$$

For brevity, the tables label this episode-specific term ΔFBEP. Higher values of $\Delta\text{FBEP}^{(b)}_{it}$ indicate bank-quarters whose local agricultural markets are more exposed to Farm Bill programs and therefore experience a larger effective reduction in policy uncertainty when uncertainty is resolved. Within each event window, $\Delta\text{FBUI}^{(b)}$ is common across banks, so identification comes from differential lending responses before and after resolution across banks with larger versus smaller exposure-weighted uncertainty declines.

Our baseline stacked Difference-in-Differences (DID) specification is

$$\log L^{(b)}_{it} = \beta(\text{post}^{(b)}_t \times \Delta\text{FBEP}^{(b)}_{it}) + \mathbf{X}'_{it}\boldsymbol{\theta} + \lambda_{\text{stack}} + \lambda_{yq} + \varepsilon^{(b)}_{it}, \tag{13}$$

where $L^{(b)}_{it}$ denotes agricultural loan amount by bank i in quarter t during episode b, and

$\text{post}_t^{(b)}$ is an indicator for post-resolution quarters. The vector $\mathbf{X}_{it}$ contains bank-level controls, while λ_{stack} and λ_{yq} denote stack and calendar-quarter fixed effects. The coefficient β measures whether agricultural lending expands more after uncertainty resolution for banks that experience larger exposure-weighted declines in Farm Bill uncertainty.

To trace dynamic responses around resolution, we also estimate a stacked event-study specification:

$$\log L_{it}^{(b)} = \sum_{\substack{\tau=-4 \\ \tau\neq-1}}^{3} \gamma_\tau \, \mathbf{1}\Big\{\text{relative quarter}_t^{(b)} = \tau\Big\} \times \Delta\text{FBEP}_{it}^{(b)} + \mathbf{X}_{it}'\boldsymbol{\theta} + \lambda_{\text{stack}} + \lambda_{yq} + \zeta_{it}^{(b)}, \quad (14)$$

with relative quarter -1 omitted as the reference period. The coefficients γ_τ describe how lending by more exposed banks evolves relative to less exposed banks at each event-time horizon. Standard errors are clustered by institution ID in single-episode models and by stack ID in the stacked model. Appendix C.4 shows that the stacked DID inference is stable under alternative clustering choices.

7.2 Evidence from Single and Pooled Farm Bill Episodes

Table D4 reports single-episode estimates. The DID results remain heterogeneous across episodes: the post-resolution coefficient is negative and statistically insignificant for the 2008 episode, and positive and statistically significant for both 2014 and 2018. The single-episode event studies (Figure D1) also show substantial cross-episode variation, with the clearest and most persistent post-resolution expansion in 2014. Importantly, Table C10 shows that the single-episode joint lead tests reject the null of zero pre-resolution coefficients in all three episodes, consistent with heterogeneous anticipatory dynamics and episode-specific confounding conditions. We therefore treat single-episode estimates as descriptive evidence only. Our identifying interpretation relies on the stacked DID/event-study design that pools episodes, absorbs stack and calendar-quarter fixed effects, and delivers a non-rejected stacked pre-trend with stable post-resolution effects.

Pooling the episodes yields clearer evidence, as shown in Table 7. In the stacked

DID specification, the interaction between the post-resolution indicator and the exposure-weighted uncertainty decline is positive and statistically significant ($\beta = 0.0750$). Under the maintained identifying assumptions, this estimate implies that a 0.10 larger ΔFBEP is associated with about a 0.75% larger post-resolution increase in agricultural loan amount for commercial banks. The stacked event study (Figure 3) shows a consistent post-resolution expansion: relative to the quarter immediately before resolution, the coefficients are positive and statistically significant at relative quarters 0, 1, 2, and 3. By contrast, pre-resolution coefficients at relative quarters -4, -3, and -2 are small and statistically insignificant, and the joint pre-trend test in the stacked model is not rejected (Table C10).

The stacked event study also points to a persistent recovery path within the estimated horizon. Lending rises on impact at resolution and remains elevated through relative quarter 3. Appendix C.4 further shows that this pattern is robust to alternative clustering assumptions, alternative event windows, and multiple-testing adjustments. Taken together, these results are consistent with a meaningful post-resolution differential lending expansion for more exposed banks.

8 Conclusions

This paper develops a new measure of Farm Bill uncertainty and demonstrates that it has first-order effects on agricultural credit markets. We make three main contributions to the literature on policy uncertainty and financial intermediation. First, we introduce the Farm Bill Uncertainty Index (FBUI), a text-based measure constructed using a two-stage BERT classifier that identifies Farm Bill–related reporting and isolates language conveying legislative uncertainty. By exploiting semantic context rather than simple keyword counts, the FBUI aligns closely with actual Farm Bill negotiation cycles, exhibits sharp spikes during periods of extended legislative gridlock, and declines sharply following enactment. This index substantially reduces the misclassification common in traditional keyword approaches and provides a targeted, scalable measure of policy risk in a setting where uncertainty is institutionally central yet historically difficult to observe.

Second, we show that Farm Bill uncertainty has meaningful effects on agricultural lending. Higher FBUI is linked to lower loan amounts, with the clearest and most consistent declines appearing for commercial banks and sizable contractions also appearing for credit unions in baseline specifications. Margin decomposition indicates that banks and credit unions adjust mainly on the extensive margin by issuing fewer loans, while the FCS pattern is more consistent with fewer total loans alongside larger average loan size. Overall, these patterns point to a real supply-side response to policy risk that changes both the amount and composition of agricultural credit.

Third, we find that these effects vary with local exposure to Farm Bill programs, although the strength of the pattern differs across lenders. Using the EXPO measure defined in Section 4, we show that commercial banks in more exposed areas adjust the structure of agricultural credit when uncertainty rises, with especially strong effects on farmland and aggregate loan amounts and average loan size. Around the 2008, 2014, and 2018 Farm Bill episodes, the stacked DID and event-study results for commercial banks show that lending rises more after uncertainty is resolved for banks with larger exposure-weighted declines in uncertainty. Under the identifying assumptions stated in Section 7, this pattern is most consistent with a supply-side channel, especially for commercial banks, rather than a short-lived movement in credit demand.

The results carry significant policy implications. Legislative delays, repeated extensions, and political standoffs surrounding Farm Bill reauthorization impose real costs on agricultural credit markets, particularly in high-exposure regions and for risk-sensitive loan categories. More predictable legislative timelines, clearer signals about program continuity, and institutional features that reduce last-minute uncertainty could help stabilize credit provision during reauthorization cycles. For regulators and lenders, the findings suggest that Farm Bill cycles and associated uncertainty merit explicit consideration in risk management and stress testing, especially for institutions with concentrated agricultural portfolios.

While this analysis establishes a clear link between policy risk and credit supply, it also has limitations. The FBUI captures uncertainty as reflected in media coverage, meaning it reflects perceptions of legislative risk rather than the full distribution of potential policy outcomes. The duplicate-publication audit suggests that exact duplicate articles are not a material concern in the corpus, and the appendix robustness checks address article volume, source composition, timing-window, demand-control, and regional-confounding concerns. Additionally, while our results point strongly to supply-side mechanisms, disentangling supply from demand at the farm level remains an important avenue for future work. Linking loan data to farm-level balance sheets, extending the framework to other policy domains, or embedding policy uncertainty into structural models of agricultural investment and credit would further clarify how legislative risk shapes rural financial stability.

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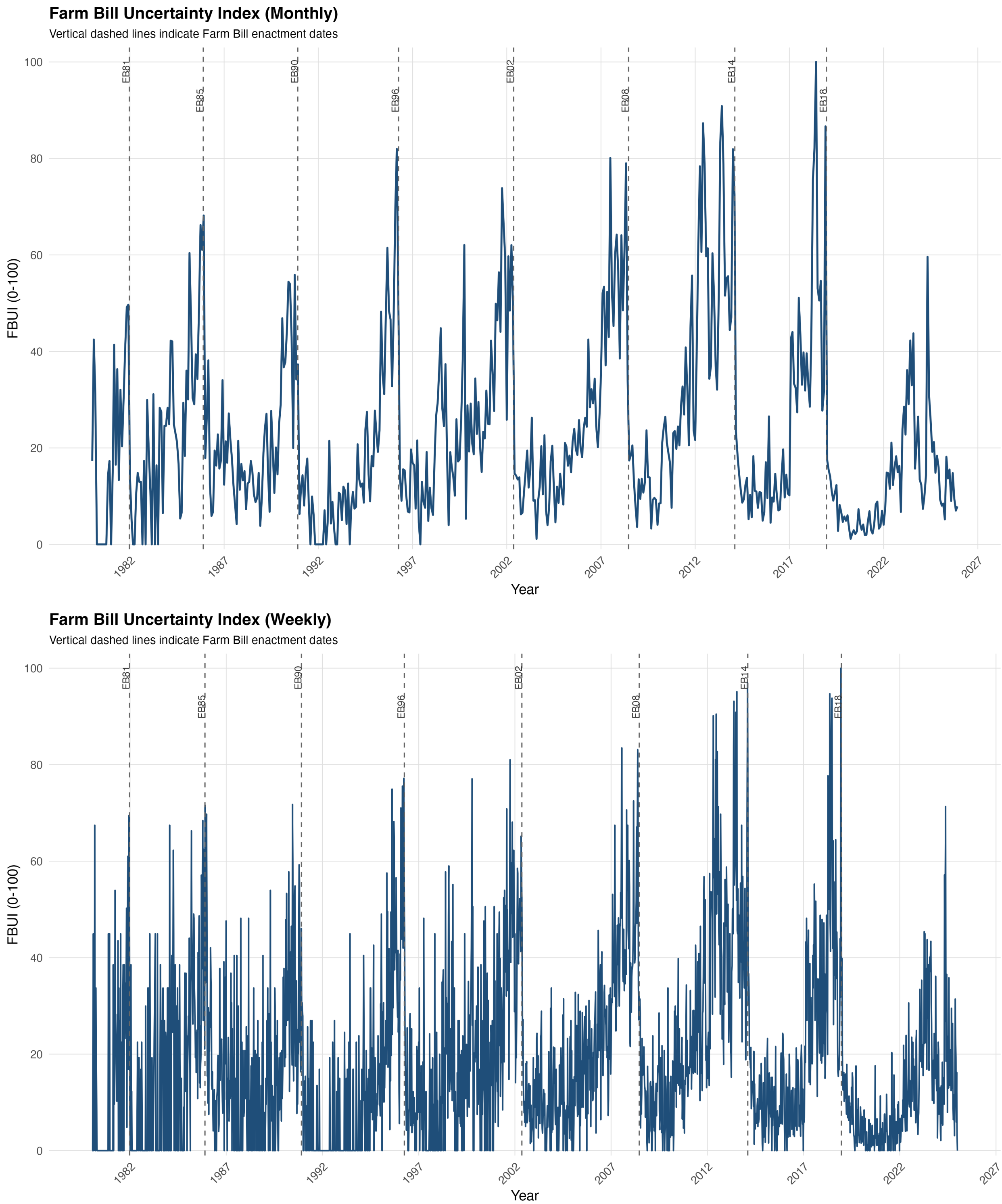


Figure 1: Farm Bill Uncertainty Index (FBUI), Monthly (Upper) and Weekly (Lower), Jan. 1980–Dec. 2025

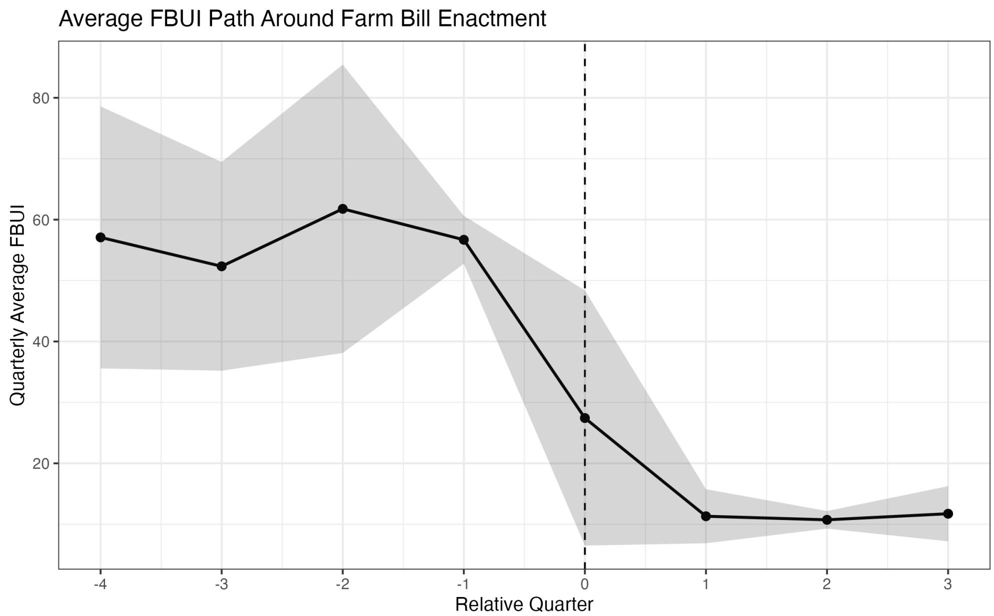


Figure 2: Average FBUI path around episode-specific resolution quarters

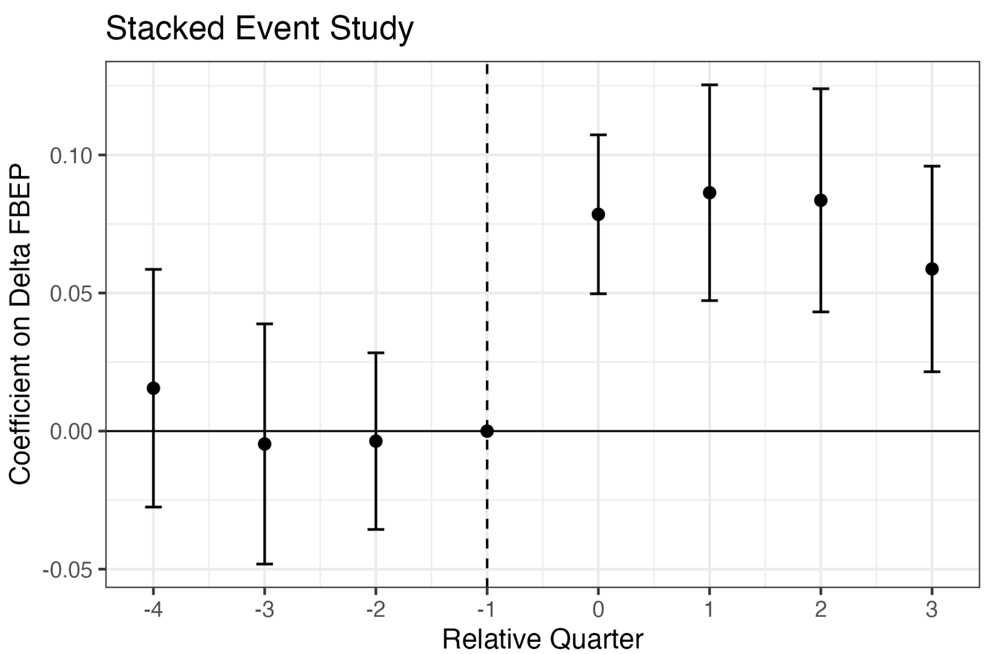


Figure 3: Stacked event-study estimates of exposure effects on log(Ag loans) around Farm Bill enactment.

Notes: Points plot the event-time interaction coefficients from the stacked event-study specification, with relative quarter -1 as the omitted quarter. Vertical bars denote 95% confidence intervals.

Table 1: Timeline of Farm Bills, Key Policies, Expected Expiration, and Extensions

Time Enacted	Title	Major Policies	Expected Expiration	Actual Passage of Next Farm Bill	Extensions
December 22, 1981	Agriculture and Food Act	Reduced price supports; expanded export loan programs; continued support for program crops and dairy.	Sept. 30, 1985	Dec. 23, 1985	None
December 23, 1985	Food Security Act	Established the Conservation Reserve Program (CRP); linked eligibility to conservation compliance; introduced export and dairy supply control programs.	Sept. 30, 1990	Nov. 28, 1990	None
November 28, 1990	Food, Agriculture, Conservation, and Trade (FACT) Act	Expanded CRP; strengthened environmental compliance; expanded export promotion programs.	Sept. 30, 1995	Apr. 4, 1996	Short extension (Oct 1995–Apr 1996)
April 4, 1996	Federal Agriculture Improvement and Reform (FAIR) Act	Replaced price supports with fixed payments; expanded planting flexibility; eliminated acreage reduction programs.	Sept. 30, 2002	May 13, 2002	None
May 13, 2002	Farm Security and Rural Investment (FSRI) Act	Introduced countercyclical payments; expanded conservation; supported renewable energy; increased rural development and nutrition spending.	Sept. 30, 2007	June 18, 2008	Multiple short extensions (2007–2008)
June 18, 2008	Food, Conservation, and Energy Act (FCEA)	Created the ACRE revenue support program; expanded conservation and energy programs; strengthened SNAP benefits.	Sept. 30, 2012	Feb. 7, 2014	One-year extension (2013)
February 7, 2014	Agricultural Act	Eliminated direct payments; introduced Price Loss Coverage (PLC) and Agricultural Risk Coverage (ARC); consolidated conservation programs; expanded crop insurance.	Sept. 30, 2018	Dec. 20, 2018	Short extension (Oct–Dec 2018)
December 20, 2018	Agricultural Improvement Act	Continued PLC and ARC; legalized hemp; expanded conservation and energy programs; preserved SNAP benefits.	Sept. 30, 2023	Pending (authorities extended through Sept. 30, 2026)	Multiple extensions (2023–2026)

Notes: CRP = Conservation Reserve Program. FACT = Food, Agriculture, Conservation, and Trade Act. FAIR = Federal Agriculture Improvement and Reform Act. FSRI = Farm Security and Rural Investment Act. FCEA = Food, Conservation, and Energy Act. SNAP = Supplemental Nutrition Assistance Program. ACRE = Average Crop Revenue Election program. PLC = Price Loss Coverage program. ARC = Agricultural Risk Coverage program. "Extensions" refers to temporary legislative measures enacted when Congress did not complete reauthorization before the Farm Bill's scheduled expiration. The status of the 2018 Farm Bill row reflects extensions in effect as of June 2026 (U.S. Congress, 2026; U.S. Department of Agriculture, Natural Resources Conservation Service, 2026).

Table 2: Summary Statistics of Agricultural Lending by Institution Type

	Commercial Bank	Credit Union	Farm Credit System
Panel A: Loan amounts (million $)			
Total agricultural loans	37.2 (97.0)	43.4 (93.3)	2,493.7 (4,510.3)
Production and operating loans	19.0 (58.9)	25.1 (37.6)	725.4 (1,271.7)
Farmland loans	18.1 (49.7)	38.3 (92.6)	1,768.3 (3,324.7)
Panel B: Number of loans			
Total agricultural loans	310 (2,795)	302 (412)	12,695 (26,390)
Production and operating loans	227 (2,780)	218 (283)	—
Farmland loans	83 (154)	124 (223)	—
Panel C: Loan size (thousand $)			
Total agricultural loans	102.1 (41.1)	129.0 (106.8)	253.4 (161.7)
Production and operating loans	72.9 (39.4)	115.6 (107.9)	—
Farmland loans	160.2 (54.4)	233.8 (98.4)	—
Panel D: Control variables (million $)			
Total assets	216.9 (609.1)	185.9 (316.9)	3,235.5 (6,174.0)
Total loans	135.2 (425.6)	131.6 (238.4)	3,013.5 (5,677.6)
Total equity	22.4 (68.1)	23.4 (41.0)	585.3 (1,091.0)
Total delinquency loans	1.030 (4.789)	1.354 (2.541)	25.276 (52.023)
Allowance for loan and lease losses	2.026 (8.784)	1.099 (1.893)	14.169 (26.429)

Notes: Entries report institution-level summary statistics. The sample includes institution-quarters from 1990 onward with agricultural-loan share above 10%. For the Farm Credit System, we retain association-level lenders in the main FCS panel.
Values are shown as mean (standard deviation) within each institution type and variable.
Large standard deviations reflect the skewed lender-size distribution; main regressions use log outcomes and institution fixed effects to absorb persistent scale differences.
"—" indicates that the variable is unavailable for that institution type.

Table 3: Effects of FBUI on Agricultural Loan Amounts and Ratios

	Production Loan	Farmland Loan	Agricultural Loan
Panel A: Dependent variable = log(*loan amount*)			
FBUI × FCS	-0.015^{***}	0.005	-0.006^{**}
	(0.003)	(0.005)	(0.002)
FBUI × Bank	-0.044^{**}	-0.025^{**}	-0.037^{**}
	(0.020)	(0.010)	(0.016)
FBUI × CU	-0.084^{***}	-0.035^{**}	-0.054^{***}
	(0.010)	(0.015)	(0.012)
Panel B: Dependent variable = Loan Ratio (percentage points)			
	Production Loan Ratio	Farmland Loan Ratio	Agricultural Loan Ratio
FBUI × Bank	-0.203^{*}	0.025	-0.194^{***}
	(0.105)	(0.032)	(0.045)
FBUI × CU	-1.455^{***}	-0.616	-2.355^{***}
	(0.375)	(0.378)	(0.559)
FCS Observations	3,917	3,941	3,922
Bank Observations	280,425	260,256	421,405
CU Observations	1,856	1,906	5,425
FCS Institutions	73	78	78
Bank Institutions	3,609	3,341	5,028
CU Institutions	40	38	70

Fixed effects: Institution (ID), year, and quarter-of-year.
Std. errors: Two-way clustered by state and year–quarter.

Notes: Panel A reports FBUI regressions with dependent variable log(loan amount). Panel B reports FBUI regressions with dependent variable in percentage points (Bank and CU only). Each institution row reports the FBUI coefficient from a separate regression estimated on that institution's sample. In all columns, FBUI is scaled to $[0, 1]$, and controls are lagged equity-to-assets, lagged allowance-to-loans, lagged log total assets, lagged delinquent loan ratio, and quarterly average VIX. All models include institution, year, and quarter fixed effects.
Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4: Effects of FBUI on Agricultural Loan Counts and Average Loan Size

	Production Loan	Farmland Loan	Agricultural Loan
Panel A: Dependent variable = log(*number of loans*)			
FBUI × FCS	—	—	-0.025^{***}
			(0.005)
FBUI × Bank	-0.023^{***}	-0.014^{***}	-0.025^{***}
	(0.007)	(0.002)	(0.003)
FBUI × CU	-0.067^{***}	-0.038	-0.081^{***}
	(0.015)	(0.022)	(0.016)
Panel B: Dependent variable = log(*average loan size*)			
FBUI × FCS	—	—	0.019^{***}
			(0.002)
FBUI × Bank	-0.028^{**}	-0.003^{**}	-0.007^{***}
	(0.012)	(0.001)	(0.001)
FBUI × CU	-0.017	0.003	0.027
	(0.019)	(0.018)	(0.019)
FCS Observations	—	—	3,922
Bank Observations	67,760	84,514	117,630
CU Observations	1,856	1,906	5,425
FCS Institutions	—	—	78
Bank Institutions	1,472	1,875	2,473
CU Institutions	40	38	70

Fixed effects: Institution (ID), year, quarter-of-year.
Std. errors: Two-way clustered by state and year–quarter.

Notes: Panel A reports FBUI regressions with dependent variable log(number of loans). Panel B reports FBUI regressions with dependent variable log(average loan size). Each institution row reports the FBUI coefficient from a separate regression estimated on that institution's sample. In all columns, FBUI is scaled to $[0, 1]$, and controls are lagged equity-to-assets, lagged allowance-to-loans, lagged log total assets, lagged delinquent loan ratio, and quarterly average VIX. All models include institution, year, and quarter fixed effects.
FCS coefficients in production/farmland columns are unavailable where those outcomes are not estimated.
Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5: Effects of Exposure-Weighted FBUI on Agricultural Loan Amounts and Ratios (2005–2025)

	Production Loan	Farmland Loan	Agricultural Loan
Panel A: Dependent variable = log(*loan amount*)			
FBEP × FCS	0.065	0.080*	0.057
	(0.095)	(0.047)	(0.037)
FBEP × Bank	0.015	−0.173***	−0.068*
	(0.052)	(0.058)	(0.039)
FBEP × CU	−0.097	0.208	0.163
	(0.233)	(0.287)	(0.155)
Panel B: Dependent variable = loan ratio (percentage points)			
FBEP × Bank	−0.744	−3.449***	−2.531**
	(1.242)	(1.048)	(1.102)
FBEP × CU	−5.993	3.187	−1.250
	(6.244)	(7.133)	(5.630)
FCS Observations	3,917	3,941	3,922
Bank Observations	110,370	136,786	189,159
CU Observations	1,198	1,321	2,874
FCS Institutions	73	78	78
Bank Institutions	1,805	2,275	2,962
CU Institutions	27	27	47

Fixed effects: Institution (ID), year–quarter.
Std. errors: Two-way clustered by ID and year–quarter.

Notes: FBEP denotes lender-specific exposure-weighted FBUI, where both exposure and FBUI are scaled to $[0, 1]$. Panel A reports semi-elasticities for log(loan amount); Panel B reports effects on loan ratios in percentage points (Bank/CU only). Each institution row reports the FBEP coefficient from a separate regression estimated on that institution's sample. Specifications include institution and year–quarter fixed effects, with two-way clustering by institution and year–quarter; controls are lagged equity-to-assets, lagged allowance-to-loans, lagged log total assets, and lagged delinquent loan ratio.
Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6: Effects of Exposure-Weighted FBUI on Loan Counts and Average Loan Size (2005–2025)

	Production Loan	Farmland Loan	Agricultural Loan
Panel A: Dependent variable = log(*number of loans*)			
FBEP × FCS	—	—	0.086
			(0.093)
FBEP × Bank	0.102*	0.039	0.078*
	(0.053)	(0.042)	(0.044)
FBEP × CU	−0.213	0.246	0.130
	(0.381)	(0.286)	(0.238)
Panel B: Dependent variable = log(*average loan size*)			
FBEP × FCS	—	—	−0.029
			(0.089)
FBEP × Bank	−0.061	−0.230***	−0.165**
	(0.055)	(0.080)	(0.063)
FBEP × CU	0.116	−0.038	0.033
	(0.286)	(0.192)	(0.162)
FCS Observations	—	—	3,922
Bank Observations	58,739	76,391	103,832
CU Observations	1,198	1,321	2,874
FCS Institutions	—	—	78
Bank Institutions	1,379	1,802	2,358
CU Institutions	27	27	47

Fixed effects: Institution (ID), year–quarter.
Std. errors: Two-way clustered by ID and year–quarter.

Notes: FBEP denotes lender-specific exposure-weighted FBUI, where both exposure and FBUI are scaled to $[0, 1]$. Panel A reports effects on log(number of loans); Panel B reports effects on log(average loan size). Each institution row reports the FBEP coefficient from a separate regression estimated on that institution's sample. Specifications include institution and year–quarter fixed effects, with two-way clustering by institution and year–quarter; controls are lagged equity-to-assets, lagged allowance-to-loans, lagged log total assets, and lagged delinquent loan ratio.
FCS coefficients are omitted in production/farmland columns where those outcomes are not estimated in the corresponding EXPO count/size estimations.
Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 7: Stacked DID and Event-Study Estimates around the 2008, 2014, and 2018 Farm Bills

	DID	Event study
	(1)	(2)
Panel A: DID exposure effect		
Post $\times\Delta$FBEP	0.0750***	
	(0.0167)	
Panel B: Event-study exposure effects (baseline relative quarter $= -1$)		
Relative quarter $= -4$ $\times\Delta$FBEP		0.0155
		(0.0220)
Relative quarter $= -3$ $\times\Delta$FBEP		-0.0047
		(0.0222)
Relative quarter $= -2$ $\times\Delta$FBEP		-0.0036
		(0.0163)
Relative quarter $= 0$ $\times\Delta$FBEP		0.0785***
		(0.0147)
Relative quarter $= 1$ $\times\Delta$FBEP		0.0863***
		(0.0199)
Relative quarter $= 2$ $\times\Delta$FBEP		0.0836***
		(0.0206)
Relative quarter $= 3$ $\times\Delta$FBEP		0.0587***
		(0.0190)
Observations	54,200	54,200
R^2	0.9928	0.9928

Fixed effects: bank-episode stack ID and calendar quarter (yq).
Std. errors: One-way clustered by bank-episode stack ID.

Notes: Estimates pool the 2008, 2014, and 2018 Farm Bill episodes and are based on the commercial-bank sample only. The dependent variable is log(agricultural loan amount). Column (1) reports the stacked DID coefficient on post$\times\Delta$FBEP. Column (2) reports stacked event-study coefficients on relative-quarter interactions with ΔFBEP, omitting relative quarter -1 as the reference period.

Here, ΔFBEP is institution exposure multiplied by the episode-specific decline in FBUI from the pre-resolution window to the post-resolution window; models additionally control for lagged equity-to-assets, lagged allowance-to-loans, lagged log total assets, and lagged delinquent loan ratio.

A bank-episode stack ID denotes a bank's appearance in one Farm Bill episode window, so banks can contribute separate stacks across the 2008, 2014, and 2018 episodes.

Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendix

A Additional Details on FBUI Construction

This appendix provides expanded details on index construction, validation, and benchmarking for the Farm Bill Uncertainty Index (FBUI), complementing the main text in Section 4.

A.1 Corpus Retrieval and Cleaning Details

The ProQuest TDM Studio corpus initially contains 208,293 articles matching the keyword "farm bill" over 1980–2025. We apply two baseline filters: (i) retain only English-language U.S. news content, removing 8,663 records; and (ii) exclude non-news formats (for example, blogs, podcasts, scholarly journals, and theses), removing 43,210 records.

The cleaned corpus contains 156,420 articles from 1,861 publishers in 427 cities. Before aggregating article counts into the monthly and quarterly FBUI, we collapse repeated title–date–publication records identified in the duplicate-publication audit in Section 4. This removes the roughly 3.0% repeated title–date–publication entries from the index construction step. Table A1 summarizes the filtering process before this duplicate-record collapse.

Table A1: Corpus Filtering Summary

Description	Count
Initial keyword matches	208,293
Foreign-language documents removed	8,663
Non-news formats removed	43,210
Final corpus	156,420

Table A2 lists the ProQuest databases included in the keyword search.

Table A2: List of Databases for Keyword Search

Agricultural Science Collection
Agriculture Science Database
Agricultural & Environmental Science Collection
eLibrary
Environmental Science Collection
Environmental Science Database
ProQuest Historical Newspapers: Los Angeles Times
ProQuest One Business
ProQuest Historical Newspapers: The Chicago Tribune
ProQuest Historical Newspapers: The New York Times
ProQuest Historical Newspapers: The Wall Street Journal
ProQuest Historical Newspapers: The Washington Post
Technology Collection
The Chicago Tribune
The Los Angeles Times
The New York Times
The Washington Post
The Wall Street Journal
U.S. Major Dailies
U.S. Midwest Newsstream
U.S. Newsstream
U.S. North Central Newsstream
U.S. Northeast Newsstream
U.S. South Central Newsstream
U.S. Southeast Newsstream
U.S. West Newsstream

A.2 Annotation Protocol

The two-stage classification is built on manually labeled samples and a common coding logic. In Stage 1, labels indicate whether an article is substantively related to U.S. Farm Bill legislation. In Stage 2, conditional on Stage-1 relevance, labels indicate whether the article describes forward-looking legislative uncertainty (for example, delay, deadlock, temporary extension, or unresolved negotiations) that is relevant to agricultural credit through farm cash flow, collateral values, repayment risk, lender monitoring, program compliance costs, or related channels. Validation samples are manually re-labeled after model prediction to assess out-of-sample performance under the same coding rules.

A.3 Operational Label Rules and Annotation Consistency

To improve reproducibility of the training labels, we apply a fixed rulebook in both stages. In Stage 1, an article is labeled "related" only if Farm Bill legislation is a substantive part of the article's current U.S. policy discussion (for example, negotiations, provisions, committee actions, or reauthorization timing). Articles are labeled "not related" when "farm bill" appears only as a passing, historical, metaphorical, or non-U.S. reference. In Stage 2, conditional on Stage-1 relevance, an article is labeled "uncertainty" if it contains unresolved, forward-looking legislative ambiguity (for example, delay, extension risk, bargaining impasse, or unresolved program rules) and the unresolved issue has a plausible agricultural-credit channel. Such channels include uncertainty over commodity support, crop insurance, conservation compliance, payment timing, program eligibility, or other provisions that can affect borrower income, repayment capacity, collateral valuation, or lenders' monitoring and risk-management decisions. Articles are labeled "not uncertainty" when they are descriptive updates with no unresolved policy state, or when the unresolved political issue lacks a plausible link to agricultural credit.

Borderline cases are resolved using adjudication under the same rulebook before finalizing training labels. Because the final labeling workflow relies on adjudicated labels rather than independent parallel coding of all records, a corpus-wide inter-annotator kappa is not available in archived logs. To address consistency directly, we report confusion-matrix-based out-of-sample diagnostics and full classification metrics below. Table A3 provides illustrative examples of articles classified under each label category.

A.4 Model Architecture and Training Setup

We use BERT (Bidirectional Encoder Representations from Transformers) within ProQuest's closed TDM Studio environment. This setting requires local fine-tuning and inference and does not rely on external APIs. The pipeline has two supervised stages: relevance classification first, uncertainty classification second.

Table A3: Illustrative Examples from the Newspaper Corpus

	Classified as True	Classified as False
Farm Bill related	By a strong, veto-proof majority, the House passed a $290 billion farm bill with increased subsidies for farmers and food stamps for the poor amid rising grocery prices, while adding district-specific provisions lawmakers can highlight during the election year.	The city council debated a new recycling ordinance Tuesday. During public comment, one speaker joked that the proposal read "longer than the Farm Bill," drawing laughs before the meeting returned to pothole repairs and bus-route delays.
Uncertainty related	Congress is gearing up for one of its periodic battles over a farm bill. Past negotiations have failed to produce lasting reform, and this year's debate is already marked by delays and disagreement. President Bush has submitted a proposal that would eliminate commodity subsidies for farmers earning more than $200,000 annually.	Lawmakers on Capitol Hill this week reviewed proposed changes to crop insurance and commodity programs as part of the next five-year farm bill, debating how subsidy payments should be distributed among large and small producers.

We use BERT BASE (110M parameters), WordPiece tokenization, and standard sequence truncation/padding. The first-stage relevance model is trained on 825 manually labeled articles (345 external-source examples plus 480 ProQuest examples), with an 85:15 train-validation split, batch size 3, learning rate 10^{-6}, and 20 epochs. The second-stage uncertainty model is trained on 1,000 manually labeled Farm-Bill-relevant articles using the same split and hyperparameter configuration.

A.5 Classifier Performance

Applied to the cleaned corpus, Stage 1 classifies 26,509 articles as Farm-Bill-related. In a stratified validation sample of 2,000 articles, it achieves 90.9% accuracy, with precision of 92.9%, recall of 89.2%, specificity of 92.6%, and negative predictive value of 88.8%. Stage 2 classifies 22,709 of those 26,509 articles as uncertainty-related. In a corresponding 2,000-article validation sample, it achieves 88.4% accuracy, with precision of 90.2%, recall of 87.0%, specificity of 89.8%, and negative predictive value of 86.5%. Table A4 reports both confusion matrices.

Table A4: Confusion Matrices for Two-Stage BERT Classifiers

Panel A: Farm-Bill-Relevance Classifier

	True Label	
	Related	Not related
Predicted Related	929	71
Predicted Not related	112	888
Accuracy	0.9085	

Panel B: Uncertainty-Relevance Classifier

	True Label	
	Uncertainty	Not uncertainty
Predicted Uncertainty	902	98
Predicted Not uncertainty	135	865
Accuracy	0.8840	

A.6 Class Balance and Full Evaluation Metrics

Table A5 reports class composition and complete out-of-sample metrics. The validation sets are close to balanced by construction (positive-label shares of 52.1% and 51.9% in Stages 1 and 2), while the production-stage class composition is more skewed in Stage 1 (16.9% related in the full cleaned corpus). Beyond accuracy and recall, both stages show high precision and F1: Stage 1 precision is 92.9% with F1 of 91.0%, and Stage 2 precision is 90.2% with F1 of 88.6%.

Table A5: Class Balance and Full Validation Metrics for the Two-Stage Classifier

Metric	Stage 1 (Farm-Bill relevance)	Stage 2 (Uncertainty relevance)
Validation sample size	2,000	2,000
Validation positive-label share	52.1%	51.9%
Accuracy	90.9%	88.4%
Precision	92.9%	90.2%
Recall	89.2%	87.0%
Specificity	92.6%	89.8%
Negative predictive value	88.8%	86.5%
F1 score	91.0%	88.6%
Full-corpus positive share after Stage 1	16.9% (26,509/156,420)	85.7% (22,709/26,509)

A.7 Index Aggregation and Normalization

For each month t, let n_t denote the total number of ProQuest news articles containing "farm bill" and let m_t denote the subset classified as both Farm-Bill-related and uncertainty-related. We first form the smoothed frequency ratio

$$\tilde{u}_t = \frac{m_t}{n_t + 4}.$$

The pseudo-count in the denominator reduces mechanical volatility in low-coverage months, especially early in the sample. We then linearly rescale $\tilde{u}_t$ so that its minimum over 1980–2025 maps to 0 and its maximum maps to 100, yielding the monthly FBUI in $[0, 100]$. The same logic applied to weekly article counts yields a weekly FBUI.

A.8 Validation and Keyword Benchmark

To evaluate external validity, we compare FBUI with independent policy outcomes and with a keyword-based benchmark index. Figure A1 overlays lagged annual FBUI with two policy-

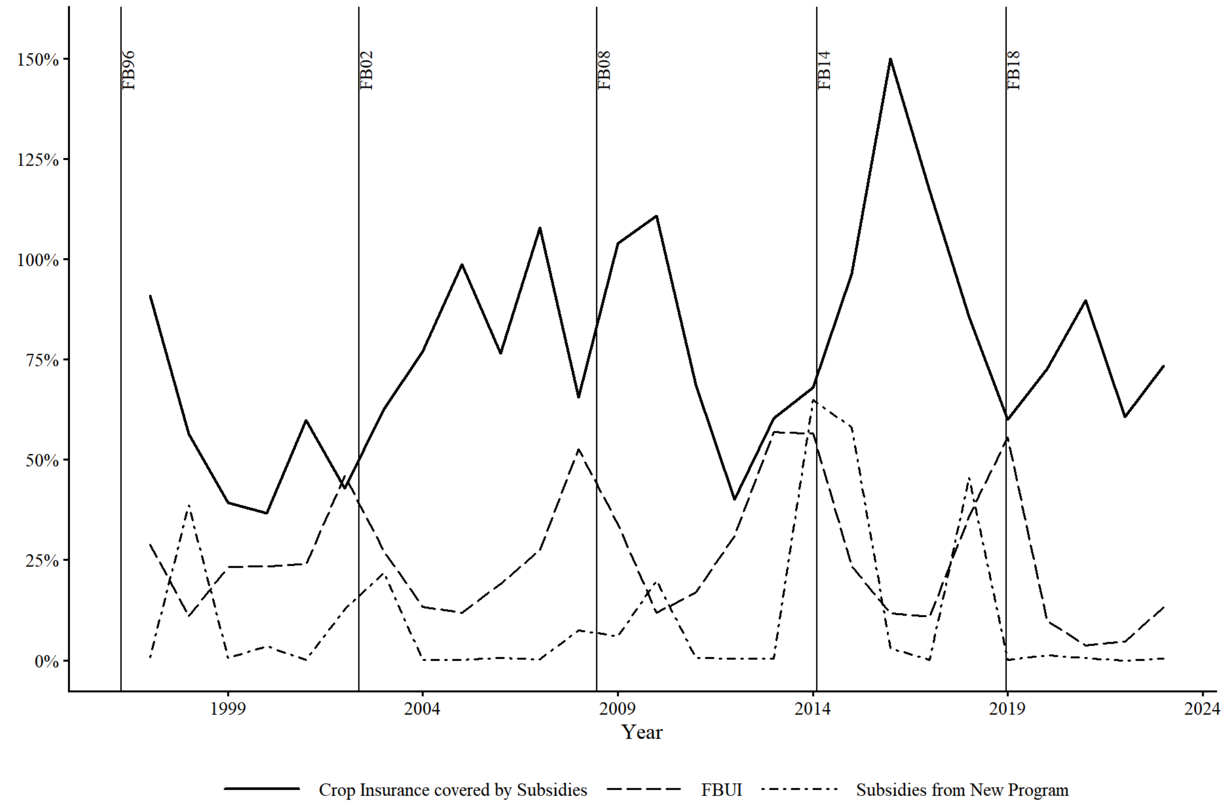


Figure A1: FBUI, Subsidies from New Programs and Crop Insurance covered by Subsidies

outcome proxies: (i) the share of support delivered through newly created programs and (ii) the share of crop-insurance premia covered by federal subsidies.

Periods of elevated FBUI are followed by a higher share of support through newly established programs (correlation ≈ 0.34), while FBUI is negatively correlated with the insurance-subsidy share (correlation ≈ -0.38). FBUI is also weakly correlated with the CBOE VIX, indicating that it captures a Farm Bill-specific uncertainty component rather than broad market volatility.

For benchmarking, we construct a keyword index based on phrases such as "uncertain farm bill," "delayed farm bill," and "farm bill gridlock." Figure A2 compares keyword and BERT series at monthly and weekly frequencies. The BERT-based FBUI tracks Farm Bill negotiation cycles with clearer spikes and less noise, while the keyword series is more erratic, particularly in early years with sparse coverage.

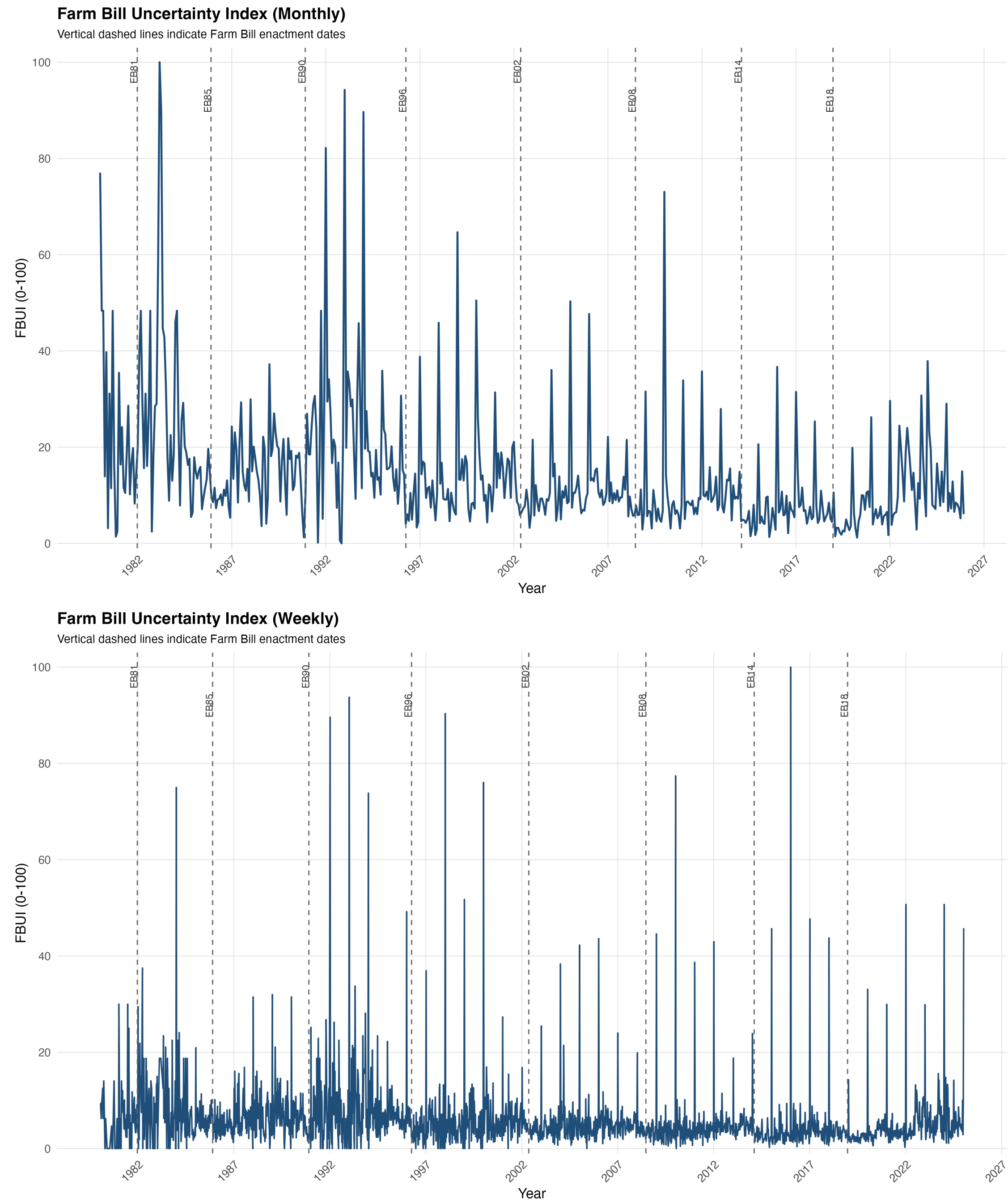


Figure A2: Keyword-Based Farm Bill Uncertainty Index (Monthly, Upper; Weekly, Lower), Jan 1980–Dec 2025.

Table A6 reports the corresponding regression benchmark discussed in Section 5, in which the keyword-based index produces mixed and difficult-to-interpret estimates across lender types.

Table A6: Keyword-Based FBUI and Agricultural Loan Amounts

	log(Production Loan)	log(Farmland Loan)	log(Agricultural Loan)
FBUI × FCS	0.013	0.018	0.021***
	(0.011)	(0.016)	(0.007)
FBUI × Bank	−0.078	−0.062*	−0.076
	(0.054)	(0.035)	(0.047)
FBUI × CU	0.319***	−0.018	−0.043*
	(0.062)	(0.055)	(0.022)
FCS Observations	3,917	3,941	3,922
Bank Observations	280,425	260,256	421,405
CU Observations	1,856	1,906	5,425

Fixed effects: Institution (ID), year, and quarter.
Std. errors: Two-way clustered by state and year–quarter.

Notes: This table re-estimates the baseline loan-amount models using a keyword-based FBUI measure constructed from the same newspaper corpus. The dependent variable is log(loan amount). Each institution row reports the FBUI coefficient from a separate regression estimated on that institution's sample. FBUI is scaled to $[0, 1]$. Controls are lagged equity-to-assets, lagged allowance-to-loans, lagged log total assets, lagged delinquent loan ratio, and quarterly average VIX.
Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

B Formal Lender Model

Consider a representative agricultural borrower whose income in period $t+1$ is given by:

$$Y_{t+1} = p_{t+1}q_{t+1} + S_{t+1}, \tag{B-1}$$

where $p_{t+1}q_{t+1}$ is market revenue and S_{t+1} represents Farm Bill-related transfers, including commodity payments and crop insurance net indemnities. At time t, the future realization of S_{t+1} is uncertain due to legislative negotiations. We define

$$S_{t+1} = \bar{S} + \tilde{S},$$

where $\mathbb{E}[\tilde{S}] = 0$ and $\mathrm{Var}(\tilde{S}) = \sigma_S^2(U)$. The parameter U denotes the Farm Bill Uncertainty Index (FBUI), with $\partial\sigma_S^2/\partial U > 0$. The total variance of borrower income is therefore

$$\mathrm{Var}(Y_{t+1}) = \sigma_{pq}^2 + \sigma_S^2(U), \tag{B-2}$$

where σ_{pq}^2 captures idiosyncratic price and yield risk.

A borrower defaults on a loan of size L at interest rate r if realized income falls below the required debt service net of collateral C:

$$Y_{t+1} < (1+r)L - C. \tag{B-3}$$

The default probability is $D(L, U) = \Pr(Y_{t+1} < (1+r)L - C)$. Under standard distributional assumptions, an increase in Farm Bill uncertainty raises default risk:

$$\frac{\partial D}{\partial U} > 0.$$

Let j index lender types (e.g., FCS, commercial banks, credit unions), and let $\theta_j \in [0, 1]$ denote the share of lender j's portfolio exposed to agricultural risk. Greater exposure implies that policy-induced shocks to farm income translate more directly into portfolio losses. At the same time, lenders differ in how easily they can adjust lending in response to those shocks. We capture this by introducing a lender-specific adjustment-cost parameter $\kappa_j > 0$, which measures the cost of deviating from a target lending level $\bar{L}_j$. The lender solves:

$$\begin{aligned}\max_{L}\ \Pi_j(L,U) &= (1+r)L - \rho L - (1-\alpha_j)\theta_j D(L,U)L - \frac{1}{2}\kappa_j(L-\bar{L}_j)^2, \\ \text{s.t.}\quad & 0 \le L \le \bar{L}_j^{cap}(A_j, K_j, \Lambda_j, D_j),\end{aligned} \tag{B-4}$$

where ρ is the marginal cost of funds and $\alpha_j \in (0,1)$ is the recovery rate. The constraint $\bar{L}_j^{cap}(\cdot)$ captures liquidity, capital, risk-limit, monitoring-capacity, and borrower-demand constraints. The interior first-order condition below characterizes the local mechanism when this constraint is slack; if the constraint binds, observed lending can be less responsive to marginal risk changes.

The first-order condition is:

$$(1+r-\rho) - (1-\alpha_j)\theta_j\left[D(L,U) + L\frac{\partial D(L,U)}{\partial L}\right] - \kappa_j(L-\bar{L}_j) = 0. \tag{B-5}$$

Totally differentiating with respect to U yields:

$$\frac{\partial L_j^*}{\partial U} = -\frac{(1-\alpha_j)\theta_j\left[L_j^*\frac{\partial^2 D}{\partial L \partial U} + \frac{\partial D}{\partial U}\right]}{(1-\alpha_j)\theta_j\left[2\frac{\partial D}{\partial L} + L_j^*\frac{\partial^2 D}{\partial L^2}\right] + \kappa_j}. \tag{B-6}$$

Under standard second-order and monotone default-risk conditions, the bracketed numerator and the denominator are positive. The leading negative sign therefore implies:

$$\frac{\partial L_j^*}{\partial U} < 0. \tag{B-7}$$

This expression highlights two distinct sources of heterogeneity. First, greater agricultural exposure θ_j increases the effect of policy uncertainty on expected losses. Second, greater adjustment frictions κ_j dampen the lender's response by making it more costly to alter lending volumes or other credit-exposure margins. Hence, the magnitude of the credit-market response depends jointly on exposure and flexibility:

$$\left|\frac{\partial L_j^*}{\partial U}\right| = h(\theta_j, \kappa_j), \qquad \frac{\partial h}{\partial \theta_j} > 0, \qquad \frac{\partial h}{\partial \kappa_j} < 0. \tag{B-8}$$

This framework rationalizes why more specialized lenders may exhibit weaker short-run responses despite higher agricultural exposure. The FCS has high θ_j because its portfolio is concentrated in agriculture, but it may also face high effective adjustment costs due to its specialized mandate and persistent sectoral commitment. Commercial banks may have lower agricultural exposure, but lower adjustment costs, allowing them to contract lending more sharply when policy uncertainty rises. Credit unions may lie between these cases or display less systematic responses because of heterogeneity in scale and operating constraints.

Hypothesis 1 (Aggregate Effect): Higher Farm Bill uncertainty reduces agricultural credit exposure by increasing the variance of expected repayment and expected default losses.

Hypothesis 2 (Institutional Heterogeneity): The sensitivity of credit-market adjustment to Farm Bill uncertainty depends jointly on agricultural exposure and adjustment frictions. Lenders with lower adjustment costs, such as commercial banks, may exhibit larger adjustments in loan amounts, portfolio shares, loan counts, or average loan sizes even if their agricultural exposure is lower than that of specialized lenders.

Loan types may also respond through different margins. Production and operating loans, L_{prod}, depend primarily on current and near-term farm income, so uncertainty affects them mainly through expected repayment risk. Farmland loans, L_{land}, are secured by real estate, whose value reflects the discounted stream of expected future farm returns. Farm Bill uncertainty may therefore affect farmland lending not only through repayment risk, but also through collateral values if expected future policy support is capitalized into land prices.

Let $V(U, E_s)$ denote the value of land collateral, where U is Farm Bill uncertainty and E_s is state-level exposure to Farm Bill programs. Then

$$\frac{\partial V}{\partial U} < 0, \qquad \left|\frac{\partial V}{\partial U}\right| \text{ may increase with } E_s,$$

because higher-exposure regions rely more heavily on Farm Bill support. The relative response of production and farmland lending is therefore theoretically ambiguous and depends on whether short-run cash-flow effects or longer-run collateral-value effects dominate. Aggregate uncertainty may primarily affect production lending, while exposure-weighted uncertainty may generate larger responses in farmland lending through the collateral channel.

We parameterize the geographic exposure channel as

$$\sigma_S^2(U, E_s) = E_s \cdot g(U), \qquad g'(U) > 0,$$

so that national legislative uncertainty has larger effects in regions more reliant on Farm Bill support. Allowing for both institutional and geographic heterogeneity, the credit response satisfies

$$\left|\frac{\partial M_{js}^{m,*}}{\partial U}\right| = f_m(E_s, \theta_j, \kappa_j), \qquad \frac{\partial f_m}{\partial E_s} > 0, \tag{B-9}$$

where m indexes the empirical margin: loan amount, portfolio share, loan count, or average loan size. For margins that directly measure credit exposure, such as balances, shares, or intensive-margin loan size, the expected adjustment is generally negative when uncertainty rises. When total lending is decomposed into loan counts and average loan size, however, the model does not require loan counts to decline if lenders substitute toward smaller and more granular loans while reducing balances or portfolio exposure.

Hypothesis 3 (Loan Composition): Production and operating loans contract more sharply than farmland loans in the baseline uncertainty channel. Farmland lending may still respond in high-exposure markets when policy risk affects collateral valuation, loan renewal risk, or intensive-margin lending decisions.

Hypothesis 4 (Spatial Identification): The credit-market adjustment is larger in high-exposure regions, especially for lenders whose lending policies are more responsive to local risk conditions:

$$\frac{\partial}{\partial E_s}\left|\frac{\partial M_{js}^{m,*}}{\partial U}\right| > 0.$$

These hypotheses guide the empirical analysis in Sections 5 through 7.

C Additional Robustness Checks

C.1 Media and Regional Confounding

Tables C1–C4 report additional checks that assess whether the commercial-bank estimates are sensitive to broad media attention, moving-average timing windows, source composition, or regional heterogeneity. The loan-amount estimates are the most sensitive part of the commercial-bank evidence, so these checks also report the margins that are less mechanically tied to raw article cycles: loan shares, loan counts, and average loan size. We use the same sample restrictions, institution controls, fixed effects, and clustering conventions as the corresponding main specifications unless noted otherwise. Let $y_{it}^{m,k}$ denote outcome margin m for commercial bank i, quarter t, and loan category $k \in \{\text{production}, \text{farmland}, \text{agricultural}\}$, where m is log(loan amount), loan share in percentage points, log(loan count), or log(average loan size). Let $\mathbf{X}_{it}$ denote lagged equity-to-assets, lagged allowance-to-loans, lagged log total assets, lagged delinquent-loan ratio, and, in the national FBUI specifications, quarterly average VIX. Institution fixed effects are denoted by μ_i; year and quarter-of-year fixed effects by λ_y and λ_q; and year–quarter fixed effects by λ_t.

Article-volume controls. The first check asks whether the estimated national FBUI effect is simply a broad agricultural-news attention effect. We use a quarterly count of ProQuest U.S. Newsstream newspaper articles returned by the search query "agricultural OR agriculture." The count is transformed as $\log(1 + N_t)$ and scaled to $[0, 1]$, yielding V_t. This specification is conservative because it controls for general agricultural news attention rather than only Farm Bill news attention. For each outcome margin, the national commercial-bank specification is

$$y_{it}^{m,k} = \beta^{m,k}\,\text{FBUI}_t + \delta^{m,k} V_t + \mathbf{X}_{it}'\theta + \mu_i + \lambda_y + \lambda_q + \varepsilon_{it}.$$

Table C1 reports these estimates. The commercial-bank loan-amount coefficients remain negative and statistically significant across production, farmland, and aggregate agricultural lending. Loan counts and average loan sizes also remain negative across all three categories; production and aggregate loan shares remain negative, while the farmland-share coefficient is small and statistically insignificant.

Table C1: Article-Volume Robustness Checks for Commercial Banks

	Production	Farmland	Agricultural
log(loan amount)	-0.040**	-0.023***	-0.034**
Loan share (pp)	-0.202**	0.018	-0.200**
log(loan count)	-0.023***	-0.017***	-0.026***
log(average loan size)	-0.029**	-0.005***	-0.009***

Notes: The table reports commercial-bank coefficients on FBUI after adding a broad agricultural-news volume control. The control is the quarterly count of ProQuest U.S. Newsstream newspaper articles returned by the search query "agricultural OR agriculture," transformed as $\log(1+N_t)$ and scaled to $[0,1]$. Loan-share outcomes are measured in percentage points.
Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Moving-average timing windows. The second check examines whether agricultural credit decisions respond to Farm Bill uncertainty over a seasonal planning horizon rather than only contemporaneously. Starting from the quarterly FBUI scaled to $[0, 1]$, we therefore report two cumulative timing windows:

$$U_t^h \in \left\{ \frac{\text{FBUI}_t + \text{FBUI}_{t-1}}{2}, \ \frac{1}{4}\sum_{\ell=0}^{3} \text{FBUI}_{t-\ell} \right\}.$$

For each window h, the national commercial-bank regression is

$$y_{it}^{m,k} = \beta_h^{m,k} U_t^h + \delta_h^{m,k} V_t + \mathbf{X}_{it}'\theta + \mu_i + \lambda_y + \lambda_q + \varepsilon_{it},$$

where V_t is the broad agricultural-news volume control defined above. Rows without the volume control omit V_t. The moving-average windows correspond directly to cumulative uncertainty over the planning horizon, but they also smooth the high-frequency legislative spikes that the FBUI is designed to capture. This matters especially because the national specifications include year and quarter-of-year fixed effects. In the commercial-bank regression sample, the standard deviation of quarter-to-quarter changes is 0.096 for the 2-quarter moving average and 0.065 for the 4-quarter moving average. After residualizing the FBUI windows on year and quarter-of-year fixed effects, the residual standard deviation falls from 0.094 for the 2-quarter window to 0.069 for the 4-quarter window; equivalently, the 4-quarter residual variance is about 55% of the 2-quarter residual variance. The 4-quarter window should therefore be interpreted as a conservative over-smoothing check rather than as the preferred timing of Farm Bill uncertainty. Table C2 reports the resulting national FBUI estimates for the margins that remain most informative under timing variation. The 2-quarter moving-average amount estimates remain negative for all three loan categories and significant for farmland and aggregate agricultural lending; moving-average count estimates remain negative for production and aggregate agricultural lending across both windows, and the aggregate loan-share estimates remain negative after adding the broad agricultural-news volume control. The weaker 4-quarter loan-amount estimates are consistent with the smaller identifying variation left after smoothing and fixed-effect absorption.

Table C2: Moving-Average National FBUI Robustness Checks for Commercial Banks

	Production	Farmland	Agricultural
Panel A: log(*loan amount*)			
2Q MA; No volume	-0.021	-0.010***	-0.020**
2Q MA; + ag volume	-0.022	-0.013***	-0.022**
4Q MA; No volume	-0.019	0.000	-0.014
4Q MA; + ag volume	-0.020	-0.004	-0.016
Panel B: Loan share (percentage points)			
2Q MA; No volume	-0.278**	0.036	-0.273***
2Q MA; + ag volume	-0.257	0.034	-0.254***
4Q MA; No volume	-0.483***	-0.011	-0.393***
4Q MA; + ag volume	-0.450**	-0.024	-0.369***
Panel C: log(*loan count*)			
2Q MA; No volume	-0.021***	-0.010***	-0.021***
2Q MA; + ag volume	-0.021**	-0.013***	-0.022***
4Q MA; No volume	-0.016**	0.002	-0.012***
4Q MA; + ag volume	-0.013*	0.001	-0.010**
Panel D: log(*average loan size*)			
2Q MA; No volume	-0.021	0.007**	-0.003***
2Q MA; + ag volume	-0.021	0.007*	-0.006***
4Q MA; No volume	-0.027	0.013**	-0.005
4Q MA; + ag volume	-0.027	0.014**	-0.009**

Notes: The table reports national commercial-bank coefficients on moving-average FBUI windows. "No volume" uses the baseline national FBUI controls; "+ ag volume" additionally controls for the quarterly count of ProQuest U.S. Newsstream newspaper articles returned by the search query "agricultural OR agriculture," transformed as $\log(1 + N_t)$ and scaled to $[0, 1]$. FBUI is scaled to $[0, 1]$ before constructing moving averages. The 4-quarter moving average is a conservative over-smoothing check; relative to the 2-quarter window, it leaves substantially less high-frequency variation after year and quarter-of-year fixed effects.
Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Source-composition controls. The third check examines sensitivity to digitization, syndication, and archive composition. Complementing the broad agricultural-news volume control in Table C1, the national source-composition check uses a separate quarterly vector $\mathbf{S}_t^A$ constructed from all English Farm Bill keyword-search news articles: log number of distinct publishers, log number of distinct publisher cities, wire-feed share, and source-type Herfindahl index. Count variables are transformed as $\log(1+x)$; all components are scaled to $[0,1]$. The national specification is

$$y_{it}^{m,k} = \beta^{m,k}\,\mathrm{FBUI}_t + \left(\mathbf{S}_t^A\right)'\gamma + \mathbf{X}_{it}'\theta + \mu_i + \lambda_y + \lambda_q + \varepsilon_{it}.$$

For the exposure-weighted check, we use a more targeted quarterly source vector $\mathbf{S}_t^U$ constructed from the uncertainty-labeled Farm Bill article corpus: log total uncertainty articles, log publishers, log publisher cities, and wire-feed share. Since $\mathbf{S}_t^U$ itself is absorbed by year–quarter fixed effects, we estimate

$$y_{it}^{m,k} = \beta^{m,k}(\mathrm{EXPO}_{it} \times \mathrm{FBUI}_t) + \left(\mathrm{EXPO}_{it} \times \mathbf{S}_t^U\right)'\gamma + \mathbf{X}_{it}'\theta + \mu_i + \lambda_t + \varepsilon_{it}.$$

Table C3 reports these source-composition checks. The national count and average-size estimates remain negative across all loan categories. The exposure-weighted average-size estimates remain negative and statistically significant, including for farmland and aggregate agricultural lending.

Table C3: Source-Composition Robustness Checks for Commercial Banks

	Production	Farmland	Agricultural
Panel A: Baseline FBUI with source-composition controls			
Loan share (pp)	-0.358**	0.061	-0.326***
log(loan count)	-0.021***	-0.008*	-0.020***
log(average loan size)	-0.054***	-0.020***	-0.023***
Panel B: Exposure-weighted FBUI with uncertainty-article source controls			
log(average loan size)	-0.302*	-0.450***	-0.376***

Notes: Panel A reports coefficients on FBUI after adding source-composition controls constructed from all English ProQuest news articles retrieved by the Farm Bill keyword search: log number of publishers, log number of publisher cities, wire-feed share, and source-type HHI, all scaled to $[0, 1]$. Article volume is excluded from Panel A because it is examined separately in Table C1. Panel B reports coefficients on EXPO $\times$ FBUI after adding EXPO interacted with source controls constructed from the uncertainty-labeled Farm Bill article corpus: log total uncertainty articles, log publishers, log publisher cities, and wire-feed share.

Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Regional and demand controls. The fourth check asks whether the exposure-weighted coefficient is driven by regional farm-demand conditions or persistent regional differences rather than Farm Bill dependence. We first add annual state-year demand controls $\mathbf{D}_{s,t}$ from USDA ERS Farm Income and Wealth Statistics: net farm income, crop cash receipts, and government payments, transformed with inverse hyperbolic sine and standardized. For bank i located in state $s(i)$, this specification is

$$y_{it}^{m,k} = \beta^{m,k}(\text{EXPO}_{it} \times \text{FBUI}_t) + \mathbf{D}'_{s(i),t}\psi + \mathbf{X}'_{it}\theta + \mu_i + \lambda_t + \varepsilon_{it}.$$

We then construct two pre-period regional principal components. The first summarizes pre-2005 farm structure and financial conditions: crop-receipt share, specialty-crop share, log total commodity cash receipts, debt-to-assets, interest-to-gross-income ratio, and asset-turnover ratio. The second summarizes pre-2005 banking structure: state bank agricultural-loan exposure and average bank size. All inputs are standardized across states before principal-component extraction. The regional interaction specification is

$$y_{it}^{m,k} = \beta^{m,k}(\text{EXPO}_{it} \times \text{FBUI}_t) + \rho_F\left(\text{FBUI}_t \times P^F_{s(i)}\right) + \rho_B\left(\text{FBUI}_t \times P^B_{s(i)}\right) + \mathbf{X}'_{it}\theta + \mu_i + \lambda_t + \varepsilon_{it}.$$

Table C4 reports both checks. The farmland and aggregate agricultural effects remain negative for amount, share, and average-size outcomes under both regional-control approaches.

Table C4: Regional and Demand-Control Robustness Checks for Commercial Banks

	Production	Farmland	Agricultural
Panel A: State-year farm-income demand controls			
log(loan amount)	0.018	-0.174***	-0.064
Loan share (pp)	-0.692	-3.506***	-2.563**
log(average loan size)	-0.066	-0.225***	-0.161**
Panel B: Pre-period regional principal-component interactions			
log(loan amount)	-0.002	-0.161***	-0.080*
Loan share (pp)	-0.766	-3.165***	-2.815**
log(average loan size)	-0.035	-0.202***	-0.139**

Notes: The table reports coefficients on EXPO × FBUI. Panel A adds annual state-level net farm income, crop cash receipts, and government payments from USDA ERS Farm Income and Wealth Statistics. Panel B adds FBUI interacted with two pre-period regional principal components: one summarizing farm structure and financial conditions, and one summarizing pre-2005 banking structure. Specifications include institution and year–quarter fixed effects and institution-level controls.
Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

C.2 Demand-Control Robustness for FBUI and Exposure Results

This subsection reports robustness checks for the Section 5 and Section 6 regressions after adding annual state-level demand controls: net farm income, crop cash receipts, and government payments. These controls are intended to absorb time-varying farm income conditions at the state level. Appendix Table C5 reports the FBUI specifications, and Appendix Table C6 reports the exposure-weighted FBUI specifications.

Table C5: FBUI Regressions with State-Year Demand Controls

Lender	Loan type	Baseline	+ Demand controls	Obs.
Panel A. Dependent variable: log(*loan amount*)				
FCS	Production loan	-0.015^{***}	-0.014^{***}	3,917
		(0.003)	(0.005)	
FCS	Farmland loan	0.005	0.005	3,941
		(0.005)	(0.005)	
FCS	Agricultural loan	-0.006^{**}	-0.004	3,922
		(0.002)	(0.003)	
Commercial bank	Production loan	-0.044^{**}	-0.043^{**}	280,425
		(0.020)	(0.021)	
Commercial bank	Farmland loan	-0.025^{**}	-0.025^{**}	260,256
		(0.010)	(0.010)	
Commercial bank	Agricultural loan	-0.037^{**}	-0.037^{**}	421,405
		(0.016)	(0.017)	
Credit union	Production loan	-0.084^{***}	-0.085^{***}	1,856
		(0.010)	(0.020)	
Credit union	Farmland loan	-0.035^{**}	-0.036^{**}	1,906
		(0.015)	(0.015)	
Credit union	Agricultural loan	-0.054^{***}	-0.055^{**}	5,425
		(0.012)	(0.025)	
Panel B. Dependent variable: loan ratio (pp)				

Continued on next page

Table C5 (continued)

Lender	Loan type	Baseline	+ Demand controls	Obs.
Commercial bank	Production loan	-0.203^{*}	-0.200^{*}	280,425
		(0.105)	(0.117)	
Commercial bank	Farmland loan	0.025	0.025	260,256
		(0.032)	(0.033)	
Commercial bank	Agricultural loan	-0.194^{***}	-0.195^{***}	421,405
		(0.045)	(0.069)	
Credit union	Production loan	-1.455^{***}	-1.465^{***}	1,856
		(0.375)	(0.392)	
Credit union	Farmland loan	-0.616	-0.651	1,906
		(0.378)	(0.461)	
Credit union	Agricultural loan	-2.355^{***}	-2.400^{***}	5,425
		(0.559)	(0.669)	
Panel C. Dependent variable: log(*#loans*)				
FCS	Agricultural loan	-0.025^{***}	-0.020^{***}	3,922
		(0.005)	(0.006)	
Commercial bank	Production loan	-0.023^{***}	-0.023^{***}	67,760
		(0.007)	(0.005)	
Commercial bank	Farmland loan	-0.014^{***}	-0.014^{***}	84,514
		(0.002)	(0.002)	
Commercial bank	Agricultural loan	-0.025^{***}	-0.025^{***}	117,630
		(0.003)	(0.002)	
Credit union	Production loan	-0.067^{***}	-0.068^{***}	1,856
		(0.015)	(0.019)	
Credit union	Farmland loan	-0.038	-0.037	1,906
		(0.022)	(0.022)	
Credit union	Agricultural loan	-0.081^{***}	-0.081^{***}	5,425
		(0.016)	(0.020)	
Panel D. Dependent variable: log(*avg loan size*)				

Continued on next page

Table C5 (continued)

Lender	Loan type	Baseline	+ Demand controls	Obs.
FCS	Agricultural loan	0.019***	0.016***	3,922
		(0.002)	(0.003)	
Commercial bank	Production loan	−0.028**	−0.028***	67,760
		(0.012)	(0.008)	
Commercial bank	Farmland loan	−0.003**	−0.003**	84,514
		(0.001)	(0.002)	
Commercial bank	Agricultural loan	−0.007***	−0.007***	117,630
		(0.001)	(0.001)	
Credit union	Production loan	−0.017	−0.017	1,856
		(0.019)	(0.019)	
Credit union	Farmland loan	0.003	0.002	1,906
		(0.018)	(0.018)	
Credit union	Agricultural loan	0.027	0.026	5,425
		(0.019)	(0.021)	

Notes: Each entry reports the coefficient on FBUI from a separate regression. The "+ Demand controls" columns add annual state-level net farm income, crop cash receipts, and government payments from USDA ERS Farm Income and Wealth Statistics (February 5, 2026 release). For 2025 quarterly observations, these controls are matched to the most recent available annual values (2024).

All specifications include institution, year, and quarter fixed effects. Standard errors are two-way clustered by state and year–quarter. Coefficient signs are unchanged in all 29 comparable specifications, and 10 percent significance is preserved in 28 of 29 specifications. Significance levels are denoted by $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Table C6: Exposure-Weighted FBUI Regressions with State-Year Demand Controls

Lender	Loan type	Baseline	+ Demand controls	Obs.
Panel A. Dependent variable: log(*loan amount*)				
FCS	Production loan	0.065	0.050	3,917
		(0.095)	(0.097)	
FCS	Farmland loan	0.080*	0.086*	3,941
		(0.047)	(0.050)	
FCS	Agricultural loan	0.057	0.058	3,922
		(0.037)	(0.038)	
Commercial bank	Production loan	0.015	0.018	110,370
		(0.052)	(0.052)	
Commercial bank	Farmland loan	−0.173***	−0.174***	136,786
		(0.058)	(0.058)	
Commercial bank	Agricultural loan	−0.068*	−0.064	189,159
		(0.039)	(0.040)	
Credit union	Production loan	−0.097	−0.139	1,198
		(0.233)	(0.241)	
Credit union	Farmland loan	0.208	0.206	1,321
		(0.287)	(0.283)	
Credit union	Agricultural loan	0.163	0.189	2,874
		(0.155)	(0.150)	
Panel B. Dependent variable: loan ratio (pp)				
Commercial bank	Production loan	−0.744	−0.692	110,370
		(1.242)	(1.236)	
Commercial bank	Farmland loan	−3.449***	−3.506***	136,786
		(1.048)	(1.057)	
Commercial bank	Agricultural loan	−2.531**	−2.563**	189,159
		(1.102)	(1.173)	

Continued on next page

Table C6 (continued)

Lender	Loan type	Baseline	+ Demand controls	Obs.
Credit union	Production loan	−5.993	−7.280	1,198
		(6.244)	(6.233)	
Credit union	Farmland loan	3.187	2.627	1,321
		(7.133)	(6.814)	
Credit union	Agricultural loan	−1.250	−0.279	2,874
		(5.630)	(5.329)	
Panel C. Dependent variable: log(*#loans*)				
FCS	Agricultural loan	0.086	0.083	3,922
		(0.093)	(0.099)	
Commercial bank	Production loan	0.102*	0.107**	58,739
		(0.053)	(0.052)	
Commercial bank	Farmland loan	0.039	0.035	76,391
		(0.042)	(0.041)	
Commercial bank	Agricultural loan	0.078*	0.078*	103,832
		(0.044)	(0.043)	
Credit union	Production loan	−0.213	−0.193	1,198
		(0.381)	(0.374)	
Credit union	Farmland loan	0.246	0.240	1,321
		(0.286)	(0.287)	
Credit union	Agricultural loan	0.130	0.123	2,874
		(0.238)	(0.231)	
Panel D. Dependent variable: log(*average loan size*)				
FCS	Agricultural loan	−0.029	−0.025	3,922
		(0.089)	(0.095)	
Commercial bank	Production loan	−0.061	−0.066	58,739
		(0.055)	(0.055)	
Commercial bank	Farmland loan	−0.230***	−0.225***	76,391
		(0.080)	(0.079)	

Continued on next page

Table C6 (continued)

Lender	Loan type	Baseline	+ Demand controls	Obs.
Commercial bank	Agricultural loan	-0.165^{**}	-0.161^{**}	103,832
		(0.063)	(0.062)	
Credit union	Production loan	0.116	0.053	1,198
		(0.286)	(0.294)	
Credit union	Farmland loan	-0.038	-0.034	1,321
		(0.192)	(0.182)	
Credit union	Agricultural loan	0.033	0.066	2,874
		(0.162)	(0.163)	

Notes: Each entry reports the coefficient on the exposure-weighted FBUI measure from a separate regression. The "+ Demand controls" columns add annual state-level net farm income, crop cash receipts, and government payments from USDA ERS Farm Income and Wealth Statistics (February 5, 2026 release). For 2025 quarterly observations, these controls are matched to the most recent available annual values (2024).

All specifications include institution and year–quarter fixed effects. Standard errors are two-way clustered by institution and year–quarter. Coefficient signs are unchanged in all 29 comparable specifications, and 10 percent significance is preserved in 28 of 29 specifications. Significance levels are denoted by $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

C.3 Credit Unions in North Dakota

We report the full-sample credit-union results in Table C7, while the main text excludes North Dakota credit unions as a sample-homogeneity restriction. North Dakota has a distinct institutional setting for agricultural credit, including the Bank of North Dakota (BND) partnership model and state guidance on agricultural restructurings (Bank of North Dakota, 2026a,b; North Dakota Department of Financial Institutions, 2020), so reduced-form coefficients there need not be comparable to those in other states.

Empirically, including North Dakota yields positive and statistically significant coefficients for production-loan amounts, total agricultural loan amounts, and farmland loan counts. Excluding North Dakota attenuates these estimates and leaves the credit-union coefficients statistically insignificant across loan amounts, loan ratios, loan counts, and average loan size. We therefore treat the full-sample estimates as a state-specific robustness check and use the exclusion sample for sector-level inference on credit unions.

Table C7: Effects of Exposure-Weighted FBUI on Credit Union Agricultural Lending (CU Full Sample, including ND)

	Production Loan	Farmland Loan	Agricultural Loan
Panel A: Dependent variable = log(*loan amount*)			
FBEP × CU	0.294*	0.135	0.236**
	(0.150)	(0.154)	(0.096)
Panel B: Dependent variable = loan ratio (percentage points)			
FBEP × CU	2.125	0.502	2.280
	(3.077)	(3.808)	(2.896)
Panel C: Dependent variable = log(*number of loans*)			
FBEP × CU	0.203	0.375**	0.239
	(0.213)	(0.161)	(0.153)
Panel D: Dependent variable = log(*average loan size*)			
FBEP × CU	0.091	−0.240	−0.003
	(0.183)	(0.154)	(0.118)
Observations	1,856	1,906	3,946

Fixed effects: Institution (ID), year–quarter.
Std. errors: Two-way clustered by ID and year–quarter.

Notes: FBEP denotes lender-specific exposure-weighted FBUI, where both exposure and FBUI are scaled to $[0, 1]$. Panel A reports semi-elasticities for log(loan amount); Panel B reports effects on loan ratios in percentage points; Panel C reports effects on log(number of loans); and Panel D reports effects on log(average loan size). Each panel reports a separate credit-union regression estimated on the full sample with North Dakota included.

All specifications include institution and year–quarter fixed effects, two-way clustering by institution and year–quarter, and controls for lagged equity-to-assets, lagged allowance-to-loans, lagged log total assets, and lagged delinquent loan ratio.

Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

C.4 Robustness Checks for DID

This subsection consolidates four additional robustness diagnostics for the DID design in Section 7: few-cluster inference (Table C8), event-window sensitivity (Table C9), joint tests of pre- and post-resolution coefficients (Table C10), and multiple-testing adjustments (Table C11). The updated baseline in this section uses the stacked commercial-bank sample with relative quarter in $[-4, 3]$, bank-episode stack and calendar-quarter fixed effects, and standard errors clustered by bank-episode stack ID. This is the baseline inference choice because treatment variation is defined at the stacked-cohort level.

Table C8: Few-Cluster Robustness of Stacked DID Estimates

Specification	Coefficient on post×ΔFBEP	Std. Error	p-value
Baseline cluster: bank-episode stack ID	0.075***	(0.017)	<0.001
Two-way cluster: bank-episode stack ID and relative-quarter bin	0.075***	(0.016)	0.003
One-way cluster: relative-quarter bin	0.075***	(0.008)	<0.001
Heteroskedasticity-robust (HC)	0.075***	(0.010)	<0.001
IID standard errors	0.075***	(0.010)	<0.001
Leave-one-relative-quarter-out (baseline-clustered) summary			
Coefficient range	0.071 to 0.082		
p-value range	<0.001 to <0.001		
Share with $p < 0.10$	100.0%		
Share with $p < 0.05$	100.0%		

Notes: Estimates use the commercial-bank stacked event-study sample in Section 7. The baseline specification clusters standard errors by bank-episode stack ID. The leave-one-relative-quarter-out exercise re-estimates the baseline DID after dropping one relative-quarter bin at a time.
Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C9: Event-Window Sensitivity of Stacked DID Estimates

Window (rel. quarter)	Obs.	Bank-episode stack IDs	Rel.-quarter bins	DID coef.	DID p-value	Pretrend joint p	Post joint p
(-4, 3) baseline	54,200	6,775	8	0.075***	$<$0.001	0.568	$<$0.001
(-5, 3)	62,317	6,949	9	0.071***	$<$0.001	0.758	$<$0.001
(-6, 3)	70,123	7,069	10	0.063***	0.003	0.004	$<$0.001
(-5, 4)	69,958	7,056	10	0.071***	$<$0.001	0.723	$<$0.001
(-6, 4)	77,681	7,159	11	0.063***	0.003	0.014	$<$0.001

Notes: Each row re-estimates the Section 7 stacked DID using the indicated relative-quarter window. The DID coefficient is on post$\times\Delta$FBEP. Pre-trend and post-trend columns report joint Wald-test p-values from the corresponding stacked event-study model.
Significance for DID coefficient: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C10: Joint Wald Tests for DID Event-Time Coefficients

Model	Joint null hypothesis	F-statistic	df1	df2	p-value
2008 episode	Pre-treatment coefficients = 0	21.88	3	2,450	<0.001
2008 episode	Post-treatment coefficients = 0	12.55	4	2,450	<0.001
2014 episode	Pre-treatment coefficients = 0	13.83	3	2,278	<0.001
2014 episode	Post-treatment coefficients = 0	24.43	4	2,278	<0.001
2018 episode	Pre-treatment coefficients = 0	17.28	3	2,044	<0.001
2018 episode	Post-treatment coefficients = 0	6.74	4	2,044	<0.001
Stacked sample	Pre-treatment coefficients = 0	0.67	3	6,774	0.568
Stacked sample	Post-treatment coefficients = 0	7.99	4	6,774	<0.001

Notes: Wald tests are computed from event-study regressions with relative quarter −1 omitted. "Pre-treatment coefficients" jointly tests all available leads in the estimation window; "Post-treatment coefficients" jointly tests all available lags in the estimation window.

Standard errors are clustered by institution ID in single-episode models and by bank-episode stack ID in the stacked model.

Table C11: Multiple-Testing Adjustments for DID Inference

Panel	Estimate	Raw p	Within family Holm	Within family BH	Global Holm	Global BH
Panel A: DID main-effect tests (post$\times\Delta FBEP$)						
2008 episode	-0.028	0.343	0.343	0.343	1.000	0.381
2014 episode	0.159^{***}	<0.001	<0.001	<0.001	<0.001	<0.001
2018 episode	0.071^{**}	0.033	0.066	0.044	0.295	0.055
Stacked sample	0.075^{***}	<0.001	<0.001	<0.001	<0.001	<0.001
Panel B: Number of significant tests at the 5% level						
Family	Total tests	Raw p	Holm	BH	Holm	BH
DID main effect tests	4	3	2	3	2	2
Event-study post-period tests	16	10	9	9	9	9

Notes: "Within" adjustments are applied within each family of hypotheses (DID main effects or event-study post-period effects). "Global" adjustments are applied across all DID tests included in this robustness exercise.

Adjustment methods: Holm step-down family-wise error-rate control and Benjamini–Hochberg (BH) false-discovery-rate control.

Significance stars in Panel A are based on raw p-values: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

D Supplementary Results and Diagnostics

Table D1: Sample Diagnostics for Exposure Measures

Panel A: EXPO distribution							
Sample	N	Mean	SD	P10	Median	P90	Max
States, raw EXPO	50	3.988	3.218	0.941	2.839	7.979	14.039
States, scaled EXPO	50	0.266	0.235	0.044	0.182	0.557	1.000
FCS institution-quarters	6,008	0.309	0.202	0.087	0.291	0.532	1.000
Bank institution-quarters	751,013	0.385	0.201	0.103	0.423	0.600	1.000
CU institution-quarters	30,370	0.334	0.194	0.085	0.306	0.541	0.859
Panel B: Institution counts in the main regression tables							
Specification cell	Production	Farmland	Agricultural				
Table 2 Panel A, FCS	73	78	78				
Table 2 Panel A, Bank	3,609	3,341	5,028				
Table 2 Panel A, CU	40	38	70				
Table 3 Panel A/B, Bank	1,472	1,875	2,473				
Table 3 Panel A/B, CU	40	38	70				
Table 4 Panel A, Bank	1,805	2,275	2,962				
Table 4 Panel A, CU	27	27	47				
Table 5 Panel A/B, Bank	1,379	1,802	2,358				
Table 5 Panel A/B, CU	27	27	47				
Panel C: Quarterly growth benchmark							
Sample	N changes	Mean	Median	Median abs.	P25	P75	
Bank total agricultural loan amount	411,652	0.774%	0.836%	5.356%	-4.528%	6.054%	

Notes: Panel A reports the distribution of the state EXPO measure and the scaled institution-quarter EXPO used in the exposure-weighted regressions. Raw state EXPO is the pre-2005 state average constructed from government payments, crop-insurance subsidies, and the operating-cost/gross-income ratio. Panel B reports unique institutions in selected main-table cells; Tables 2–5 now also report these counts directly. Panel C reports quarter-to-quarter log changes in total agricultural loan amounts for the commercial-bank sample used in Table 3, converted to percentage points.

Table D2: Spec-Level Sample Map Across Main Estimation Designs

Specification family	Sample scope	Fixed effects	Cluster dimension	Observation map
FBUI baseline amount/share (Table 3)	FCS, commercial banks, credit unions	Institution ID + year + quarter-of-year	State and year–quarter	Amounts (production / farmland / total ag): FCS 3,917 / 3,941 / 3,922; Bank 280,425 / 260,256 / 421,405; CU 1,856 / 1,906 / 5,425. Share regressions use Bank and CU samples (same N by column).
FBUI baseline count/size (Table 4)	FCS, commercial banks, credit unions	Institution ID + year + quarter-of-year	State and year–quarter	Counts and average size (production / farmland / total ag): FCS — / — / 3,922; Bank 67,760 / 84,514 / 117,630; CU 1,856 / 1,906 / 5,425.
Exposure-weighted FBUI amount/share (Table 5)	FCS, commercial banks, credit unions (North Dakota CU excluded in baseline)	Institution ID + year–quarter	Institution ID and year–quarter	Amounts (production / farmland / total ag): FCS 3,917 / 3,941 / 3,922; Bank 110,370 / 136,786 / 189,159; CU 1,198 / 1,321 / 2,874. Share regressions use Bank and CU samples (same N by column).
Exposure-weighted FBUI count/size (Table 6)	FCS, commercial banks, credit unions (North Dakota CU excluded in baseline)	Institution ID + year–quarter	Institution ID and year–quarter	Counts and average size (production / farmland / total ag): FCS — / — / 3,922; Bank 58,739 / 76,391 / 103,832; CU 1,198 / 1,321 / 2,874.
Single-episode DID/event study (Table D4)	Commercial banks only; separate windows for 2008, 2014, and 2018 episodes	Institution ID + calendar quarter	Institution ID	Observations by episode (2008 / 2014 / 2018): 19,608 / 18,232 / 16,360 (same N for DID and event-study columns within each episode).
Stacked DID/event study (Table 7)	Commercial banks only; pooled stacked panel for 2008, 2014, and 2018 episodes	Bank-episode stack ID + calendar quarter (yq)	Bank-episode stack ID	54,200 observations in both DID and event-study specifications; each stack corresponds to a bank's appearance in one Farm Bill episode window.

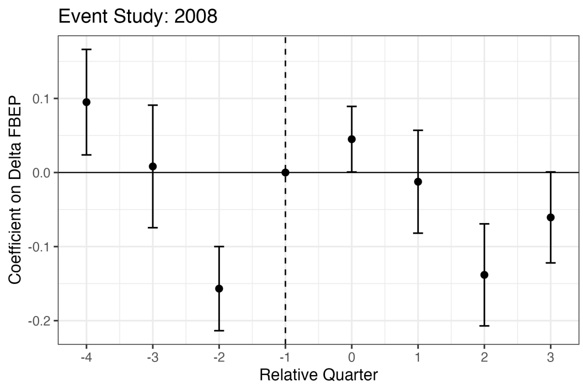
Notes: "—" indicates outcome-institution cells not estimated in the corresponding design. For lender-level designs, production/farmland/total-ag ordering follows the column order in the referenced tables.

Table D3: Commercial Bank Agricultural Lending by Loan-Size Bucket, 1994–2025

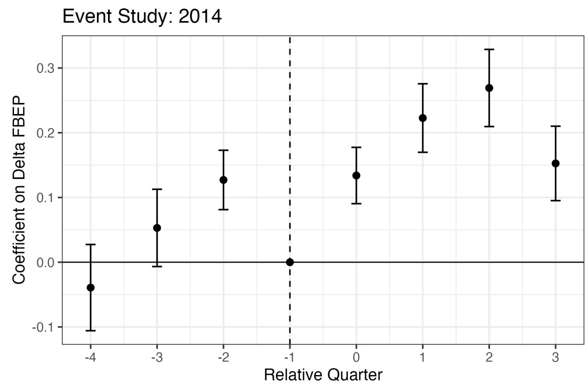
	Production loans			Farmland loans		
	$\leq$ \$100k	\$100k −−\$250k	\$250k −−\$500k	$\leq$ \$100k	\$100k −−\$250k	\$250k −−\$500k
Panel A. asinh(*Amount*)						
FBUI	-0.030^{***}	-0.040^{*}	-0.050^{**}	-0.003	-0.011^{***}	-0.020^{***}
	(0.007)	(0.022)	(0.022)	(0.003)	(0.003)	(0.004)
Panel B. asinh(#*Loans*)						
FBUI	-0.029^{***}	-0.031^{***}	-0.019^{***}	-0.008^{***}	-0.014^{***}	-0.014^{***}
	(0.003)	(0.009)	(0.004)	(0.002)	(0.003)	(0.003)
Panel C. log(*Average Loan Size*)						
FBUI	-0.001	-0.009	-0.031^{*}	0.005^{***}	0.003	-0.006^{*}
	(0.008)	(0.010)	(0.016)	(0.001)	(0.002)	(0.003)

Fixed effects: Institution, year, and quarter.
Std. errors: Two-way clustered by state and year–quarter.

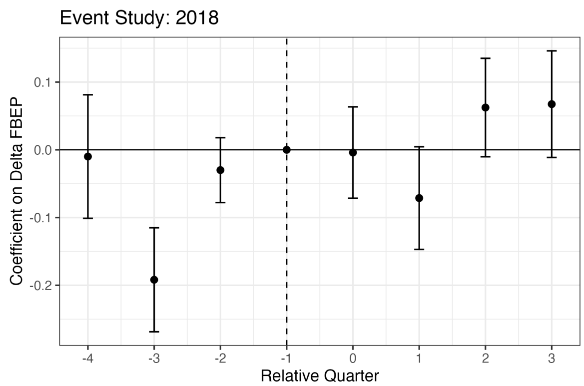
Notes: Each column reports a separate regression for commercial banks, with FBUI scaled to $[0, 1]$. Panel A uses asinh(loan amount), Panel B uses asinh(loan count), and Panel C uses log(loan amount/loan count). Controls are lagged equity-to-assets, lagged allowance-to-loans, lagged log total assets, lagged delinquent loan ratio, and quarterly average VIX.
The sample is restricted to commercial banks in the analysis sample states, with nonmissing controls and VIX, calendar year 1994 onward, agricultural loan share above 10 percent, positive dependent variable, and at least 20 quarterly observations per institution.
Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.



(a) 2008 Farm Bill



(b) 2014 Farm Bill



(c) 2018 Farm Bill

Figure D1: Single-episode event-study estimates of exposure-differential effects on log(Agricultural loans)

Notes: Points report the event-time interaction coefficients from the single-episode regressions, with relative quarter -1 as the omitted quarter. Vertical bars indicate 95% confidence intervals.

Table D4: Single-Episode DID and Event-Study Estimates for Farm Bill Episodes

	DID			Event study		
	2008	2014	2018	2008	2014	2018
Panel A: DID exposure effects						
post $\times\Delta$FBEP	-0.0281	0.1593***	0.0714**			
	(0.0297)	(0.0248)	(0.0334)			
Panel B: Event-study exposure effects (baseline relative quarter = -1)						
Relative quarter = -4 $\times\Delta$FBEP				0.0950***	-0.0392	-0.0099
				(0.0363)	(0.0340)	(0.0465)
Relative quarter = -3 $\times\Delta$FBEP				0.0082	0.0530*	-0.1918***
				(0.0422)	(0.0305)	(0.0392)
Relative quarter = -2 $\times\Delta$FBEP				-0.1568***	0.1271***	-0.0300
				(0.0290)	(0.0234)	(0.0244)
Relative quarter = 0 $\times\Delta$FBEP				0.0450**	0.1339***	-0.0040
				(0.0226)	(0.0222)	(0.0344)
Relative quarter = 1 $\times\Delta$FBEP				-0.0124	0.2227***	-0.0712*
				(0.0354)	(0.0270)	(0.0387)
Relative quarter = 2 $\times\Delta$FBEP				-0.1382***	0.2691***	0.0624*
				(0.0351)	(0.0304)	(0.0371)
Relative quarter = 3 $\times\Delta$FBEP				-0.0606*	0.1526***	0.0674*
				(0.0313)	(0.0293)	(0.0401)
Observations	19,608	18,232	16,360	19,608	18,232	16,360
R^2	0.9907	0.9921	0.9950	0.9907	0.9922	0.9951

Fixed effects: institution (ID) and calendar quarter (yq).
Std. errors: One-way clustered by institution ID.

Notes: Commercial-bank sample; dependent variable is log(agricultural loan amount). Columns (1)–(3) report single-episode DID coefficients on post$\times\Delta$FBEP. Columns (4)–(6) report single-episode event-study coefficients on relative-quarter interactions with ΔFBEP, with relative quarter -1 omitted.
ΔFBEP equals institution exposure multiplied by the episode-specific FBUI decline (pre minus post). Regressions include institution and calendar-quarter fixed effects and lagged equity-to-assets, lagged allowance-to-loans, lagged log total assets, and lagged delinquent loan ratio.
Significance: $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.