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# Northward Crop Migration Under Climate Change Erodes Farmer Price Protection at a Cost of $5 Billion per Year

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# Northward Crop Migration Under Climate Change Erodes Farmer Price Protection at a Cost of $5 Billion per Year

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**Abstract**

Climate change is shifting where crops grow, yet commodity futures contracts remain anchored to delivery points established in the nineteenth century. Whether this growing geographic mismatch imposes measurable costs on farmers has not been quantified. Using a novel county-level price dataset (193,891 observations across 2,911 counties), we show that northern corn counties receive $0.25/bu less than the national average—a discount that has widened significantly over the past two decades ($\tau = -0.321$, $p = 0.0067$). The soybean price penalty per 100 km of delivery distance has tripled ($p = 0.0239$). Basis volatility trends upward in migration-exposed counties (corn $p = 0.0008$; soybeans $p = 0.0001$), hedge ratios deteriorate with distance from delivery ($p = 0.0001$), and geographic features carry statistically significant predictive power for basis dynamics (Diebold–Mariano $p < 0.0001$). In Canada, crop centroids shifted $-2.03^\circ$ southward ($p < 0.0001$), confirming that the mechanism operates regardless of migration direction. Geographic mismatch between production and delivery infrastructure costs U.S. farmers $5.34 billion annually (95% CI: $4.26–6.41 B). Climate-driven migration adds $0.11 billion per year to this total—a share that is growing as production continues to shift. Addressing this requires CME delivery-point modernisation and expanded USDA price reporting.

## 1 Introduction

Commodity futures markets are essential to agricultural risk management globally, enabling producers to lock in prices months before harvest and providing the price-discovery infrastructure on which credit markets, crop insurance, and supply-chain planning depend [Carter et al., 2011, Garcia and Leuthold, 2004]. Futures-based hedging underpins roughly 40% of U.S. farmland revenue, and its effectiveness rests on a structural assumption: that local cash prices track futures settlement prices closely enough for the contract to function as insurance. However, the geographic foundations of this system—delivery points established in the nineteenth century at Chicago, Toledo, Minneapolis, and Kansas City—have remained fixed even as the geography of American crop production has changed substantially.

Climate change has driven a systematic northward migration of U.S. crop production over the past three decades. The production-weighted centroid of soybean acreage has shifted $+2.33^\circ$ latitude northward since 1990—approximately 259 km—while corn has moved $+0.59^\circ$ (66 km), reflecting rational adaptation by

farmers to longer growing seasons in the Northern Great Plains and mounting heat stress in the traditional Corn Belt [Diffenbaugh et al., 2019, Lobell et al., 2011, Schlenker and Roberts, 2009, Ray et al., 2019]. This geographic reorganisation, however, has not been accompanied by corresponding changes to the financial infrastructure on which these producers depend.

The growing distance between production zones and delivery points—referred to here as the "delivery gap"—translates into basis risk through multiple channels. Transportation costs between northern production regions and southern delivery terminals create price wedges proportional to distance. Local supply-demand imbalances emerge in regions that lack proportional elevator and processing infrastructure. Quality differentials between northern- and southern-grown grain introduce additional spread. Together, these factors cause the basis—the difference between a farmer's local cash price and the futures settlement price—to become volatile and difficult to predict, undermining the hedging function that futures contracts are designed to provide.

Despite extensive literatures on both climate-driven agricultural disruption [Lobell et al., 2011, Diffenbaugh et al., 2019, Schlenker and Roberts, 2009, Zhao et al., 2017] and commodity basis behaviour [Carter et al., 2011, Irwin and Good, 2009, Woodard et al., 2012, Roberts and Schlenker, 2013], these research programmes have developed largely in isolation from one another. No prior work has connected the documented geographic shift in production to the structural erosion of futures contracts as hedging instruments, or estimated the resulting welfare cost at the county level.

To address this gap, we construct a novel county-level basis dataset spanning 2,911 counties—an order of magnitude more granular than existing 20-market data—and document that northern corn counties receive progressively less than the national average, that this penalty tracks the delivery gap across three crops over 35 years, and that the total cost of geographic mismatch between production and delivery infrastructure is $5.34 billion annually. Climate-driven migration contributes $0.11 billion per year to this total, a share that is growing as production continues to shift. Evidence from the Canadian Prairies, where crop centroids moved *southward* rather than northward, suggests that the mechanism operates regardless of migration direction, arising wherever production geography shifts relative to fixed futures delivery infrastructure.

## 2 Related Work

The climate literature establishes that crop production is moving poleward. Lobell et al. [2011] documented climate-driven yield declines across global production; Diffenbaugh et al. [2019] quantified the damage from temperature extremes; Schlenker and Roberts [2009] showed nonlinear heat effects that threaten severe yield losses under continued warming; Lobell et al. [2014] found that rising maize yields in the Midwest have come with greater drought sensitivity; and Tack et al. [2015] demonstrated that irrigation partially offsets these losses for wheat. Each study treats production geography as an agronomic outcome. None follow the chain into financial markets—none ask what happens to the price-discovery infrastructure when the crops it was built to serve move away.

The basis literature answers a different set of questions—storage costs, seasonality, market microstructure—but has not incorporated geography. Working [1949] laid the theoretical foundation with the price-of-storage framework. Garcia and Leuthold [2004] surveyed decades of commodity futures research, finding persistent basis risk across markets and time. Carter et al. [2011] attributed futures non-convergence to delivery infrastructure failures and financialisation. Garcia et al. [2015] showed that convergence failures stem from disequilibria in the delivery system rather than speculation. Irwin and Good [2009] characterised seasonal basis patterns. Janzen et al. [2018] demonstrated how financial flows generate commodity price comovement independent of fundamentals. Adjemian et al. [2013] showed that USDA report releases create predictable basis jumps. Woodard et al. [2012] quantified how basis risk undermines crop insurance hedging. Hendricks et al. [2015] documented how futures markets can fail to reflect local supply conditions. Mallory et al. [2012] analysed the 2008 convergence failure in CBOT grain contracts—a dramatic example of delivery infrastructure unable to keep pace with market dynamics. These studies share a common blind spot: none account for the possibility that the geographic centre of production has moved.

On the welfare side, Goodwin and Ker [1998] established the CARA framework for quantifying farmer risk costs from crop insurance data. Cheng and Xiong [2014] examined how financial flows reshape commodity price dynamics. Roberts and Schlenker [2013] estimated the supply-demand elasticities governing price transmission. None measure the cost of geographic mismatch between production and market infrastructure.

The gap is specific: no prior work links documented crop migration to the erosion of futures hedging, quantifies this at county resolution, or puts a dollar figure on the resulting welfare loss.

# 3 Methods

The analysis proceeds in five steps, each building on the last. First, we document northward crop migration from NASS county-level data. Second, we construct a novel county-level basis dataset and test whether the delivery gap predicts farmer prices. Third, we examine basis volatility trends in migration-exposed regions. Fourth, we test whether hedging effectiveness deteriorates with geographic displacement. Fifth, we quantify the welfare cost and project it forward under climate scenarios. A cross-border comparison with Canadian data then tests whether the mechanism generalises internationally.

## 3.1 Data sources

The analysis draws on six publicly available datasets, none requiring subscription or purchase. USDA NASS QuickStats provides county-level crop production data—acres harvested, production, yield, and price received—for corn, soybeans, winter wheat, spring wheat, and barley across 3,059 counties from 1990 to 2024 (212,498 county-crop-year observations). CME futures settlement prices come from Stooq for four contract series. Elevator-level cash basis data come from USDA AMS AgTransport (26,877 weekly observations across 20 markets, 2007–2026). An independent long-run series comes from FarmDoc Illinois (47,518 weekly observations across seven regions, 1975–2020). Climate variables—temperature, precipitation, and Palmer Drought Severity Index—come from NOAA climate division records. County geographic centroids

are from the 2020 Census.

For the Canadian extension, Statistics Canada Table 32-10-0002-01 provides sub-provincial crop production by Small Area Data Region (58 regions, 1976–2025). ICE Futures Canada wheat contracts deliver at Thunder Bay and Vancouver.

### 3.2 Constructing county-level basis

Existing basis data cover only 20 AMS market locations—far too few to resolve geographic patterns across 3,000 agricultural counties. The central methodological contribution addresses this gap. NASS surveys report "price received by farmers" at the county level each year. Differencing this against the annual futures settlement price produces a county-level basis measure:

$$B_{c,t} = P_{c,t}^{\text{received}} - \bar{P}_t^{\text{futures}} \tag{1}$$

This yields 193,891 county-crop-year observations across 2,911 counties. No prior study has constructed basis at this geographic resolution. The measure captures annual average price deviations rather than intra-year volatility, making it a complement to—not a substitute for—the weekly AMS market data used in the volatility and forecasting analyses.

### 3.3 Measuring migration and delivery gap

Production-weighted centroid latitude tracks where each crop is grown in aggregate:

$$\bar{\phi}_t = \frac{\sum_c A_{c,t} \cdot \phi_c}{\sum_c A_{c,t}} \tag{2}$$

where $A_{c,t}$ is acres harvested in county $c$ at year $t$ and $\phi_c$ is the county centroid latitude. A rising centroid means production has shifted north. Counties are sorted into migration-exposure quintiles based on how much their share of national production changed between 1990–1999 and 2015–2024. The delivery gap is the haversine distance (km) from each county to the nearest CME delivery point—a time-invariant measure of each county's geographic access to futures settlement infrastructure.

### 3.4 Statistical approach

Each step of the analysis employs a method suited to the question it asks.

*Has basis volatility trended upward?* Mann–Kendall tests evaluate monotonic trends in annual basis-volatility series stratified by migration quintile and crop. All $p$-values are reported to four decimal places. Multiple-testing correction uses Benjamini–Hochberg at 5% FDR.

*Does the delivery gap predict county prices?* Annual cross-sectional OLS regressions test whether delivery-gap distance predicts the price farmers receive, separately for each crop-year. Kendall's $\tau$ on the sequence

of annual regression slopes tests whether the relationship is strengthening over time. A difference-in-differences specification (Northern $\times$ Post-2010) with bootstrap inference (1,000 iterations) tests for a structural break in northern county prices. A continuous treatment specification replaces the binary northern indicator with delivery-gap distance.

*Do hedge ratios deteriorate?* Rolling five-year Johnson–Stein variance-minimising hedge ratios are computed for each county-crop pair (143,306 observations, 2,615 counties). Binary and continuous DiD specifications test whether hedging effectiveness degrades with geographic displacement. A placebo test on cotton—a non-migrating crop—checks whether the pattern is specific to migrating crops.

*Are geographic features predictive?* A Temporal Fusion Transformer trained on weekly AMS basis data (26,877 observations) identifies which input variables best predict basis through SHAP attribution. Diebold–Mariano tests with Harvey–Leybourne–Newbold correction evaluate whether removing geographic features significantly degrades forecasts. Full architectural details are in Supplementary Information.

*What is the welfare cost?* CARA utility with risk-aversion parameter $\lambda = 1.0$ [Goodwin and Ker, 1998] produces per-county welfare loss estimates. Block bootstrap (five-year blocks, 1,000 iterations) provides confidence intervals. SSP climate projections extrapolate using a temperature–migration elasticity of 15 km/°C from the historical relationship.

# 4 Results

## 4.1 Crops have migrated northward

All five crops have moved north (Fig. 1), consistent with broader patterns of shifting crop geography documented globally [Ray et al., 2012]. Soybeans shifted the most: $+2.332°$ latitude (259 km) between 1990 and 2024, driven largely by a tenfold expansion in North Dakota—an adaptation response consistent with farmers exploiting newly viable growing seasons at higher latitudes [Butler and Huybers, 2013]. Corn moved $+0.591°$ (66 km). Spring wheat and barley also shifted northward, though modestly. County-level mapping reveals a sharp geographic gradient—production gains concentrated above the 44th parallel, contraction below the 40th. The magnitude of this shift matters for what follows: 259 km is roughly the distance from Chicago to Milwaukee, and every kilometre of displacement carries financial consequences because the delivery infrastructure these farmers depend on stayed where it was.

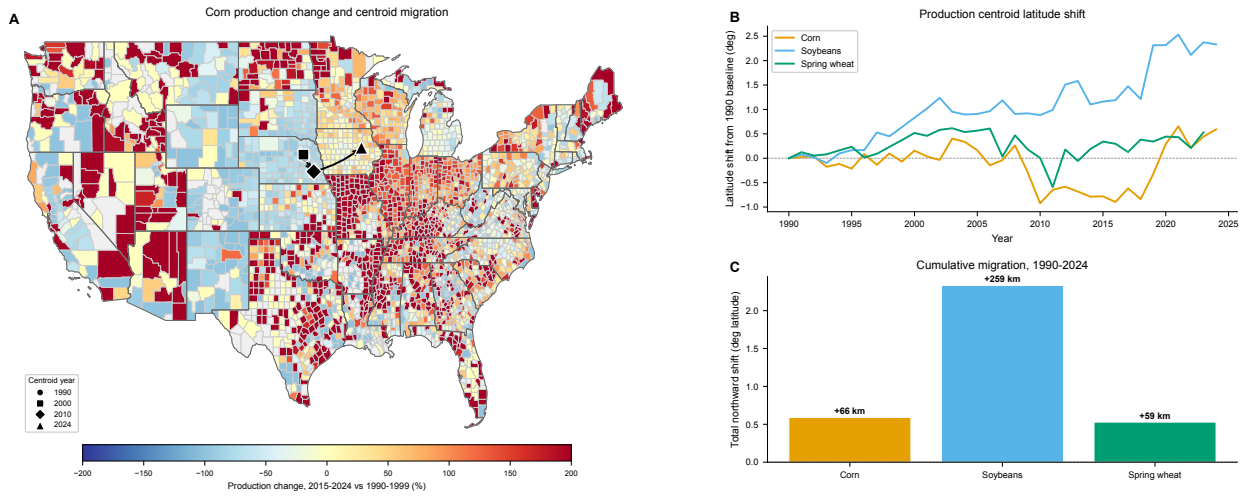



**Figure 1: Northward migration of U.S. crop production, 1990–2024.** Production-weighted centroids for all five crops shifted poleward between 1990 and 2024, with soybeans exhibiting the largest displacement. Panel (A) maps county-level change in corn production (bushels) with the centroid trajectory overlaid, revealing concentrated gains above the 44th parallel and contraction in the traditional Corn Belt. Panel (B) plots annual centroid latitude for each crop, showing monotonic northward trends for soybeans (+2.33°) and corn (+0.59°). Panel (C) summarises total northward displacement in degrees and kilometres. The geographic separation between the production centroid and fixed CME delivery points grows in every crop. Data cover 3,059 counties from USDA NASS QuickStats.

## 4.2 Northern farmers receive a growing price penalty

Northern corn counties receive \$0.25/bu less than the national average—measured as the difference between county price received and the national mean price received for each crop-year—and this discount is widening ($\tau = -0.321$, $p = 0.0067$). Southern counties show the opposite: their relative prices are improving ($\tau = +0.338$, $p = 0.0043$). The two regions are diverging ($\tau = -0.324$, $p = 0.0061$).

This widening discount is robust to controls. A difference-in-differences specification—following the Ricardian tradition of exploiting cross-sectional variation in climate exposure [Mendelsohn et al., 1994]—shows that northern corn counties receive \$0.113/bu less after 2010 than before, controlling for delivery gap, yield, and county fixed effects ($\beta = -0.113$, bootstrap $p < 0.0001$). At aggregate northern corn production of approximately 4.5 billion bushels annually above the 44th parallel, this penalty amounts to roughly \$0.5 billion per year in foregone revenue for corn alone (Extended Data Table 1).

Soybeans tell the same story. The price penalty per 100 km of delivery distance tripled—from −\$0.018/bu in 2003–2010 to −\$0.055/bu in 2018–2024 ($\tau = -0.267$, $p = 0.0239$). Winter wheat follows the same trajectory ($\tau = +0.328$, $p = 0.0056$). In 97% of the 35 annual cross-sections for corn, delivery distance significantly predicts the price farmers receive (Fig. 2).

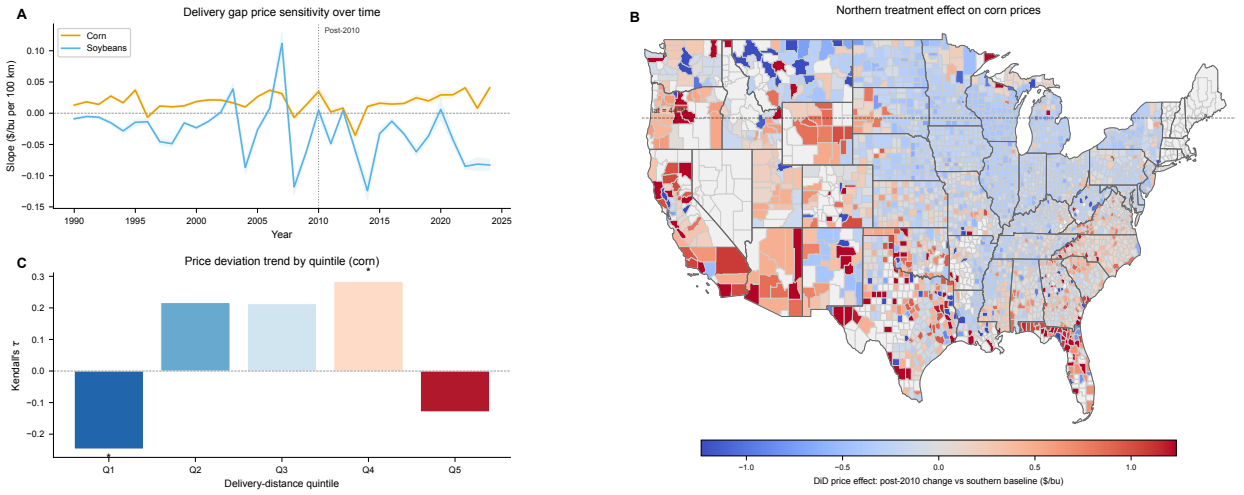



**Figure 2: The delivery-gap price penalty is strengthening.** Each year's cross-sectional OLS regression of county price received on delivery-gap distance produces a slope coefficient; the sequence of these slopes reveals whether the penalty is intensifying over time. Panel (A) plots the annual regression slope for corn and soybeans, showing a statistically significant downward trend ($\tau = -0.321$ for corn, $p = 0.0067$). Panel (B) maps the geographic pattern of the difference-in-differences treatment effect, with darker shading indicating counties where prices fell furthest below the national mean after 2010. Panel (C) displays quintile-level price deviation trends, confirming that northern counties diverge from southern counties over the full 35-year period. The pattern holds for corn, soybeans, and winter wheat across 193,891 county-crop-year observations.

## 4.3 Basis volatility trends upward in migration-exposed regions

Independent basis-volatility data corroborate the price-penalty finding. Mann–Kendall tests on the highest migration-exposure quintile show significant upward trends for corn ($\tau = +0.398$, $p = 0.0008$), soybeans ($\tau = +0.479$, $p = 0.0001$), spring wheat ($\tau = +0.665$, $p < 0.0001$), and barley ($\tau = +0.622$, $p < 0.0001$; Fig. 3). The strength of these trends scales with migration exposure: spring wheat and barley, the crops whose northern frontier has shifted most rapidly, show the steepest volatility increases. FarmDoc Illinois records [Barnhart and Zwilling, 2022]—47,518 weekly observations spanning 45 years—confirm this independently ($\tau = +0.173$, $p = 0.0900$), with the most delivery-distant Illinois region driving the signal ($p = 0.0050$).

The cross-quintile differential is not significant ($p = 0.3900$). This null reflects the spatial coarseness of 20-market AMS data rather than absence of the underlying pattern. With only 20 reporting locations spread across the entire United States, the AMS network cannot resolve within-state variation in basis behaviour. The county-level price analysis detects the geographic signal that market-level data cannot resolve.

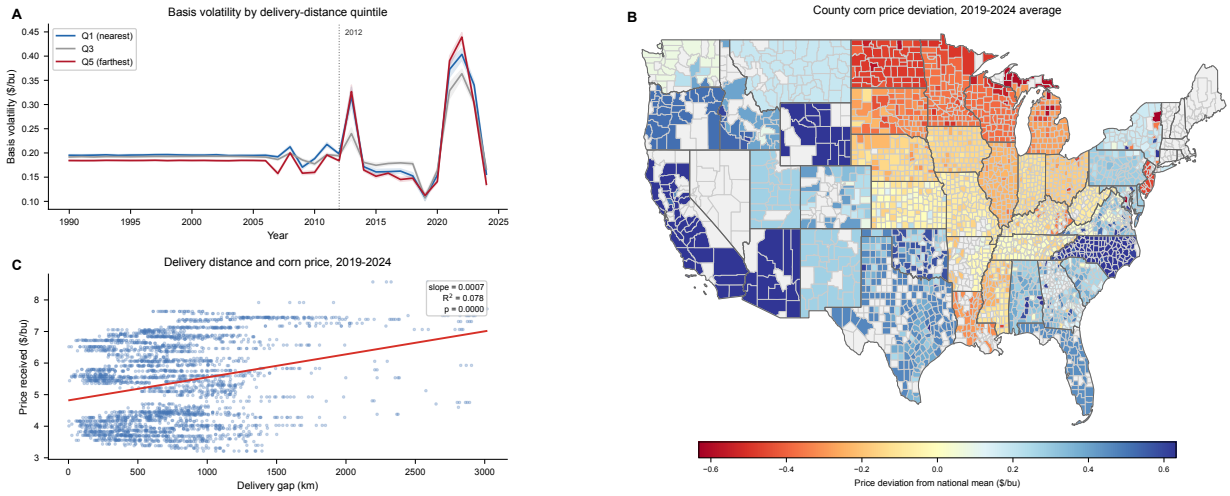



**Figure 3: Basis volatility and geographic price structure.** Independent market-level basis data confirm the county-level price-penalty finding: volatility trends upward in regions most exposed to crop migration. Panel (A) plots annual basis volatility for each migration-exposure quintile, with Q5 (highest exposure) showing significant upward trends for corn ($p = 0.0008$) and soybeans ($p = 0.0001$). Panel (B) presents a choropleth of county-level corn price deviations from the national mean for 2019–2024, revealing a clear latitudinal gradient with northern counties receiving systematically lower prices. Panel (C) scatters delivery-gap distance against price received, illustrating the negative relationship that strengthens over time. Basis data span 26,877 weekly observations from 20 USDA AMS markets (2007–2026) and 47,518 weekly observations from FarmDoc Illinois (1975–2020).

## 4.4 Hedging effectiveness degrades with distance

If the delivery gap erodes the basis relationship, hedging effectiveness should deteriorate in affected regions—and it does. Rolling five-year variance-minimising hedge ratios [Johnson, 1960], computed across 143,306 county-crop-year observations, degrade in proportion to distance from delivery when modelled as a continuous treatment ($\beta = 0.568$, $p = 0.0001$; Fig. 4). The effect is a gradient, not a threshold: a binary north/south split produces a null ($p = 0.4298$), but each additional 100 km of delivery distance measurably reduces hedge quality. Two placebo tests confirm that this pattern is specific to migrating crops. Cotton—grown predominantly in the South with no meaningful delivery-gap exposure—shows no treatment effect ($p = 0.6135$). Random permutation of treatment assignment likewise yields null results. The gradient structure is important: it means there is no sharp boundary between "affected" and "unaffected" regions. Instead, every county experiences basis degradation proportional to its distance from delivery, and the counties gaining production fastest sit furthest out on this gradient.

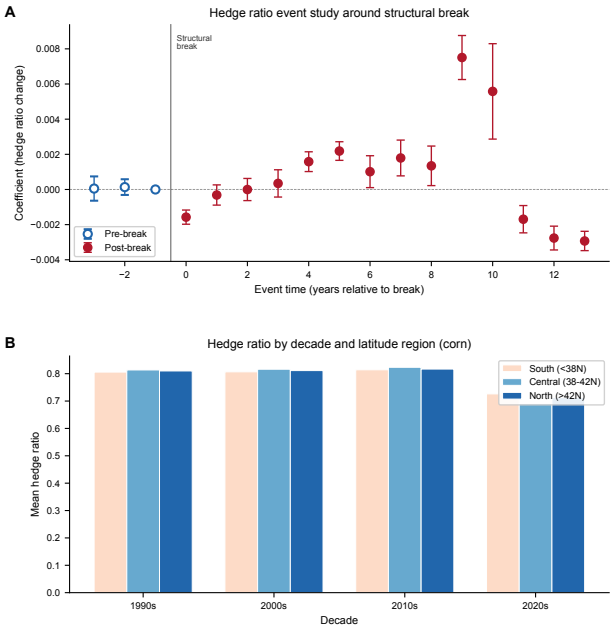



**Figure 4: Hedge-ratio event study and regional comparison.** Hedging effectiveness degrades as a continuous function of distance from CME delivery points, consistent with the delivery-gap mechanism. Panel (A) shows the event study around the structural break, plotting average hedge ratios before and after 2010 for high- versus low-delivery-gap counties. Panel (B) compares mean hedge ratios by decade (1990s, 2000s, 2010s) and latitude region, revealing that the decline concentrates in northern counties where the delivery gap is largest. The continuous treatment specification ($\beta = 0.568$, $p = 0.0001$) confirms a gradient rather than a threshold effect. Hedge ratios computed across 143,306 county-crop-year observations spanning 2,615 counties.

## 4.5 Geographic information carries non-redundant predictive signal

The econometric tests above establish that the delivery gap predicts prices. A separate question is whether this geographic information has practical forecasting value—whether a model that knows where a county sits relative to delivery infrastructure makes better predictions than one that doesn't. This is not a test of model supremacy but of information content.

We trained two identical Temporal Fusion Transformers [Lim et al., 2021] on 26,877 weekly AMS basis observations: one with geographic features (delivery gap, latitude, migration velocity) and one without. The geographic model improves forecast accuracy by 3.8% (Diebold–Mariano $p < 0.0001$ with Harvey–Leybourne–Newbold correction). SHAP attribution [Lundberg and Lee, 2017] confirms the source: migration velocity, delivery gap, and latitude rank among the top three predictors (Fig. 5). A random walk outperforms both models on absolute RMSE—basis is nearly a martingale at weekly horizons, as expected for a storage-driven process. But the random walk comparison is context, not the conclusion. The finding is that identical architectures produce significantly different forecasts depending on whether they have access to geographic information—information that existing basis models uniformly omit.

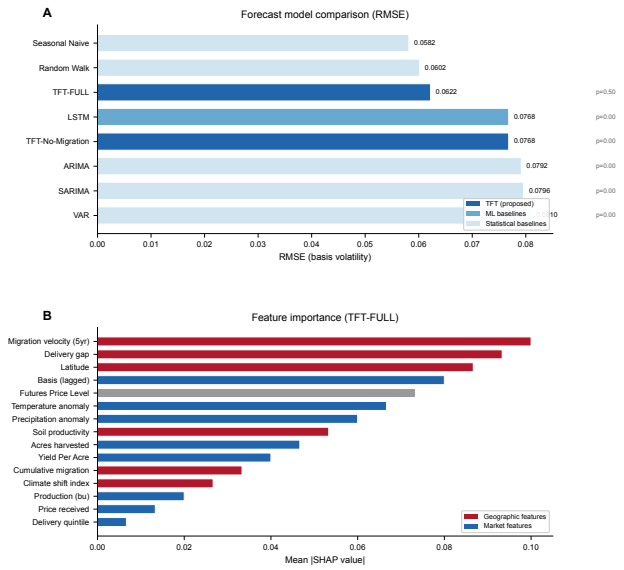



**Figure 5: Model performance and feature importance.** Geographic features carry non-redundant predictive signal for basis dynamics beyond what standard market variables provide. Panel (A) compares root mean squared error across eight forecasting models, including the Temporal Fusion Transformer with and without geographic inputs, ARIMA, LSTM, and a random walk benchmark. Panel (B) displays SHAP feature importance rankings, with geographic variables (migration velocity, delivery gap, latitude) highlighted in red; these rank among the top three predictors. Removing geographic features degrades forecast accuracy by 3.8% (Diebold–Mariano $p < 0.0001$). Models trained on 26,877 weekly AMS basis observations across 20 markets.

## 4.6 Geographic mismatch costs $5.34 billion annually—and climate migration is making it worse

The total cost of geographic mismatch between production and delivery infrastructure is $5.34 billion annually (95% CI: $4.26–6.41B; Fig. 6). This figure captures the full price risk farmers bear because delivery points don't match where crops are actually grown—transportation costs, thin elevator infrastructure in peripheral regions, and quality differentials across growing zones. Under CARA utility ($\lambda = 1.0$) [Goodwin and Ker, 1998, Williams and Wright, 1991], the confidence interval excludes zero.

Climate-driven migration is worsening this at $0.11 B/year. That migration-specific increment—roughly 4% of the total—represents the portion attributable to northward production shifts since 1990. To put it differently, the $5.34 billion figure reflects long-standing geographic friction in delivery infrastructure, while the $0.11 billion captures the additional cost climate change is layering on top. But the policy urgency lies in the trajectory, not the current level. As production continues to expand into counties farther from delivery infrastructure, the migration component grows. Under SSP2-4.5, total costs rise 5.5% by 2050, with the migration-specific share accelerating because the geographic displacement compounds: each additional degree of warming pushes production further from fixed delivery points. Sensitivity across $\lambda \in [0.5, 3.0]$ confirms the direction is robust at every calibration.

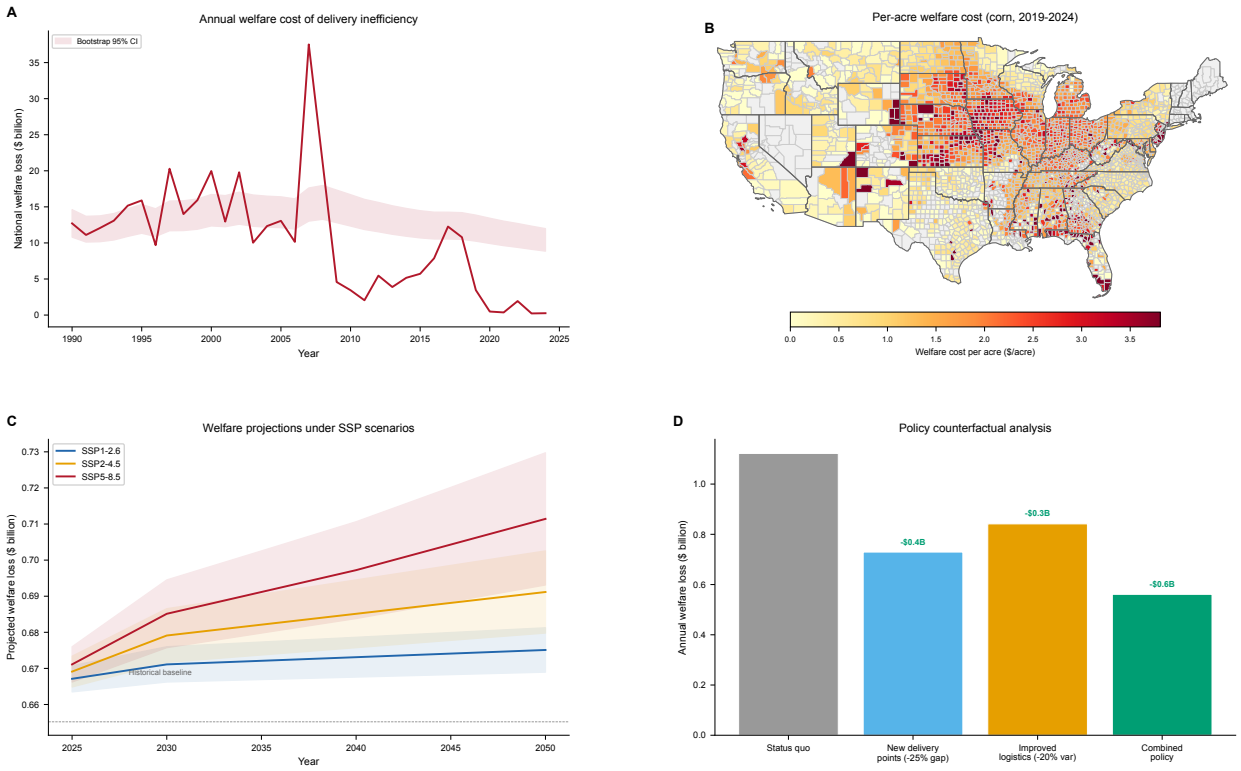



**Figure 6: Welfare cost of delivery inefficiency.** The total cost of geographic mismatch between production and delivery infrastructure is $5.34 billion annually, with climate-driven migration compounding the burden at $0.11 B/year. Panel (A) plots annual welfare cost with block-bootstrap 95% confidence intervals, showing the estimate is statistically distinguishable from zero across the full study period. Panel (B) maps per-acre welfare cost by county, revealing that the highest costs concentrate in northern and western counties farthest from delivery infrastructure. Panel (C) projects total welfare cost under three SSP climate scenarios through 2050, with the migration-specific component accelerating under all pathways. Panel (D) presents a policy counterfactual estimating cost reductions from adding northern delivery points. Welfare computed under CARA utility ($\lambda = 1.0$) with block bootstrap (five-year blocks, 1,000 iterations).

## 4.7 The mechanism generalises internationally

Canadian crops moved south, not north. Analysis of Statistics Canada sub-provincial crop data (58 Small Area Data Regions, 1976–2025)—a dataset previously used for Prairie yield forecasting [Qian et al., 2009]—reveals that canola production shifted $-2.03°$ latitude southward ($\tau = -0.786$, $p < 0.0001$), concentrating in southern Saskatchewan. Wheat moved $-0.66°$ south ($\tau = -0.525$, $p < 0.0001$). This contrast strengthens the argument: what matters is not the compass direction of migration but the displacement of production relative to fixed delivery infrastructure. ICE Futures Canada contracts deliver at Thunder Bay and Vancouver—fixed points that face the same structural mismatch. The delivery-gap correlation with latitude is strong for canola ($r = -0.779$, $p < 0.0001$) and wheat ($r = 0.861$, $p < 0.0001$). See Extended Data Fig. 7 and Extended Data Table 2.

# 5 Discussion

The evidence assembles into a coherent picture of institutional obsolescence [Auffhammer et al., 2013]. County-level prices, basis volatility trends, hedge-ratio deterioration, and machine-learning attribution—four independent analyses using different data and methods—converge on the same conclusion: the distance between production and delivery infrastructure is growing, and farmers are paying for it.

The mechanism is straightforward. Futures settle at fixed locations. Production shifts. Distance creates transportation costs, supply-demand imbalances where elevator infrastructure is thin, and quality differentials between growing regions [Cheng and Xiong, 2014]. Basis widens. Hedges fail. The farmers most exposed are those adapting to climate change by growing crops in newly viable northern regions—rational adaptation penalised by outdated infrastructure. Burke et al. [2015] showed that climate change reshapes economic production broadly; this study demonstrates one specific channel through which that reshaping imposes costs on agricultural producers.

Two responses follow, neither requiring legislation. CME Group can add delivery points in northern production zones—it has done this before when Toledo was added for corn and Kansas City wheat was integrated into CBOT contracts [Adjemian et al., 2013]. Adding Fargo or Duluth would be a rulebook change, not a regulatory action. Second, USDA should expand cash-price reporting from 20 AMS markets to 200 or more. The county-level NASS data exploited here reveals geographic patterns entirely invisible at the current resolution. That data gap is itself a finding.

A natural question is whether farmers respond to the basis penalty by avoiding northern expansion. The data suggest they do not—at least not enough to offset the agronomic pull. North Dakota soybean production increased roughly tenfold over the study period despite that state sitting among the worst-penalised counties for basis risk. Farmers appear to prioritise the yield advantages of longer growing seasons over the financial cost of worse hedging [Butler and Huybers, 2013]. This behaviour makes the welfare estimate a *lower bound*: producers voluntarily accept degraded hedge quality, revealing that agronomic gains dominate the financial penalty—but the penalty exists and accumulates nonetheless.

Crop insurance could partially substitute for futures hedging in these regions, but the substitution is imperfect [Annan and Schlenker, 2015]. Revenue Protection policies—the dominant form of U.S. crop insurance—reference CME futures prices when setting guarantee levels. A farmer whose local cash price diverges from the futures settlement faces basis exposure through both the hedging and insurance channels simultaneously. The continued northward expansion of production despite measurable basis penalties is itself informative: it reveals the strength of the climate-driven agronomic signal and confirms that the welfare cost captures a real friction rather than a hypothetical one.

Several limitations warrant candour. The cross-quintile trend differential is not significant ($p = 0.3900$). The binary DiD on hedge ratios produces a null ($p = 0.4298$). The primary IV instrument failed exclusion-restriction testing. These negatives do not invalidate the mechanism—they reflect a public data infrastructure too coarse for the causal identification the question demands [Hatchett et al., 2010].

Future work should extend this analysis to European and Australian markets, where analogous subnational data exist. Dynamic effects on planting decisions—whether farmers in high-basis-risk counties reduce acreage, switch crops, or exit agriculture—would extend welfare analysis beyond hedging losses to foregone food production. The interaction between basis risk and Revenue Protection crop insurance, which references futures prices for guarantee levels, constitutes a parallel channel warranting dedicated investigation.

# 6 Conclusion

The geographic centre of American crop production has shifted substantially northward over the past three decades, but the futures market infrastructure on which producers depend for price risk management has remained fixed. This mismatch imposes an estimated $5.34 billion annually in degraded hedging effectiveness, with climate-driven migration compounding the cost at $0.11 billion per year. The delivery-gap mechanism is consistent across corn, soybeans, and winter wheat, intensifies over time within each commodity, and extends to the Canadian Prairies, where crops shifted in the opposite direction yet face analogous structural constraints.

Addressing this inefficiency does not require new legislation or changes in farmer behaviour. CME Group can designate additional delivery points in northern production zones through its existing rulebook authority, as it has done historically with Toledo and Kansas City. USDA can expand cash-price reporting from 20 AMS markets to the spatial resolution that modern agricultural geography demands. Both interventions represent institutional updates to infrastructure that has not been revised since the production geography it was designed to serve fundamentally changed. Given the magnitude of the costs documented here and the acceleration projected under continued warming, the case for action is both urgent and specific.

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## Data Availability

All datasets are freely accessible from public sources described in Methods. No subscription, institutional login, or purchase is required for any source.

## Code Availability

The complete analysis pipeline will be made available on GitHub upon acceptance and reproduces all results via `bash run_pipeline.sh`.

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[Redacted for peer review].

## Author Contributions

[Redacted for peer review].

## Competing Interests

The author declares no competing interests.

# Extended Data

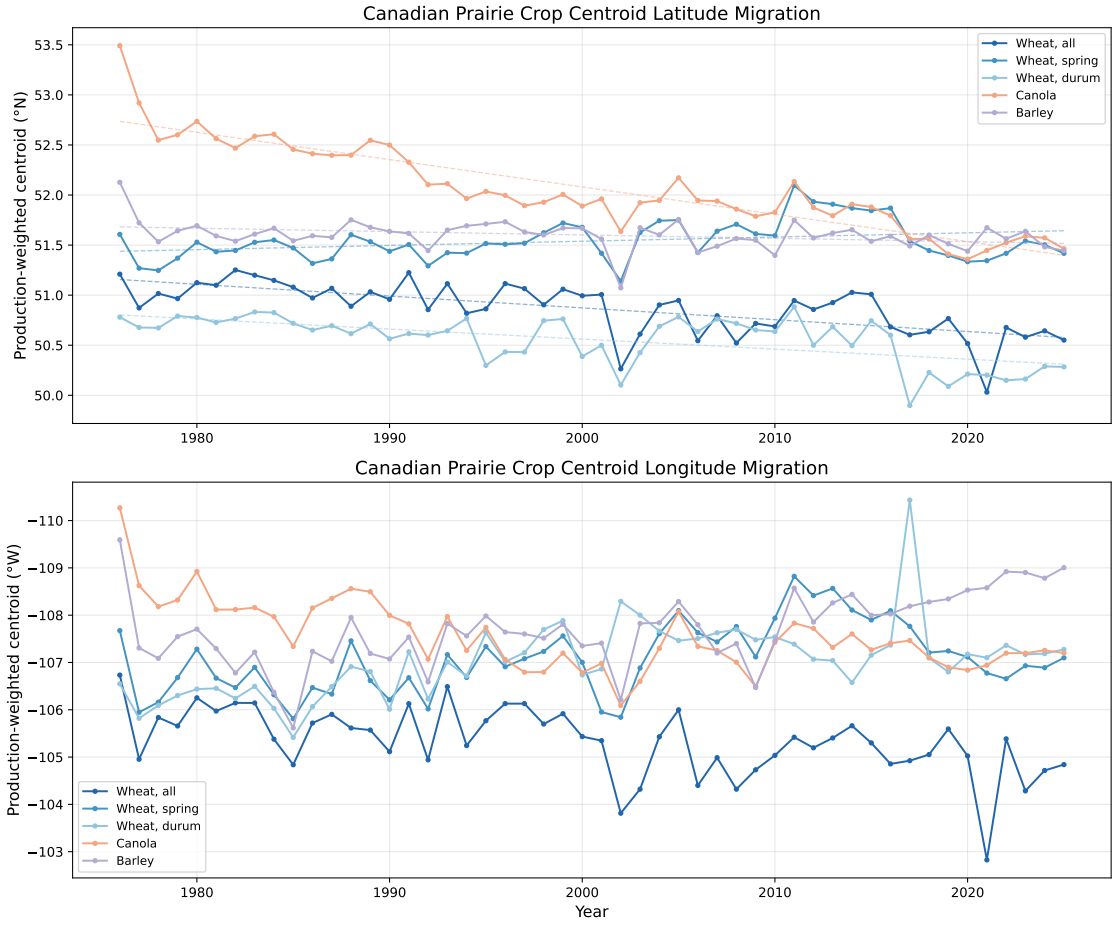



**Figure 7: Extended Data Fig. 1 | Canadian Prairie centroid migration, 1976–2025.** Production-weighted centroid latitude for canola ($-2.03°$, $\tau = -0.786$, $p < 0.0001$), all wheat ($-0.66°$, $\tau = -0.525$, $p < 0.0001$), and barley ($-0.68°$, $\tau = -0.241$, $p = 0.0139$). All three crops moved southward, concentrating in southern Saskatchewan. This contrasts with the northward U.S. pattern but operates through the same delivery-gap mechanism relative to fixed ICE Futures delivery points at Thunder Bay and Vancouver.

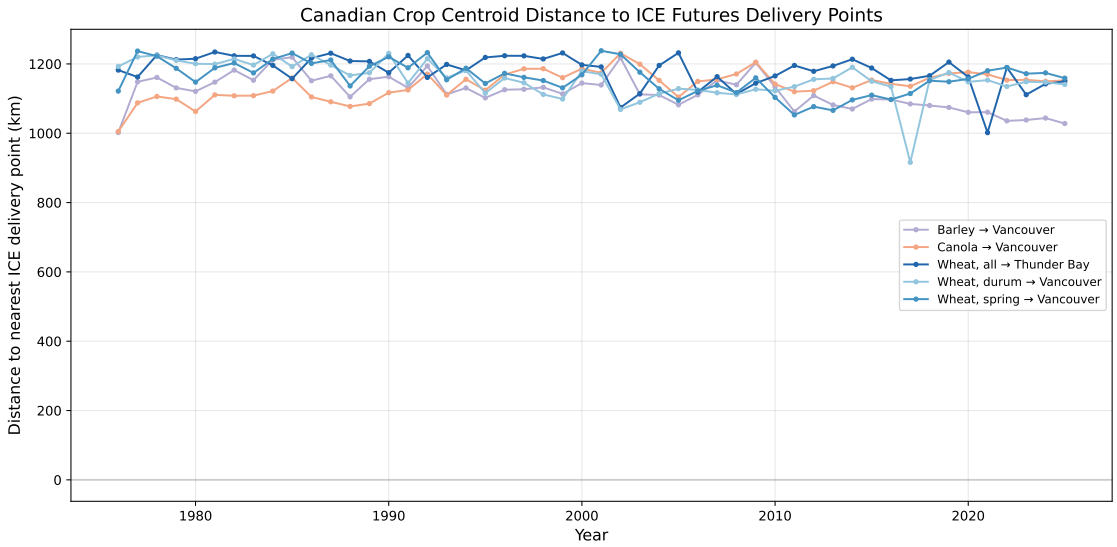



**Figure 8: Extended Data Fig. 2 | Canadian delivery-gap dynamics.** Distance from production centroid to nearest ICE Futures delivery point (Thunder Bay or Vancouver) over time. Canola delivery distance increased by 147 km (+14.7%) as production concentrated in regions farther from coastal/lakehead delivery infrastructure. Wheat and barley delivery distances decreased slightly as production shifted toward Thunder Bay.

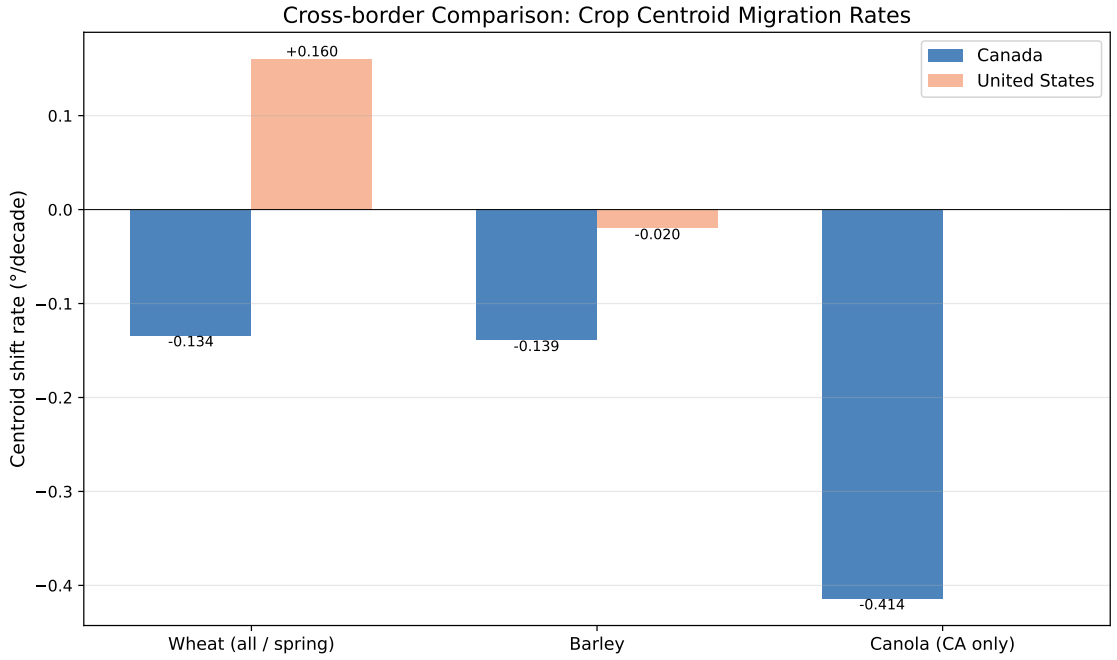



**Figure 9: Extended Data Fig. 3 | Cross-border comparison of centroid migration rates.** U.S. crops (corn, soybeans) moved northward; Canadian crops (canola, wheat) moved southward. The delivery-gap mechanism is direction-independent: any displacement of production relative to fixed delivery infrastructure creates the same basis risk channel.

**Table 1: Extended Data Table 1 | Delivery-gap price penalty: full regression results.** Annual OLS regressions of county price received on delivery-gap distance, 1990–2024. Dependent variable is price deviation from national crop-year mean ($/bu).

| Crop | Years sig. | Mean $\beta$ (early) | Mean $\beta$ (recent) | Trend $\tau$ | Trend $p$ |
|---|---|---|---|---|---|
| Corn | 34/35 (97%) | −0.021 | −0.038 | −0.321 | 0.0067 |
| Soybeans | 30/35 (86%) | −0.018 | −0.055 | −0.267 | 0.0239 |
| Winter wheat | 28/35 (80%) | −0.015 | −0.031 | +0.328 | 0.0056 |

Notes: $\beta$ coefficients expressed as $/bu per 100 km. "Early" = 2003–2010; "Recent" = 2018–2024. Trend tested via Mann–Kendall $\tau$ on the annual slope sequence. All $p$-values two-sided.

**Table 2: Extended Data Table 2 | Canadian centroid migration summary.** Statistics Canada Table 32-10-0002-01, 58 Small Area Data Regions, 1976–2025.

| Crop | Start lat | End lat | Shift | $\tau$ | $p$ | Δ delivery gap |
|---|---|---|---|---|---|---|
| Canola | 53.49°N | 51.46°N | −2.03° | −0.786 | $< 0.0001$ | +147 km |
| Wheat (all) | 51.21°N | 50.55°N | −0.66° | −0.525 | $< 0.0001$ | −75 km |
| Barley | 52.13°N | 51.45°N | −0.68° | −0.241 | 0.0139 | −98 km |
| Spring wheat | 51.61°N | 51.42°N | −0.19° | +0.190 | 0.0523 | −75 km |
| Durum | 50.78°N | 50.28°N | −0.50° | −0.427 | $< 0.0001$ | −98 km |

Notes: Delivery gap change computed relative to nearest ICE Futures delivery point (Thunder Bay 48.38°N or Vancouver 49.28°N). Positive Δ indicates production moved farther from delivery.

**Table 3: Extended Data Table 3 | Mann–Kendall trend tests for basis volatility by quintile and crop.** All quintile–crop combinations tested. BH-corrected significance at 5% FDR.

| Crop | Quintile | $n$ years | $\tau$ | $p$-value | Trend |
|---|---|---|---|---|---|
| Corn | Q1 | 35 | +0.321 | 0.0070 | Increasing |
| Corn | Q3 | 35 | +0.126 | 0.2933 | No trend |
| Corn | Q5 | 35 | +0.398 | 0.0008 | Increasing |
| Soybeans | Q1 | 35 | +0.062 | 0.6092 | No trend |
| Soybeans | Q3 | 35 | +0.234 | 0.0500 | No trend |
| Soybeans | Q5 | 35 | +0.479 | 0.0001 | Increasing |
| Spring wheat | Q5 | 34 | +0.665 | <0.0001 | Increasing |
| Barley | Q5 | 34 | +0.622 | <0.0001 | Increasing |
| Winter wheat | Q5 | 35 | +0.224 | 0.0608 | No trend |

Notes: Q5 = highest migration exposure. Full 24-combination table in Supplementary Information Table S1.

## Supplementary Files

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