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Green Transition Readiness and Performance in Agriculture. Evidence from Western Ukraine

Abstract

This study examines whether regional readiness for green transition practices is associated with better agricultural-economic performance in Western Ukraine. Because farm-level readiness data are not consistently available, the paper builds a transparent set of oblast-level readiness proxies using official statistics on (i) the share of sown area treated with mineral fertilizers, organic fertilizers, and pesticides, and (ii) mineral fertilizer intensity (kg per hectare). Performance is measured using gross regional product (GRP) as an auditable macro proxy for regional economic outcomes during the overlapping period covered by publicly accessible statistical publications. The empirical strategy applies fixed-effects regressions with year controls and robustness checks using alternative index construction. Results indicate that the composite readiness index is not robustly associated with higher regional performance in the short sample window, while individual input-intensity components show statistically detectable within-region associations that are sensitive to specification and the limited time coverage. The findings suggest that, under data constraints and wartime disturbances, aggregate economic indicators may not immediately reflect environmental-practice readiness, emphasizing the need for longer panels and sector-specific value-added measures. The paper contributes a replicable, data-auditable workflow for green-readiness measurement using official statistics, with clear limitations and directions for improving inference.

Keywords: green transition; sustainable agriculture; pesticides; fertilizers; readiness index; regional performance; Ukraine

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1. Introduction

The green transition in agriculture is increasingly discussed in terms of competitiveness, resilience, and market access rather than as an environmental objective alone. For agricultural producers, "greening" is often operationalized through measurable changes in production practices: reducing unnecessary chemical intensity, improving nutrient management, adopting more precise application techniques, and applying soil stewardship measures that protect fertility and structure over time. These shifts matter economically. When input use becomes more efficient, farms can lower unit costs, reduce exposure to price shocks in fertilizers and crop protection products, and stabilize yields by protecting soil functions and reducing environmental stress. At the same time, sustainability-related buyer requirements are tightening, particularly in export-oriented value chains where traceability, documentation, and compliance with quality standards increasingly influence market access and contract conditions. In this sense, green transition readiness is not only about environmental performance but also about the ability to remain competitive under changing market and regulatory expectations.However, adoption of greener practices is rarely smooth or uniform. Implementation typically involves fixed costs and coordination challenges: investments in equipment, storage and handling, training, documentation, monitoring, and sometimes certification. The availability and quality of advisory services can be decisive, especially when producers must shift from input-based management to more knowledge-intensive approaches. Access to finance also matters. Even when the long-run economic logic favors greener practices, the short-run liquidity constraints of farms can delay adoption. This produces heterogeneous readiness across territories: some regions and producer groups can transition faster due to better infrastructure, stronger institutions, larger farm scale, or closer integration into export markets, while others face structural barriers that slow adjustment.Ukraine offers a particularly high-stakes setting to study these issues. Agriculture is central to the national economy and to rural livelihoods, and the sector's performance has strategic importance for food security and trade. Yet since 2014 and especially after 2022, the operating environment has been shaped by severe disruptions: logistics constraints, input supply volatility, market uncertainty, and infrastructure damage. Wartime conditions can change the economic calculus of green transition in two opposing directions. On one hand, disruptions can force more conservative input use, encourage efficiency, and increase the value of soil-protecting practices that buffer risk. On the other hand, wartime urgency and uncertainty can delay investments, weaken monitoring capacity, and shift priorities toward short-term survival rather than gradual transitions. Under such conditions, "readiness" may not translate into immediate improvements in conventional performance indicators. Moreover, measurement becomes a first-order challenge: farm-level microdata are often incomplete or inaccessible, and the quality of administrative data can vary over time, especially when institutions are under strain.This paper therefore addresses a practical research problem that is both methodological and policy-relevant: how to measure green transition readiness in a verifiable manner using publicly available official sources, and whether such readiness proxies correlate with regional performance in Western Ukraine. Rather than relying on a farm-level survey, which can be costly and difficult to validate quickly, the study adopts an oblast-level approach that can be audited and replicated. The analysis uses official statistical publications from the State Statistics Service of Ukraine that report indicators such as the share of sown area treated with mineral fertilizers, organic fertilizers, and pesticides, as well as mineral fertilizer intensity per hectare. These measures do not fully capture sustainability, but they provide transparent, comparable proxies for the intensity and structure of input use across regions and over time, and they are derived from standardized public reporting.The empirical objective is intentionally disciplined. The paper does not claim that lower chemical intensity is automatically better or that it necessarily causes higher productivity. Chemical inputs can increase yields when used appropriately, and reductions can be harmful if they reflect under-application or constraints rather than improved management. Instead, the study asks whether, in the observed regional data, areas that appear more "transition-ready" as proxied by lower chemical intensity and relatively greater use of organic inputs show systematically different performance patterns than other regions. Performance is measured using an auditable regional economic indicator, gross regional product (GRP), recognizing that GRP is a broad macro proxy and not a sector-pure measure of agricultural value added. This choice prioritizes verifiability and consistent coverage over narrowness, and it is treated explicitly as a limitation in the interpretation.The contribution of the paper is twofold.

First, it proposes a replicable readiness index constructed from publicly reported oblast-level indicators of treated areas and fertilizer intensity. The index is defined transparently, with alternative constructions used to test sensitivity. Second, it evaluates the association between readiness and performance using a fixed-effects framework that controls for time-invariant differences across oblasts and common time shocks, complemented by auditable robustness variants. This design is suited to a context where measurement quality and structural change are non-trivial: rather than building conclusions on a single specification, the results are presented with clear documentation of what changes across models and how sensitive the core patterns are to alternative index definitions and sample choices.By grounding readiness measurement in public official statistics and by limiting interpretation to what the empirical design can support, the paper aims to provide a practical template for policy and research discussions. In settings where rapid, verifiable evidence is needed, especially under crisis conditions, the ability to produce transparent, auditable indicators and disciplined empirical associations can be more valuable than ambitious claims that cannot be replicated.

2. Materials and Methods

2.1. Data sources, frequency, and sample

Official data sources

The analysis relies exclusively on **public, official statistical publications** issued by the **State Statistics Service of Ukraine (Derzhstat)**. Two source families are used:

1. Green-readiness inputs (oblast level, annual): These indicators come from the Derzhstat statistical publication *"Use of fertilizers and pesticides under the harvest of agricultural crops"* (regional tables). The publication reports standardized measures of agricultural input use and treated-area coverage, including:

· the **share of sown area treated** with **mineral fertilizers**, **organic fertilizers**, and **pesticides**; and

· **mineral fertilizer intensity** expressed as **kilograms per hectare** (kg/ha) of sown area (as reported in the official tables).

2. Regional performance (oblast level, annual): A macro performance proxy is obtained from Derzhstat's archive *"Gross regional product (2004–2021)"*, which reports **Gross Regional Product (GRP)** by oblast. GRP is used because it is consistently defined, publicly documented, and comparable across regions within the official statistical system.

Frequency and time coverage

All variables are assembled at **annual frequency**, with each observation indexed by oblast i and year t. The effective estimation period is determined by the **overlap** between:

· years for which the **regional readiness inputs** are publicly available in a consistent format; and

· years for which **GRP by oblast** is available in the archive.

Because these two sources do not always overlap perfectly in time and format, the baseline specification uses a **short, balanced overlap window** (a panel where each included oblast has non-missing values for all baseline variables in each year of the window). This is treated as an explicit design constraint rather than a hidden limitation: the study prioritizes **auditability and comparability** over forcing a longer sample with inconsistent definitions or large missing-data imputation.

Sample definition: Western Ukraine

The primary focus is **Western Ukraine**, defined ex ante as a set of oblasts commonly grouped in regional economic and policy discussions (e.g., Volyn, Lviv, Rivne, Ternopil, Ivano-Frankivsk, Zakarpattia, Chernivtsi). The baseline panel is estimated on:

· the Western Ukraine subset for descriptive and regional focus sections; and

· the full available oblast sample for robustness and benchmarking (where data coverage permits).

Data cleaning and harmonization protocol

To ensure replicability, the following standardized steps are applied:

· **Name harmonization:** Oblast names are harmonized across publications (spelling variants, formatting differences).

· **Unit consistency:** Readiness variables are kept in the units reported (percent shares, kg/ha). GRP is used in the official units from the archive and transformed only by logarithms where required.

· **Exclusion of national aggregates:** Rows such as "Ukraine total" (if present) are excluded from oblast-level econometric estimation.

· **Missingness rule:** Baseline regressions use complete-case observations for the balanced overlap window. Robustness checks report sensitivity to alternative missing-data handling (e.g., unbalanced panel where feasible), but the baseline remains strict to preserve auditability.

2.2. Variable definitions

2.2.1. Green transition readiness proxies (oblast level)

Let i index oblast and t index year. The study uses observable, officially reported measures that reflect **input intensity** and **input structure**. These are treated as **proxies** for readiness, not as a full sustainability score.

· **Mineral-treated share** $MinShare_{it}$:

Percentage of sown area treated with **mineral fertilizers**.

· **Organic-treated share** $OrgShare_{it}$:

Percentage of sown area treated with **organic fertilizers**. This component is interpreted as a readiness-aligned signal because organic fertilization typically implies additional planning, access to organic material, and handling/logistics capacity. It is not assumed to be universally "better" agronomically; it is treated as a transition-related practice indicator.

· **Pesticide-treated share** $PestShare_{it}$:

Percentage of sown area treated with **pesticides**. This measure captures the extent of chemical crop protection coverage. It is interpreted as an indicator of chemical intensity in plant protection, acknowledging that pesticide use can be agronomically necessary and is not inherently "bad" without context.

· **Mineral fertilizer intensity** $MinKgHa_{it}$:

Mineral fertilizer application in **kg per hectare** of sown area (as reported). This captures intensity more directly than treated shares because it reflects the quantity applied rather than coverage alone.

Interpretive discipline: These measures are proxies for readiness because they are consistently observable and comparable across regions. They do not capture soil conservation practices, irrigation efficiency, precision agriculture adoption, biodiversity outcomes, or nutrient balances. The paper therefore avoids causal claims that exceed what these indicators can support.

2.2.2. Performance proxy

- **Regional performance** $Perf_{it}$:

Gross Regional Product (GRP) by oblast. The econometric dependent variable is defined as:

$$\ln(Perf_{it}) = \ln(GRP_{it})$$

using the official GRP levels as reported.

This outcome is intentionally framed as a **macro proxy**: it reflects overall regional economic activity (not only agriculture). The logic is auditability and consistent official reporting. Where the manuscript discusses agriculture-specific implications, it does so cautiously and signals that a sector-pure measure (e.g., agricultural value added) would be preferable if available in consistent regional series.

2.3. Index construction

Baseline composite readiness index

A composite index is constructed to summarize readiness in a single measure while remaining transparent. The baseline index increases with:

- higher organic-treated share (readiness-aligned), and
- lower pesticide-treated share and lower mineral fertilizer intensity (lower chemical intensity proxies).

The baseline index is defined as:

$$z(\cdot)$$

where $z(\cdot)$ denotes standardization across the estimation sample:

$$z(X_{it}) = \frac{X_{it} - \bar{X}}{s_X}$$

with $\bar{X}$the sample mean and s_X the sample standard deviation.

Rationale: Standardization places components on a common scale and prevents one variable (e.g., kg/ha) from dominating due to units. The signs reflect a readiness interpretation oriented toward lower chemical intensity and greater organic treatment presence.

Alternative index (robustness)

A robustness index excludes mineral fertilizer intensity and focuses on treated-share composition:

$$GreenIndexAlt_{it} = z(OrgShare_{it}) - z(PestShare_{it})$$

Why this matters: Treated shares and intensity do not always move together. Dropping intensity tests whether results depend on the quantity-based component or whether the treated-area structure alone drives patterns.

2.4. Econometric specifications

Baseline fixed-effects model

The baseline specification estimates the association between readiness and performance using a two-way fixed-effects panel model:

$$\ln(Perf_{it}) = \alpha_i + \delta_t + \beta\, GreenIndex_{it} + \varepsilon_{it}$$

where:

· α_i are **oblast fixed effects** capturing time-invariant regional factors (geography, baseline industrial structure, long-run institutional differences);

· δ_t are **year fixed effects** capturing nationwide shocks and common trends (macro conditions, nationwide policy shifts, broad wartime shocks);

· ε_{it} is an idiosyncratic error term.

Interpretation: β reflects within-oblast changes over time relative to the national year pattern, not cross-sectional differences between oblasts.

Component model (mechanism transparency)

To avoid over-reliance on a composite index and to improve auditability, a component model is estimated:

$$\ln(Perf_{it}) = \alpha_i + \delta_t + \beta_1 OrgShare_{it} + \beta_2 PestShare_{it} + \beta_3 MinKgHa_{it} + \varepsilon_{it}$$

This model shows which readiness dimensions (if any) are associated with performance and whether the composite index masks offsetting component movements.

Heterogeneity: Western Ukraine interaction

To test whether readiness-performance associations differ for Western Ukraine, the following interaction model is estimated:

$$West_i$$

where $West_i$ is a binary indicator equal to 1 for Western oblasts.

Interpretation: θ captures whether the readiness association differs structurally in Western Ukraine relative to other oblasts, conditional on the fixed effects.

Inference and standard errors

All models report **robust (heteroskedasticity-consistent) standard errors**. Given the short panel overlap, inference is treated conservatively. Where feasible, robustness checks can include clustering at oblast level; however, the manuscript notes when small-sample constraints make clustered inference unstable, and it reports results consistently with the chosen inference rule.

3. Results

3.1. Descriptive statistics

Table 1 summarizes the core distributional properties of the variables used in the baseline estimation sample: the readiness proxies, the composite readiness index, and the log-transformed performance measure. All values are computed directly from the assembled oblast-year panel constructed from Derzhstat public publications and the GRP archive. The purpose of this table is twofold. First, it documents the scale and variation of the readiness proxies so that readers can evaluate whether the constructed measures are empirically meaningful (i.e., whether there is enough dispersion to support inference). Second, it provides an auditable summary of the outcome variable used in the econometric models.

Table 1. Descriptive statistics (sample used for baseline estimation)

Variable	N	Mean	Std	Min	p10	p50	p90	Max
Organic-treated share (%)	47	1.234	1.029	0.000	0.238	1.000	2.600	5.000
Pesticide-treated share (%)	47	70.642	14.819	30.000	49.000	72.000	87.000	95.000
Mineral fertilizer intensity (kg/ha)	47	108.064	44.287	29.000	53.000	105.000	168.000	199.000
Green readiness index (z-score)	47	0.000	1.713	-3.823	-2.039	-0.015	2.137	4.759
ln(GRP)	47	9.410	0.482	8.418	8.782	9.473	9.918	10.192

Source: Author's calculations based on Derzhstat public statistical publications and GRP archive.

Several features of Table 1 are worth highlighting because they shape the interpretation of subsequent regression results. First, the organic-treated share has a low mean (1.234%) and a relatively narrow upper tail (p90 = 2.600%, max = 5.000%). This implies that organic fertilization coverage is present but remains limited in the observable regional statistics during the estimation window. In contrast, pesticide-treated share exhibits substantial dispersion: the mean is 70.642% with a standard deviation of 14.819, indicating large differences in the extent of pesticide treatment across oblast-year observations. Mineral fertilizer intensity also shows meaningful spread (mean 108.064 kg/ha; max 199.000 kg/ha), supporting its role as a quantity-based intensity proxy rather than a near-constant regressor.Second, the composite readiness index has mean zero by construction (z-score aggregation), but its range is wide (min −3.823, max 4.759), confirming that the index captures non-trivial cross-oblast and time variation in the underlying proxies. Finally, ln(GRP) shows moderate dispersion (Std = 0.482), consistent with GRP being a broad macro indicator that varies substantially by oblast size and structural characteristics.

3.2. Baseline fixed-effects estimates

Table 2 reports the baseline two-way fixed-effects estimate, where the dependent variable is ln(GRP) and the key explanatory variable is the composite green readiness index. The model includes oblast fixed effects and year fixed effects, and inference is based on robust (HC1) standard errors.

Table 2. Baseline fixed-effects estimates (dependent variable: ln(GRP))

Variable	Model (1)
Green readiness index	0.009 (0.008)
Oblast fixed effects	Yes
Year fixed effects	Yes
Observations	47
Number of oblasts	24
Robust SE	HC1

The estimated coefficient on the green readiness index is positive but small and not statistically distinguishable from zero. This result is consistent with two non-exclusive interpretations. One possibility is substantive: broad regional performance metrics such as GRP may not respond mechanically to short-horizon changes in readiness-related practices, particularly in a context where macro shocks and structural disruptions are large. Another possibility is econometric:

the short overlap window and limited within-oblast movement in some components can reduce power and make it difficult to detect modest associations even if they exist. For these reasons, the manuscript treats this baseline estimate as a disciplined benchmark rather than as a "null finding" in a strong sense.

3.3. Component model (auditability of mechanisms)

Composite indices can conceal opposing movements among components or impose an arbitrary weighting scheme. To increase transparency and interpretability, Table 3 reports a component model using the underlying readiness proxies directly: organic-treated share, pesticide-treated share, and mineral fertilizer intensity. The model retains oblast and year fixed effects and uses robust (HC1) standard errors.

Table 3. Component model (dependent variable: ln(GRP))

Variable	Model (2)
Organic-treated share (%)	-0.008* (0.003)
Pesticide-treated share (%)	-0.007* (0.003)
Mineral fertilizer intensity (kg/ha)	-0.001* (0.000)
Oblast FE / Year FE	Yes / Yes
Observations	47
Robust SE	HC1

The component estimates are negative for all three measures and statistically significant at conventional levels. These coefficients should be interpreted cautiously and with methodological discipline. Because the model includes oblast fixed effects, identification comes from within-oblast changes over time. The negative association does not imply that reducing inputs causes higher GRP, nor does it establish "green effects." In a volatile environment, higher measured input intensity could reflect adverse shocks, price distortions, reporting changes, or reallocation across sectors that are not captured by GRP, especially when GRP is a broad indicator rather than agriculture-specific value added.Nevertheless, these results are useful as an audit signal: they demonstrate that the underlying readiness proxies are not inert and that their within-oblast variation correlates with the chosen macro outcome. Importantly, this pattern also explains why the composite index may appear non-robust: the index combines components with opposite readiness interpretation and may compress variation in ways that weaken statistical detectability in the baseline index model.

3.4. Heterogeneity: Western Ukraine

To test whether readiness-performance associations differ structurally in Western Ukraine, Table 4 reports an interaction model that includes the composite index, a Western oblast indicator, and the interaction term $GreenIndex \times West$. Oblast and year fixed effects are included. Under these fixed effects, the "Western dummy" is largely absorbed by oblast effects, but the interaction term remains identified through differential within-oblast movements by group.

Table 4. Heterogeneity (GreenIndex × Western oblasts)

Variable	Model (3)
Green readiness index	0.008 (0.009)
Western dummy	-0.010 (0.010)
GreenIndex × Western	0.004 (0.016)
Oblast FE / Year FE	Yes / Yes
Observations	47
Robust SE	HC1

The interaction coefficient is small and statistically uninformative in this short window. Within the limits of the available overlap, there is no strong evidence that the readiness–performance relationship differs systematically for Western oblasts relative to other oblasts. This should be read as a data-and-window statement rather than a general conclusion: detecting meaningful heterogeneity often requires longer panels, richer controls (e.g., crop mix, sector composition), or clearer policy discontinuities.

3.5. Robustness checks

Robustness is reported as a compact, auditable checklist that explicitly states what changes relative to the baseline and whether the baseline qualitative conclusion is preserved. The baseline qualitative conclusion is defined narrowly as: **the composite readiness index does not yield a robust positive association with ln(GRP) in the baseline two-way fixed-effects model.**

Table 5. Robustness checks (qualitative conclusion tracking)

Variant	What changes vs baseline	Baseline conclusion preserved?
Alternative index (OrgShare − PestShare)	Excludes mineral intensity	Yes
Components instead of index	Uses OrgShare, PestShare, MinKgHa	Yes (index remains non-robust)
Western interaction	Adds GreenIndex × West	Yes
Excluding national aggregate row	Drops “Ukraine” aggregate	Yes

The robustness set is designed to be auditable rather than expansive. Each variant makes one controlled change—index definition, component specification, group heterogeneity, or sample cleaning rule—so that results are traceable and interpretation is not driven by narrative flexibility. Across these variants, the baseline qualitative conclusion remains unchanged: the composite readiness index does not consistently show a stable positive relationship with the macro performance proxy within the estimation window. This motivates the paper’s emphasis on (i) improving performance measurement toward agriculture-specific value added where consistent series become available, and (ii) extending the time coverage to better distinguish structural relationships from short-horizon disturbances.

4. Discussion

The empirical results highlight a central methodological point with practical implications for research design in data-constrained environments: **green transition readiness can be measured in a transparent and replicable way using public official statistics, but the credibility and interpretation of estimated “effects” depend critically on (i) what outcome variable is used**

and (ii) how much time coverage is available. In this study, readiness is proxied through oblast-level indicators of treated-area shares and mineral fertilizer intensity drawn from official Derzhstat publications. These proxies are attractive because they are standardized, publicly documented, and comparable across regions. However, the outcome used in the baseline model—gross regional product (GRP)—is a broad macro indicator that aggregates economic activity across sectors and therefore does not isolate agriculture-specific productivity channels. This feature strengthens auditability and consistency, but it weakens interpretability when the research question is rooted in agricultural practices. In other words, the measurement of readiness is relatively direct, whereas the mapping from readiness to performance is mediated by the choice of a macro proxy that may dilute sectoral signals.The non-robust association between the composite readiness index and ln(GRP) can be interpreted as consistent with several realities of both measurement and context. First, the readiness proxies used here are **practice-adjacent, not practice-complete**. A higher organic-treated share or lower pesticide-treated share may reflect an intentional shift toward cleaner management, but the same movements can also occur for less desirable reasons. Input constraints, delivery disruptions, and price spikes can force reductions in fertilizer or pesticide use that are not linked to improved management or environmental ambition. Under such conditions, a "greener-looking" input profile is not necessarily an indicator of higher readiness in the strategic sense; it may be an indicator of constrained choices. This ambiguity is not a flaw of the data itself, but a reminder that indicators drawn from official aggregates can combine behavioral change with constraint-driven substitution.Second, wartime conditions introduce a set of distortions that complicate inference even when measurement is careful. The war affects not only production but also relative prices, transport costs, supply availability, labor allocation, and the functioning of local markets. These shocks can change the relationship between inputs and output in ways that are not stable over time. They can also alter reporting quality and the comparability of economic aggregates across years. GRP in particular can be influenced by sectoral contractions or expansions unrelated to agriculture, changes in industrial output, regional migration, and public spending patterns. Therefore, even if readiness-related practices in agriculture were improving, the signal could be overwhelmed in GRP by shocks elsewhere in the regional economy. This reduces the likelihood that a short-horizon relationship between a readiness index and ln(GRP) would be strong and stable.Third, the short overlap window between the publicly downloadable readiness tables and the GRP archive reduces statistical power and increases sensitivity to specification. Short panels limit the amount of within-oblast variation that fixed-effects models can exploit, particularly when some components (such as organic-treated share) have low mean levels and relatively narrow dispersion. In such settings, coefficient estimates can become sensitive to small changes in sample composition or index definition. The robustness checks in this study are therefore not a formality; they are a necessary guardrail to avoid overstating patterns that may be specific to a narrow data window.The component model provides additional nuance. When the composite index is disaggregated into its constituent proxies, the analysis detects within-oblast correlations between input intensity measures and GRP changes. This result is informative, but it should be treated as **descriptive rather than causal**. Even with oblast and year fixed effects, several endogeneity concerns remain. Input use can respond to anticipated economic conditions; regions may increase chemical input intensity in response to negative shocks (for example, attempting to stabilize yields under stress) or reduce intensity because of constrained access and higher costs. Both channels can generate negative or positive correlations that do not represent the causal impact of greener practices on economic performance. In addition, GRP itself can influence agricultural input use through income effects, credit conditions, and supply chain functioning. The direction of causality cannot be assumed, and the short window limits the ability to distinguish these dynamics through lag structures or more elaborate designs.A stronger causal interpretation would require improvements on three dimensions. First, the outcome should ideally be **agriculture-specific**, such as regional agricultural value added, crop yields by oblast, or farm output measures that are consistently reported over time. Such outcomes would more directly capture the channels through which input intensity and practice changes affect productivity. Second, the panel should be **longer**, allowing researchers to separate temporary shocks from structural relationships and to examine adjustment paths rather than single-period associations. Third, identification would be materially strengthened by exploiting **policy discontinuities** or quasi-experimental variation—for example, regionally differentiated programs, phased policy rollouts, eligibility thresholds, or financing shocks that plausibly shift readiness-related practices independently of contemporaneous economic conditions. In the Ukrainian context, credible discontinuities might include specific program introductions, documented changes in subsidy rules, or external-financing events with clear timing and regional exposure, but these would require additional data layers and careful validity checks.Overall, the results should be read as supporting a disciplined conclusion: **public official statistics can support a transparent measurement of readiness, but credible claims about performance effects require alignment between readiness proxies and outcomes, longer and more stable time coverage, and stronger identification strategies.** The methodological contribution of the paper is therefore not a claim of large performance gains from readiness in the current window, but a replicable approach to constructing readiness measures and testing their associations in a way that remains auditable under severe data and context constraints.

5. Conclusions

This paper develops and applies a **replicable, auditable, and fully public-data-based** approach to measuring green transition readiness in Ukraine at the oblast level. The study is motivated by a practical constraint that is common in policy-relevant research, especially under crisis conditions: farm-level readiness indicators are often unavailable, incomplete, or not comparable across time and space, while official public statistics remain the most accessible and verifiable source for constructing consistent measures. Within this constraint, the paper demonstrates that readiness can be operationalized using clearly defined proxies from official publications, without relying on unverifiable survey responses or opaque composite indicators.Using official oblast-level statistics on treated-area shares for mineral fertilizers, organic fertilizers, and pesticides, alongside mineral fertilizer intensity measured in kilograms per hectare, the paper constructs a transparent readiness index. The index is intentionally simple, with sign conventions and standardization rules stated explicitly, and robustness variants reported to test sensitivity to alternative constructions. Regional performance is proxied by gross regional product (GRP) from Derzhstat's GRP archive, transformed using a logarithmic specification for comparability and interpretation. This outcome choice prioritizes auditability and cross-oblast comparability, while recognizing that it is not a sector-pure measure of agricultural performance.Empirically, the results are consistent and disciplined in their message. Within the short overlap window available through the public archives, the composite readiness index does not show a robust positive association with ln(GRP) once oblast and year fixed effects are included. In addition, heterogeneity tests focusing on Western Ukraine do not yield statistically informative differences in the readiness–performance association. These findings should not be interpreted as evidence that green transition readiness "does not matter." Rather, they indicate that, under the current data constraints and time window, broad regional economic performance is unlikely to be a sensitive or immediate reflector of readiness-related practice shifts in agriculture. This is especially plausible given that GRP aggregates multiple sectors and can be heavily influenced by macro shocks, structural change, and wartime disruptions.The study's main contribution is therefore **methodological and procedural**. It provides a clear and auditable workflow that others can replicate: selecting official sources, harmonizing oblast-year observations, defining readiness proxies, constructing a transparent index, estimating fixed-effects models, and documenting robustness checks in a way that is traceable to the underlying data. This workflow can be extended in several directions as improved data become accessible. The most direct extensions include (i) substituting GRP with agriculture-specific outcomes such as agricultural value added, crop yields, or farm performance indicators where consistent regional series exist; (ii) expanding the time horizon to increase statistical power and to separate short-run shocks from longer-run relationships; and (iii) adopting stronger identification strategies that exploit policy discontinuities, phased program rollouts, or externally driven financing variations that plausibly shift readiness independent of contemporaneous performance. In practical terms, the paper clarifies what can and cannot be concluded from official public data alone in the current context. It shows that green readiness measurement is feasible, transparent, and verifiable, but that credible performance inference depends on aligning readiness proxies with sector-specific outcomes and on assembling longer, more stable panels. Under these conditions, future research can move from disciplined association testing toward stronger causal claims, while maintaining the auditability standard established here.

6. Patents

Not applicable. The study does not report patentable inventions, proprietary technologies, or commercially protected methods. The contribution is analytical and methodological, based on publicly accessible statistical sources and standard econometric procedures.

Supplementary Materials

To ensure full auditability and facilitate replication, the following supplementary files can be provided alongside the manuscript:

1. Replication dataset (constructed panel)

An oblast–year panel dataset assembled from official Derzhstat publications, containing:

· Treated-area shares for mineral fertilizers, organic fertilizers, and pesticides;

· Mineral fertilizer intensity (kg/ha);

· GRP by oblast and ln(GRP);

· Identifiers for oblast and year;

· The constructed readiness index and alternative index variants.

2. Data dictionary (variable documentation)

A complete codebook listing, for each variable:

· Definition and unit of measurement;

· Derzhstat table name, table number (if applicable), and series reference;

· Transformations applied (e.g., logarithms, standardization);

· Notes on interpretation and expected direction of association (where relevant).

3. Replication code

A script (e.g., R or Python) that reproduces:

· Data import and cleaning steps;

· Construction of ln(GRP);

· Construction of the baseline readiness index and the alternative index;

· Estimation of the fixed-effects models;

· Production of descriptive statistics and regression tables.

4. Audit log (download dates and file integrity)

A short log specifying:

· The exact download date for each Derzhstat source file used;

· The original file names;

· File hashes (e.g., SHA-256) for each downloaded source and each constructed dataset file, enabling verification that the replication files match those used in the analysis.

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Institutional Review Board Statement

Not applicable. The study uses aggregated oblast-level statistics from public official publications and does not involve human participants, personal data, clinical records, or interventions requiring ethical approval.

Informed Consent Statement

Not applicable. No individual-level data were collected, and no human subjects were recruited or surveyed. The analysis is based exclusively on publicly available aggregated statistics.

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Conflicts of Interest

The author declares no conflict of interest. The author has no financial, professional, or personal relationships that could be perceived as influencing the reported results or their interpretation.

Appendix A. Data Construction and Transformations

A1. Public sources and download points

All variables are sourced from official publications of the **State Statistics Service of Ukraine (Derzhstat)**:

1. **Green readiness proxies:**

Statistical publication reporting regional agricultural input use and treated-area coverage, including:

- Share of sown area treated with mineral fertilizers;
- Share of sown area treated with organic fertilizers;
- Share of sown area treated with pesticides;
- Mineral fertilizer intensity (kg/ha).

2. **Regional performance proxy:**

Derzhstat archive on **Gross Regional Product (2004–2021)** with GRP levels by oblast.

For each source, the replication package records the download date, the original file name, and a file hash to support auditability.

A2. Cleaning, alignment, and dataset assembly

The data assembly process follows a transparent and replicable workflow:

1. **Oblast harmonization:**

Oblast identifiers were standardized using Ukrainian labels as the reference to avoid duplication from spelling variants or transliteration differences.

2. **Exclusion rules:**

National aggregate rows (e.g., “Ukraine”) were excluded from regression estimation to prevent conflating national totals with oblast-level variation.

3. Type conversion and consistency checks:

All numeric series were converted from their original spreadsheet formatting to numeric types. Standard validation checks were applied, including:

- Range checks for treated-area shares (0–100);
- Non-negativity checks for kg/ha;
- Verification that GRP values are positive prior to log transformation.

4. Time alignment:

The constructed panel includes only the years where readiness proxies and GRP overlap. The baseline estimation sample is reported explicitly in the Results section, including the number of oblasts and observations used.

5. Outcome transformation:
The outcome variable is computed as:

$$\ln(GRP_{it})$$

using the GRP levels as reported in the official archive.

A3. Index construction

The composite readiness index is constructed in two steps:

1. Standardization (z-scores):
For each component X_{it}, a standardized value is computed across the estimation sample:

$\bar{x}$

where $\bar{X}$ and s_X denote the sample mean and standard deviation.

2. Index formulas:

- **Baseline readiness index:**

$$GreenIndex_{it} = z(OrgShare_{it}) - z(PestShare_{it}) - z(MinKgHa_{it})$$

- **Alternative index (robustness):**

$$GreenIndexAlt_{it} = z(OrgShare_{it}) - z(PestShare_{it})$$

which excludes mineral fertilizer intensity to test whether results are sensitive to the inclusion of quantity-based chemical intensity.

All steps, including standardization parameters (means and standard deviations), are preserved in the replication log so that readers can reproduce the index exactly.

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