GRAIN COSTS DISRUPTIONS INFLUENCE ON LIVE-HOG MARKET IN UKRAINE

by

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LIST OF ABBREVIATIONS

SSSU State Statistical Service of Ukraine

WOAH World Organization of Animal Health

ASF African Swine Fever

LASSO Least Absolute Shrinkage and Selection Operator

ARIMAX Auto Regressive Integrated Moving Average Extended

SE Standard Error

EU European Union

SD standard deviation

RMSE Root Mean Square Error

IRF Impulse Response Function

MAE Mean Absolute Error

EXW Ex Works

MIDAS Mixed-data sampling

CHAPTER 1. INTRODUCTION

The stability and profitability of pig production in Ukraine are critically dependent on the cost and availability of feed grains. Over the past decade, volatility in maize, wheat, and oilseed meal markets driven by weather events, global demand shifts, and geopolitical tensions has transmitted into fluctuations in live-pig prices.

Due to the Hoste (2023) feed may be estimated as 65-71 % of the cost of production depending on the country. A one-hryvnia change in feed cost per kg carcass weight may drastically change farm profitability, thus it is one of the most important factors in live pig production, as well as energy prices and transport costs.

From food security perspective, live-hog markets, the segment of the agricultural industry, are at risk from geopolitical, social, or climate unpredictable events. It is shown by the impact of the full-scale war in Ukraine on the grains market: Previous to the war, Ukraine was shipping 5-6 million mt of grains per month, but after the beginning of the war, this was reduced to approximately 2 million mt per month. Bullock (2023) estimates that logistical costs increased between $55/mt and $125/mt2.

There is no quantitative criterion in Ukraine similar to the United States. Hog-Corn Ratio that would help compensate producers or lead to anti-crisis feed import windows. Although the hog-corn ratio in the US is simply expressed as the ratio of corn price to hog price, it may not fully reflect the profitability of hog production.

Ukrainian pork production has great potential for export due to the large markets in proximity, infrastructure of seaports that have a chance of being used for connection with the Asian markets, low labor costs, and grain prices at the farmgate. There are several institutional and epizootic factors that are to be worked out for future progress of Ukraine. As a part of the problem - the outbreak of ASF (African swine fever) is one of the top epizootic causes for export ban to the EU because of the lack of a vaccine for dozens of years and underestimation of biosecurity on farms.

World Organization of Animal Health (WOAH) reports about 5,505 outbreaks for domestic pigs and 19,249 for wild boars in Europe from January 2022 up to January 2025, which caused massive losses (near 1.38 million of domestic pigs). ASF remains major concern for Ukraine: as of February 2025, it is still present in Ukraine, as two recurrences of the disease in Kherson and Ternopil were registered.

Despite the household decreasing herd (according to SSSU ~3.5 M pigs in 2015 and ~1.7 M for October 2025), small farms still are major concern in veterinary terms, lack controls, serve as ASF incubators, and raise cross-border biohazard from russia–Belarus and Ukraine-EU borders.

Since the mid-2010s Ukraine's pork industry has undergone rapid consolidation, driven by scale-seeking integrators able to weather export shocks and currency volatility. According to the YouControll Market data for 2024, the 12 largest enterprises by revenue accounts for approximately 60% of total revenue for the industry. Cherevko, G. (2017) states that the five largest vertically integrated groups command nearly 40 % of all industrial pork output for 2017, leading the pack, APK-Invest alone accounts for 11 % of chilled-pork production, fattening up to 600 000 heads annually and processing over 42 000 t of meat in 2015 - 7 % more than the prior year. Behind APK-Invest stand Agroprodservice, Myronivsky Hliboproduct, and two other domestic leaders whose combined breeding, feed-mill and processing capacities allow them to internalize feed procurement, genetics, slaughter and cold-chain logistics. Meanwhile, mid-scale farms (6 000–24 000 heads/year) and legacy operations (1 000–3 000 heads) struggle to match the genetics, nutrition and capital backstops of these top five, hastening the exodus of smaller players.

Forecasting livestock prices introduces several difficulties. First, feed-cost pass-through into pig prices unfolds over multiple weeks, creating a dynamic dependence that standard linear models may fail to capture. Second, seasonal cycles - from spring holidays demand surge to autumn harvest pressures - impose calendar effects that interact with feed shocks.

Our research goal can be stated as two questions: How extreme weekly feed-price shocks contribute additional, measurable increases in Ukrainian live-pig prices and how strong is the link between feed-prices and hog herd?

This diploma addresses these issues by developing a forecasting framework that:

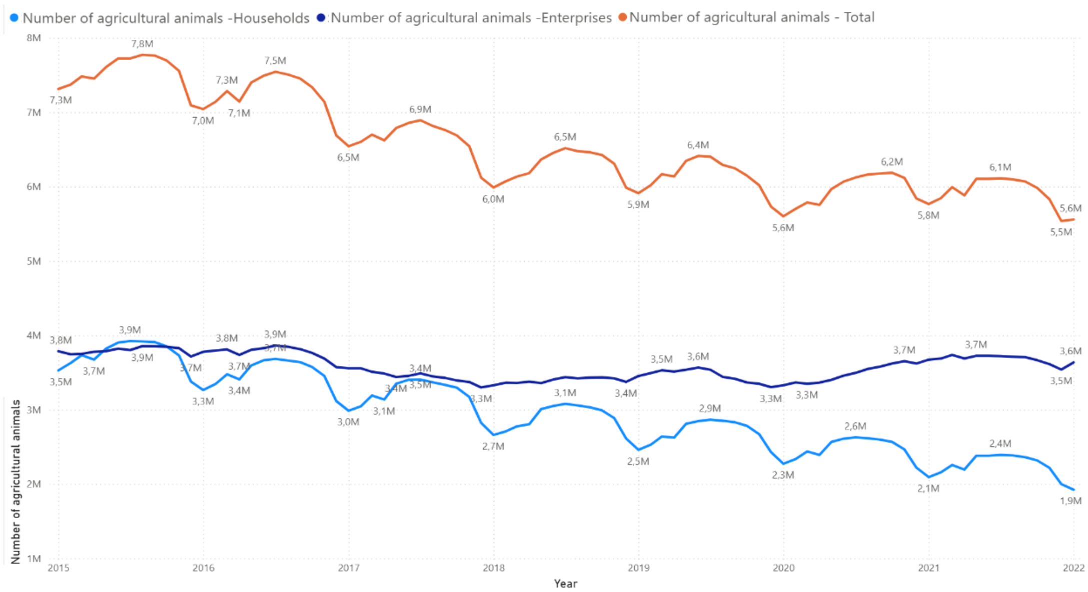
- Constructs a composite feed-cost index combining maize, wheat, barley, soybean meal, and sunflower meal according to pig-stage recipes;
- Applies penalized regression (LASSO) to select from a rich set of lagged prices, exogenous feed variables, and seasonal dummies; benchmarked against a classical ARIMAX (3,0,2) specification;
- Quantifies the dynamic impact of extreme feed shocks via impulse-response analysis
- OLS distributed lag model was used to estimate hog herd quantity connection with feed-prices, separately for households and enterprises.

CHAPTER 2. INDUSTRY OVERVIEW AND RELATED STUDIES

Ukraine faces with declining production: between 1990 and 2015 pig herd decreased from approximately 19.5 million to ~7.3 million heads - roughly a 63 % drop – which resulted in pork output decrease from 1.6 million t to under 0.8 million tons for the same period. From 2015 up to 2022 – herd decrease is estimated as from 7.3 million heads to 5.6 million or as 24 %, driven majorly by changes in households' ownership level – 45.5 % drop, while share of animals owned by enterprises stays particularly at the same level – near only 4 % decrease. Regional dynamics in terms of horde reduction shows us, that only 3 regions expected growth for period 2015-2022: Kyivska (112 500 heads or + 21.56%), Lvivska (95 900 heads or + 27.69%) and Khmelnytska (26 500 heads or + 7.96%); all other regions expected decline, the most significant of them: Odeska (252 700 heads or -66.92%), Dnipropetrovsk6a (234 700 heads or -44.54%), Zaporizka (200 100 heads or -62.01%), Vinnytska (157 500 heads or -44.47%) and Kharkivska (135 700 heads or -46.81%). In January 2022 top 5 regions by horde size were Kyivska, Lvivska, Donetska and Ternopilska regions, together accounting for 33.67% of total size.

According to the O. Kotykova (2024), wartime direct and indirect losses for pig sector was estimated 168.6 million euros with high regional dependency: Donetska, Kharkivska and Khersonska oblasts experienced the most severe consequences.

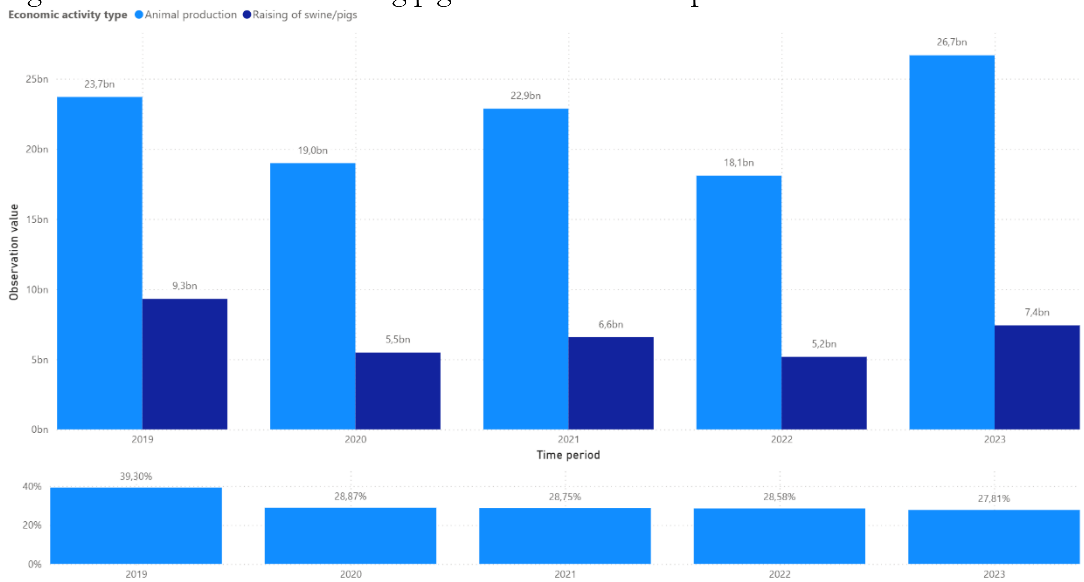
Figure 1. Number of pigs in Ukraine from 2015 to 2022



Source: SSSU

Ukrainian live pigs sector takes substantial part of Ukrainian animal production: in 2019 value added by swine farms was estimated by SSSU as 9.3 billion UAH – 39.3 % of domestic animal production. Despite the drop in 2020 and surge in total value added by animal production in 2023, in 2020 – 2023 contribution of swine farms remained relatively stable – nearly 28 %.

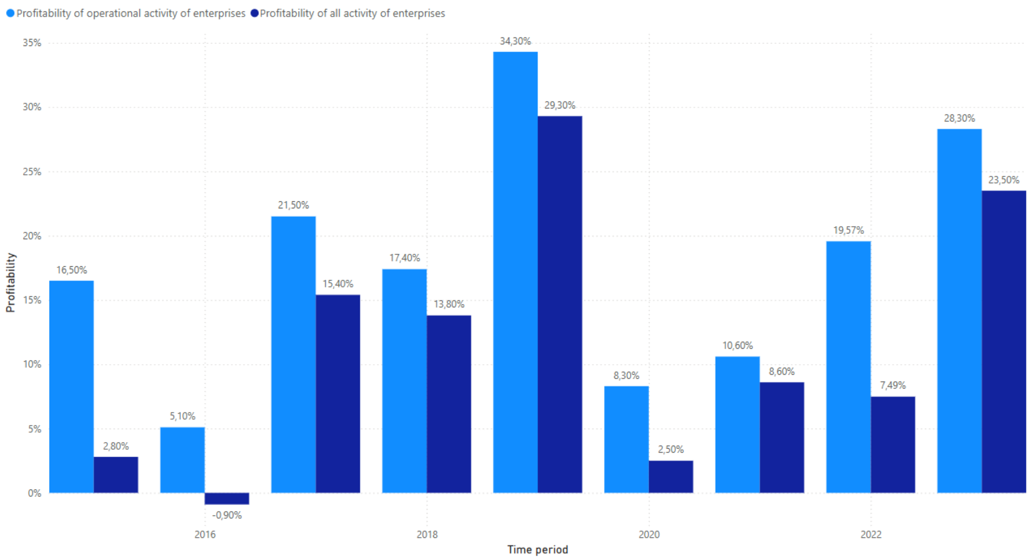
Figure 2. Value Added of Raising pigs and Total Animal production



Source: SSSU

Percent of profitable enterprises in Ukraine involved into raising pigs was 77.8 % in 2023 and fluctuated around 73.22 % from 2015 to 2023, while aggregated average operational profitability and profitability from all types of activity majorly increased from 16.5% and 2.8% in 2015 to 28.3% and 23.5% in 2023 correspondingly. On the Figure 4 we can see that, despite the war challenges, average profitability increased in 2023 with respect to 2022, on the other hand, there was a surge in 2019 consequent with massive drop in 2020 up to 8.3% operational profitability and 2.5% profitability from all activities, which can be explained by COVID-19 pandemic. While revenue, costs of sales for the industry remained relatively at the same level, total expenses grew by 5.14%, operating expenses by 5.48% and at the same time total profit dropped from 5.4 billion UAH to 1.5 billion UAH – approximately 72.22% reduction.

Figure 3. Aggregated average profitability of pig farms



Source: SSSU

Total capital investments in industry, mainly consisted from Construction & alteration of buildings (45.44% of total in 2023) and Machines & equipment (39.53% of total in 2023), increased from 2019 (2.146 billions UAH) to 2023 (3.189 billions UAH) or by 48.6%. Intangible assets, particularly purchased software, concessions, patents, licenses, trade marks and similar rights, accounts only for approximately 0.7% of total investments in 2023. Focus on tangible capital categories is obvious, as comfortable and safe buildings, modern systems of feeding and ventilation are baseline for normal production level, but underinvestment in innovations based on patents and software, may slow down further development.

Junguo Hua (2024) states that shocks to “pig farming costs”, which includes pig feed costs (corn, soybean meal) as central component of this composite external variable, produce larger and longer lasting impulse responses in pig prices than many other drivers. Changes in corn or soybean meal prices directly alter variable production costs per pig, compress producer margins when input prices rise According to the paper, feed-price shocks transmit to pig prices through at least three linked channels. First, the cost channel:

higher feed costs increase marginal costs of finishing pigs and raise the price at which producers are willing to sell, producing a positive pass-through into pig prices. Second, the supply-adjustment channel: because pig production is biological and lags decisions (breeding, finishing cycles), sustained high feed costs lead some farmers to downsize or delay restocking, reducing future slaughter volumes and amplifying price responses over several periods. Third, the risk/expectation channel: volatility in feed costs raises uncertainty and may change sellers' behavior (accelerated sales or delayed restocking), which increases short-run price volatility beyond the effect of level changes alone.

Jie Pang (2023) provides SVAR analysis, that includes pork price, corn price, pig herd, sow herd, imported pork supply, epidemic severity, finds that pork prices are highly self-reinforcing: contemporaneous shocks to pork price explain the largest share of future price variance, with the current month's price still accounting for about 29.6% of price movements 18 months later. Changes in the pig herd have the strongest influence on pork price volatility, while contribution to price variance is small at first but grows over time, peaking around the 13th month and accounting for a very large share of long-run variance, consistent with the role of herd expansion/contraction and the extended time it takes for changes in breeding stock to affect slaughter supply. By contrast, the short- and medium-run structural effects of corn price, sow herd size, and imported pork supply are quantitatively smaller, although corn (as a major feed input) exhibits a lagged positive effect on pork prices after an initial short-run offsetting movement when farmers accelerate sales to reduce losses.

CHAPTER 3. METHODOLOGY

This study develops and evaluates a forecasting framework for Ukrainian live-pig prices that captures baseline feed-price pass-through and calendar dynamics, employs penalized regression for robust variable selection, and isolates the impact of extreme feed-price shocks. Our main goal is to prove, that weeks with extreme feed-price jumps (top 5 percentile) generate additional and furthermore, measurable increase in pig prices.

All prices were included into single dataset and converted into the US dollar value. Corn and wheat are highly collinear; using them separately leads to unstable coefficient estimates and multicollinearity, so we decided to construct a single composite series, coarse_feed. For that purpose, we defined pig stage-specific recipes (starter, grower, finisher) in percentage terms, including an “others” ingredient, which consists of minor ingredients without reliable time-series.

Table 1. Growth-phase recipe specifications (percentages)

Stage	**Barley**	**Wheat**	**Maize**	**Soybean meal**	**Sunflower meal**	**Others**
Starter	50%	-	15%	12.5%	12.5%	10%
Grower	30%	40%	5%	-	20%	5%
Finisher	30%	7%	50%	-	10%	3%

Then, the “others” component was dropped and the remaining weights were rescaled, so they sum to one for each stage. Each ingredient’s market price was rescaled by its normalized weight to compute a feed cost for each pig stage:

$$feed_{stage_t} = (barley \times weight_{barley}) + (wheat \times weight_{barley}) + (maize \times weight_{maize}) + (soybean\ \times weight_{soybean}) + (sunflower\ \times weight_{sunflower}) \quad (1)$$

At the last step, three stage costs were equal-weight averaged to produce the composite coarse_feed variable:

$$coarse_{feed_t} = \frac{feed_{starter_t} + feed_{grower_t} + feed_{finisher_t}}{3} \quad (2)$$

This composite series is the main exogenous variable in the subsequent models, which was arranged by ascending order for computing one-period price changes and using binary variable $feed\_spike$ flag extreme movements – 5th percentile.

To capture autocorrelation and seasonal patterns in pig prices, we assemble a wide-format design matrix containing: two exogenous regressors, lagged levels of the response variable: lag1 through lag26 of pig prices, seasonal dummy variables for the four seasons. Rows with missing values (due to the lag construction) are dropped.

We applied a penalized regression framework using the LASSO (Least Absolute Shrinkage and Selection Operator), which performs both variable selection and penalization; comparing to ordinary least squares it has added ℓ1 penalty on the vector of coefficients. For observations $(y_i, x_i)_{i\{i=1\}}^{n}$, the LASSO solves:

$$\min_{\beta_0, \beta} \frac{1}{2n} \sum_{i=1}^{n} (y_i - \beta_0 - x_i^T \beta)^2 + \lambda \sum_{j=1}^{p} |B_j| \quad (3)$$

where β_0 is the intercept, $\beta = (\beta_1, \ldots, \beta_p)$ are feature coefficients, $\lambda \geq 0$ is the tuning parameter: as $\lambda \to 0$, the solution approaches ordinary least squares; larger λ yields sparser β.

LASSO with α=1 was used to select relevant lag terms and in the same time forcing in the exogenous variables and seasonal dummies. Penalty factor was assigned to zero to composite feed prices, feed shocks, and all seasonal dummies; penalty factor = 1 to every lag column. In our case, formula takes form with added penalty factor w:

$$\min_{\beta_0,\beta} \frac{1}{2n} \sum_{i=1}^{n} (y_i - \beta_0 - x_i^T \beta)^2 + \lambda \sum_{j=1}^{p} w_j \left| B_j \right| \tag{4}$$

Then, 10-fold cross validation was implemented to respect temporal ordering: each fold contains continuous block of time-series in chronological order, so the future data does not leak into past data.

To obtain unbiased coefficient estimates for the LASSO-selected predictors, we refit an ordinary least squares (OLS) regression using only the nonzero features identified by the LASSO. This approach improves the model in terms of interpretability and allows us to make inferences on the active variables.

We evaluate out-of-sample forecasting performance over a horizon of 10 weeks. For each origin t from an initial window of 200 weeks, we train the LASSO on each observation. Then, forecast the next 10-weeks pig prices using the trained model and compute one-step ahead errors with further aggregation of RMSE (root mean squared error) and MAE (mean absolute error) across all origins. Let $\widehat{y_i}$ be the forecast and y_i actual value over N forecast-error observations:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (\widehat{y_i} - y_i)^2} \tag{5}$$

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |\widehat{y_i} - y_i| \tag{6}$$

To test forecast stability, we retraining also only on the most recent data, repeating the procedure with a fixed sliding window of 200 weeks and using a shorter horizon of 4 weeks.

We fit an ARIMAX (3,0,2) as a classical time-series model benchmark with the same exogenous regressors x_t using maximum likelihood method to enforce stationarity.

$$\Phi(L)\, y_t = c \;+\; \beta_1\, coarse_{feed_t} \;+\; \beta_2\, feed_{spike_t} \;+\; \Theta(L)\, \varepsilon_t\;, \qquad (7)$$

where

$$\Phi(L) = 1 \;-\; \phi_1 L \;-\; \phi_2 L^2 \;-\; \phi_3 L^3, \Theta(L) = 1 \;+\; \theta_1 L \;+\; \theta_2 L^2, \qquad (8)$$

and L is lag operator.

Then, we forecast the same horizons within the rolling-origin framework and compare RMSE and MAE against the LASSO forecasts.

We quantify the dynamic effect of a typical feed-price spike on pig prices using impulse-response analysis, starting from estimation of the average feed jump Δ by calculation of mean feed price differences in the 5th percentile. Then, we constructed two future exogenous scenarios over next 10 weeks period:

- Baseline: constant feed prices at its last observed level, no spikes.

- Shock: a one-time increase of Δ in week 1, then reversion to baseline.

Forecasting pig prices under each scenario with the final LASSO model allows us estimate the influence of surges in grains on the prices for live pigs. To implement that, we formed lagged-price features from the model's own predictions and insert the scenario's values for composite feed prices and season dummies. Computation and evaluation of the impulse-response function (IRF) as the difference between shock and baseline forecasts at each horizon is a final step of our research.

Pig herd size dependence from price of feeds was estimated separately for households and enterprises. To do that, we constructed distributed lag regressors feed_lag0 … feed_lagK where feed_lag0 is the monthly feed and feed_lagK is the k-month lag for a chosen maximum lag K. A configurable completeness rule (min_non_na) controls whether observations must have the full lag vector or can be included with a relaxed number of non-missing lags; the main specification uses min_non_na = K + 1, while sensitivity checks used relaxed requirement to save sample size.

Specification of the OLS distributed lag model estimated separately for households and enterprises:

$$Y_t = \alpha + \Sigma\{k = 0..K\}\beta_k \cdot \mathrm{feed}\{t - k\} + \text{seasonal dummies} + \varepsilon_t \tag{9}$$

where y is the natural logarithm of the households or enterprises pig herd size at time t, α - constant, that marks the baseline log-herd level when all regressors (feed lags and seasonal dummies) equal zero, $\mathrm{feed}\{t - k\}$ - lagged feed index, β_k is a single-lag coefficient, that measures the association between a one-unit change in feed at lag k and the dependent variable (log herd), in the same time holding other terms constant.

Also, quarterly dummies were added to include seasonality in the model. The cumulative transmission over the lag window is summarized by $\beta_{sum} = \Sigma k * \beta_k$. Models are estimated on the sample produced using the completeness rule above.

We found the total effect β_sum using the delta method. We took the covariance matrix for the β_k estimates. We added up the covariances to get the variance of β_sum and Newey–West (HAC) covariance estimator was used for analytic SEs of coefficients. We then created a 95% confidence interval using an analytic method.

Also, we used a bootstrap method to deal with small sample issues and to check for uncertainty that doesn't fit a normal distribution. We resampled the months with replacement, put the data back together, re-ran the model, and recorded β_sum each time. The 2.5% and 97.5% percentiles of these results are our bootstrap confidence interval.

To test joint significance of the feed lags, we decided to use the joint Wald test, that compares the unrestricted model (includes feed lags) to the restricted model (does not include feed lags), which allows us to understand whether lagged predictors jointly contain information that can potentially predict the dependent variable.

For residual diagnostics we have chosen the Breusch-Godfrey test for serial correlation and the Breusch-Pagan test for heteroskedasticity. Robust covariance estimators, and sensitivity checks (alternative lag lengths, first differences) were applied, as serial correlation or heteroskedasticity were detected.

We checked how stable the results are by changing the lag window K to 2, 4, 6, and 8. We did not use a strict rule for missing data. We looked at how the sum of beta values (β_sum) and sample errors stayed the same when we changed K.

Minimal detectable effect computed for the sample and estimation variance used.

CHAPTER 4. DATA

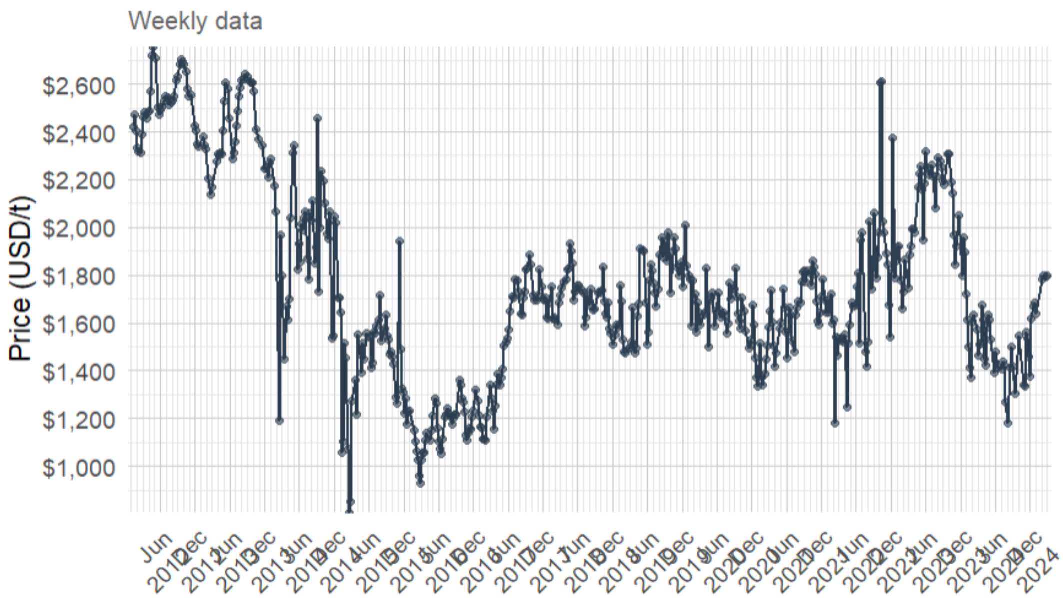
Our primary dataset contains weekly observations from January 2012 to February 2025 of pig prices and five feed inputs: corn, wheat, soybean meal, sunflower meal, and barley, which are main components of feeds for hogs.

Table 2. Datasets

Variable	Source	Frequency	Unit	Span
Live-hog price (demand)	PigUA bulletin	weekly	USD /t	Jan 2012 – Feb 2025 (576 obs after trimming)
Corn, Wheat prices, EXW	APK-Inform	weekly	USD /t	Same span
Soybean meal price, EXW	APK-Inform	weekly	USD /t	Same span
Sunflower meal & Barley (USD/t), EXW	APK-Inform	weekly	USD /t	Same span
USD/UAH	NBU weekly	weekly	UAH per USD	Same span

After the 2012 Ukrainian live pig prices experienced a decline up to 2016, which can be explained by the start of russian aggression in 2014. Stabilization and further upward movement ended in 2023: full-scale war caused a temporary massive price rise in the 2022, due to collapse of infrastructure, higher inputs prices and other war-related externalities.

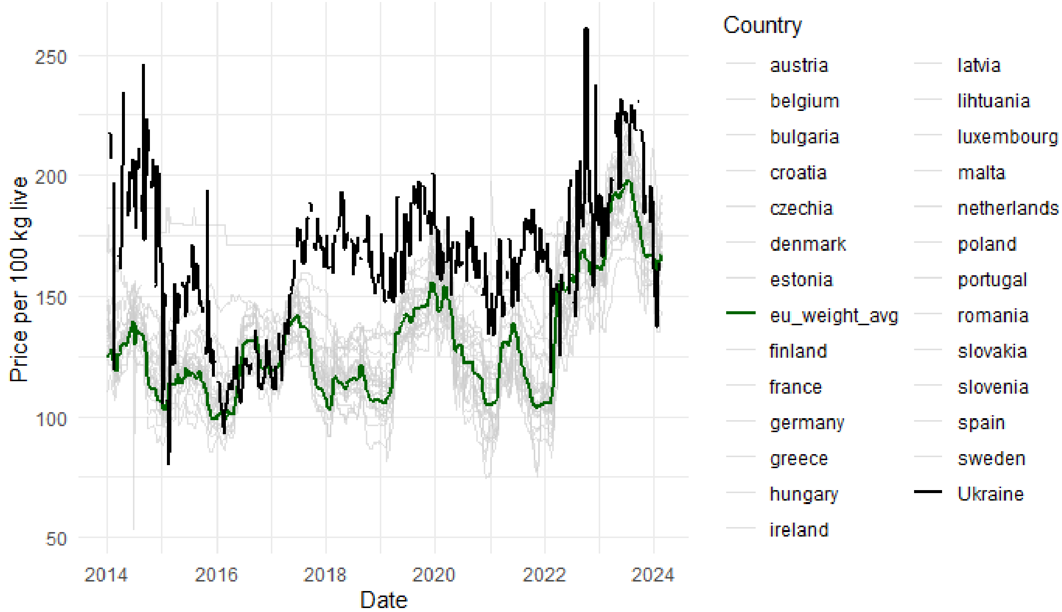
Figure 4. Ukrainian live pig prices from 2012 to 2024



Source: PigUa info

Figure 5 presents implied live-pig prices for EU countries, showing the EU weighted average (green) and Ukraine (black) from 2015 to 2024. For comparison, EU carcass prices were converted to live prices using a dressing ratio of 0.7868, as given by Vítek (2011). Both price series follow similar cycles, with shared peaks and troughs that suggest common market shocks. However, Ukraine often shows larger swings and sometimes moves unsynchronized with the EU average, especially in 2017. The EU-weighted average offers a stable benchmark, while Ukraine's prices show greater volatility and potential delays in responding to broader price changes.

Figure 5. Ukrainian and EU countries prices for live pigs



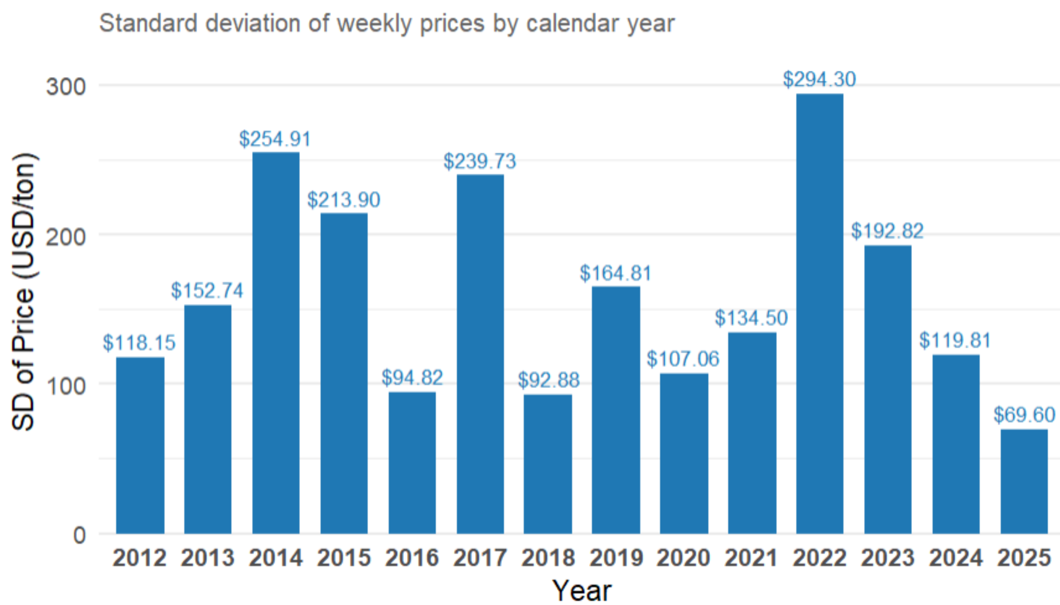
The Pearson correlations of weekly log-returns (see APPENDIX A) between Ukraine and each EU country range from −0.15 to 0.15. These small correlations show weak short-term connections. Ireland, Denmark, Romania, Germany, and Slovakia have the strongest positive links with Ukraine, while Bulgaria, Greece, Estonia, France, and Poland have the largest negative ones. The average EU weighted price correlation is also low at 0.035. Overall, the EU shows a mixed pattern rather than a single trend with Ukraine, which points to country-specific factors, timing differences, or structural differences in how prices move.

Table 3. Descriptive statistics for input grains and hog prices

Variable	Mean	SD	Min	Median	SE	Max
Barley	219.065	51.123	147.000	209.000	2.130	420.000
Sunflower meal	250.874	52.038	170.000	240.000	2.168	375.000
Soybean meal	539.216	102.924	362.500	522.626	4.288	861.485
Corn	179.761	43.886	86.777	169.310	1.829	317.226
Wheat	209.286	43.672	125.711	202.880	1.820	329.940
Pig	1751.179	398.686	807.143	1693.848	16.612	2753.264

Table 3 shows us descriptive statistics for each variable, particularly: mean, standard deviation (SD), standard error (SE), minimum (Min), maximum (Max), mean and median value. The average hog price across the dataset is roughly 1,751 USD per ton. Standard errors are small relative to standard deviations, reflecting the large enough sample. Each series possess a positive skew and rare high-value spikes, and at the same time the pig prices spikes have enormous spikes (some exceeding 50%) above mean levels. It indicates that non-feed shocks (disease outbreaks, trade or veterinary restrictions, demand shocks) play a substantial role.

Figure 6. Ukrainian annual live pig standard deviation from 2012 to 2024

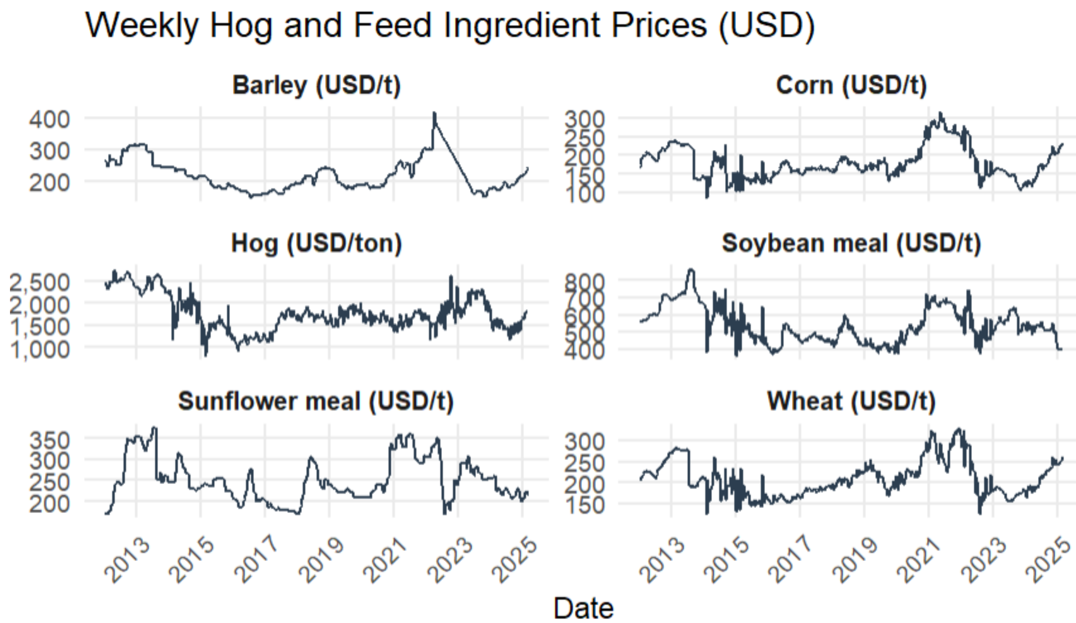


Source: PigUa info

Two years stand out as the most volatile. In 2014, the standard deviation exceeded \$250/t, reflecting the combined shock of African Swine Fever outbreaks in Eastern Europe, sharp spike in global feed costs and beginning of the war in Ukraine. A second peak appears in 2022 (SD ~ \$295/t), corresponding to war-related logistic disruptions, global grain prices crush and start of the full-scale war. In contrast, 2016 and 18 were unusually calm years (SD ~ \$90–95/t), when the market absorbed the post-2014 equilibrium, and 2024 to date shows the lowest dispersion (SD ~ \$70/t), suggesting improved market stability amid steadier feed costs and clearer trade flows.

Figure 5 plots the weekly USD-prices of live hogs (top-center) alongside five key feed inputs - barley, corn, soybean meal, sunflower meal and wheat – from January 2013 to June 2025. All series are on the same time-axis, allowing visual comparison.

Figure 7. Weekly hog and grains prices



The panels show that feed-price surges usually come before or happen at the same time as hog-price peaks. Volatility clusters in 2014–15, 2020–21 and around the 2022 war beginning - supporting our hypothesis of strong feed-to-hog pass-through and the need for shock variables in forecasting model.

A monthly SSSU report with Ukrainian herd counts by producer type is used as secondary dataset.

CHAPTER 5. RESULTS

5.1. LASSO Model Evaluation

We adopted a LASSO model to achieve a sparse, interpretable model with next penalty factor specification: feed variables and seasonal dummies were forcefully included by assigning a penalty factor equal to zero, all lagged price features have penalty factor equal to one.

The resulting post-LASSO ordinary least squares regression explains 89.2 percent of the variation in weekly pig prices, with an adjusted R-squared of 0.892. Residuals are symmetrically distributed around zero, with a standard deviation of 122 USD. Compound feed cost is positive with a coefficient of 0.24, indicating that a one-dollar increase in the feed index causes increase in pig prices by 0.24 USD. The feed shock indicator shows a large, highly significant effect: weeks with an extreme feed jump have pig prices higher by about 254 USD averagely.

Table 4. The post-LASSO ordinary least squares regression results

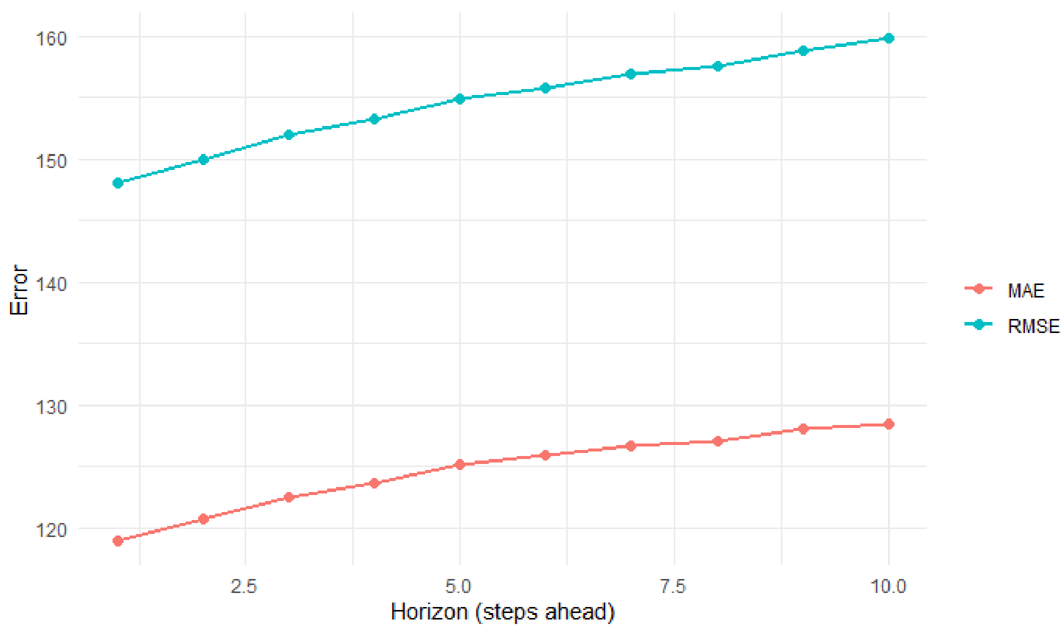
Predictor	Estimate	Std. Error	t-value	p-value	CI lower	CI upper
Intercept	-38.754	33.765	-1.148	0.252	-105.081	27.573
coarce_feed	0.243	0.137	1.766	0.078	-0.027	0.513
feed_spike	253.986	24.638	10.309	0.000	205.588	302.385
lag1	0.689	0.033	21.158	0.000	0.625	0.753
lag3	0.115	0.040	2.875	0.004	0.036	0.193
lag4	0.071	0.040	1.795	0.073	-0.007	0.150
lag7	0.081	0.030	2.697	0.007	0.022	0.140
Autumn	31.979	15.382	2.079	0.038	1.762	62.195
Spring	69.691	15.743	4.427	0.000	38.766	100.615
Summer	67.579	15.122	4.469	0.000	37.874	97.283

Among the 26 candidates of pig price lags, only four were included into model. Lag-1 carries the strongest weight (0.689) and is highly significant, reflecting short-term connection in prices. Lag-3 (0.115), lag-4 (0.072), and lag-7 (0.081) also make a positive contribution, capturing medium-term patterns with high significance.

Seasonal dummy coefficients reveal strong calendar effects. Relative to winter, average pig prices are by 32 USD higher in autumn, by 70 USD higher in spring, and by 68 USD higher in summer. All seasonal factors are statistically significant at 99% or even higher, highlighting the importance evaluating of seasonal fluctuations in the model.

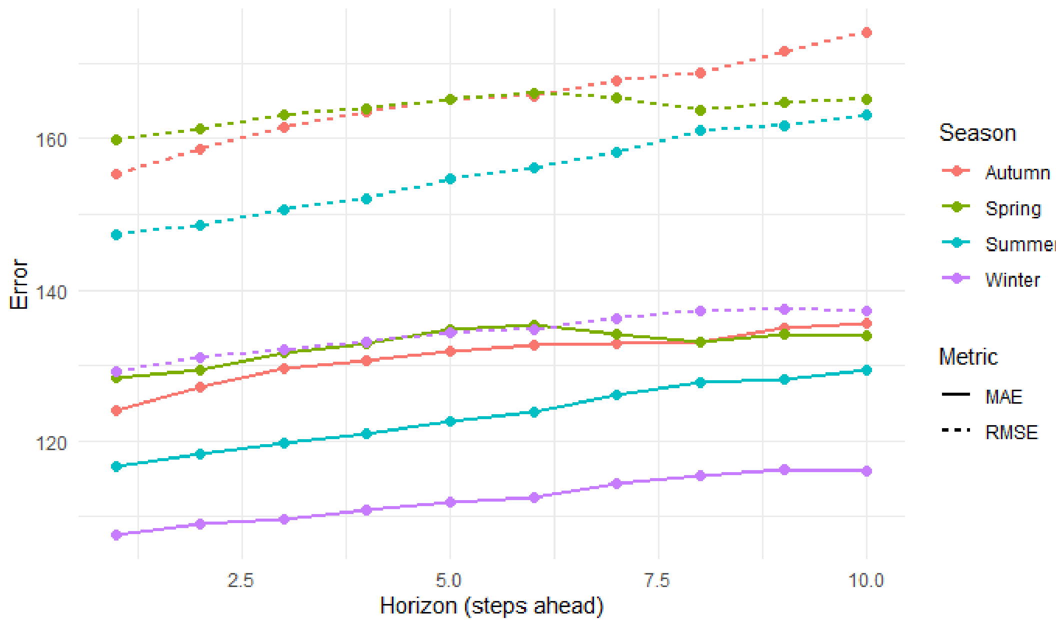
Out-of-sample forecasting performance was evaluated over horizons of one to ten weeks using expanding-window LASSO. Mean absolute error increases from 125 USD at one week ahead to 145 USD at ten weeks ahead. Root mean squared error similarly rises from 155 USD to 165 USD over the same period. Figure 7 reflects the predictable acceleration of uncertainty as the forecast horizon extends.

Figure 8. Rolling-Origin Forecast Error Metrics



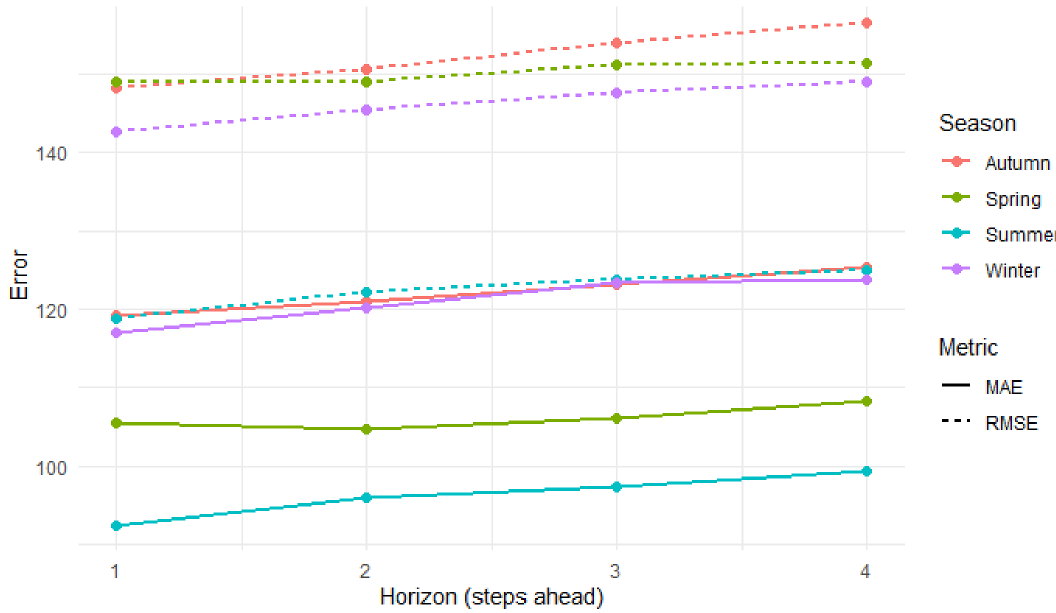
When errors are observed by season, winter forecasts consistently achieve the lowest errors at every horizon, indicating more stable price dynamics in the cold months. Autumn and summer horizons have the highest errors, particularly beyond four weeks ahead, pointing to greater volatility around harvest and peak-demand periods. Spring errors have an intermediate position, meaning transitional market conditions.

Figure 9. Rolling-Origin Seasonal Forecast Error Metrics



Both Rolling-Origin and Fixed Size Forecast Errors evaluate Summer as the most volatile season.

Figure 10. Fixed Size Seasonal Forecast Error Metrics



5.2. Comparing with ARIMAX

Table 5. Rolling-Origin Forecast Accuracy of LASSO and ARIMAX

Model	RMSE	MAE
LASSO	154.66	124.63
ARIMAX (3,0,2)	267.57	196.83

LASSO outperforms the ARIMAX (3,0,2) benchmark - reducing RMSE by about 113 USD and MAE by about 72 USD. This is the proof that the variable value selection and penalization in capturing nonlinear feed-price interactions and autocorrelated dynamics.

5.3. Shocks evaluation

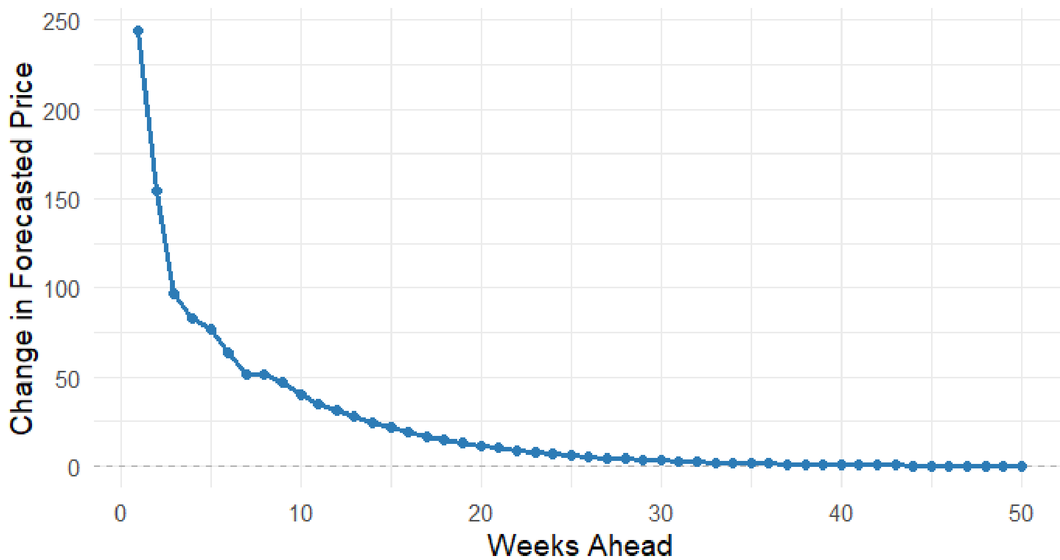
The post-LASSO estimates for a one-unit increase in the compound feed index is β_1 = 0.7912 USD per USD feed change. This coefficient represents the model's immediate response to feed cost surge. Impulse Response to a Feed Spike (Δ≈19.8 USD) - the 95th-percentile average feed jump - produces an initial price surge of ≈243.7 USD, slowing down to about 40.6 USD by week 10.

Table 6. Impulse Response to a Feed Spike (Δ≈19.8 USD)

Weeks ahead	1	2	3	4	5
IRF (Δ=19.8)	243.74	153.93	97.21	83.11	76.71
Weeks ahead	6	7	8	9	10
IRF (Δ=19.8)	63.75	51.85	51.79	47.14	40.58

The longer-horizon IRF (plotted at the Figure 10) shows a steep decline in the first ten weeks, followed by a slow movement to zero. This pattern highlights a massive but gradually declining impact of extreme feed spikes on pig prices, with detectable effect even up to 50 weeks ahead.

Figure 11. Impulse Response of Price to Feed Shock



5.4. Evaluation of feed prices influence on pig herd size

We estimated distributed-lag OLS models with lags 0–6 separately for household and enterprise herds, compute the cumulative transmission β_sum = Σ0..6 β_k, and report inference using robust covariance estimators and month-block bootstrap (R = 2000, seed = 123). Sensitivity analyses vary the lag window K ∈ {2,4,6,8} and relax the lag-completeness requirement to preserve sample size.

Main estimates (K = 6) are shown as Table 7. Due to the results, a one-unit increase in the monthly feed index is associated with ≈ −0.357% cumulative change in household herd over the 0 - 6 month window (≈ −3.5% for a 10-unit feed increase). No statistically meaningful contemporaneous or cumulative effect of monthly feed on enterprise herd size were discovered.

Table 7. Newey–West SE reported. N = 79 months

Main estimates (K = 6)	Contemporaneous coefficient (feed_lag0)	Cumulative effect (β_sum, lags 0–6)
Households	β0 = −0.003; SE ≈ 0.001, $p \approx 0.039$	β_sum = −0.004; analytic 95% CI ≈ [−0.004, −0.003]; bootstrap (percentile) 95% CI ≈ [−0.004, −0.003].
Enterprises	β0 ≈ 0.000033 (SE ≈ 0.00063, $p \approx 0.959$)	β_sum ≈ 0.000214; analytic and bootstrap CIs include zero

Residual diagnostics indicate strong serial correlation in OLS residuals for both groups (Breusch–Godfrey $p < 0.001$) and heteroskedasticity in the enterprise model (Breusch–Pagan $p \approx 0.035$).

Inference therefore relies on robust covariance estimators (Newey-West) and bootstrap percentile CIs for β_sum. These corrections are used in reported standard errors and confidence intervals.

Sensitivity across lag windows for Households stays that β_sum is consistently negative and stable across K = 2, 4, 6, 8; the sign, magnitude and confidence intervals are robust to lag length choice; thus, the result is unlikely to be caused by a particular lag choice and therefore more credible.

Table 8. Sensitivity across lag windows for Households

K	β_sum	NW SE	CI	N
K = 2	−0.003	≈ 0.0003	≈ [−0.004, −0.003]	83
K = 4	−0.003	≈ 0.0004	≈ [−0.004, −0.003],	83
K = 6	−0.004	≈ 0.0003	≈ [−0.004, −0.003]	83
K = 8	−0.004	≈ 0.0004	≈ [−0.005, −0.003]	82

For Enterprises β_sum remains small and statistically indistinguishable from zero across K: values range roughly 0.00017–0.00022 and all CIs include zero, with similar N used across specifications.

A simple power check indicates the minimal detectable cumulative effect (80% power) is on the order of 1e-4 for the sample and estimation variance used. The observed household β_sum (≈ −3.6e-3) is substantially larger than this threshold, consistent with a well-powered detection. The enterprise estimate (~2.1e-4) lies near or below the detectability threshold, meaning null results for enterprises may reflect small true effects below current detectability.

CHAPTER 6. CONCLUSIONS AND RECOMMENDATIONS

Based on the results, a LASSO-selected model outperforms the ARIMAX (3,0,2) benchmark across all horizons, reducing the one-week RMSE by approximately USD 113. Market transmission is rapid. Impulse responses indicate that extreme shocks to feed costs have an immediate impact on prices; this indicates limited short-run supply flexibility. Feed costs increase, and price pass-through along the value chain occurs quickly. Feed supply shocks will cause price volatility, and the rapid response will occur at the buyer, processor, and risk manager levels. Monitoring the market and short-term hedging (or forward contracting) will allow all participants to manage effectively the rapid transmission of feed supply shocks.

Using distributed-lag OLS on monthly herd data (lags 0–6), households exhibit a small but statistically robust negative cumulative association with feed ($\beta sum \approx -0.00357$, bootstrap and Newey–West CIs exclude zero), while enterprises show no detectable contemporaneous or cumulative effect at monthly frequency. Household results are stable across lag windows (K = 2,4,6,8), Newey–West SEs and month-block bootstrap; residual serial correlation and some heteroskedasticity were present and addressed via robust inference.

Using distributed-lag OLS with lags 0-6 on monthly herd data. Using distributed-lag OLS with lags 0-6 on monthly herd data, households exhibit a small but statistically valid negative cumulative association with feed ($\beta sum \approx -0.00357$, bootstrap and Newey-West CIs exclude zero) while enterprises show no cumulative contemporaneous effect at a monthly frequency. Households exhibit result consistency regardless of lag window (K = 2,4,6,8) while Newey-West SE and month-block bootstrap showed the presence of residual serial correlation and some heteroskedasticity, which were robustly addressed with inference.

Small producers (households) are price-sensitive. The cumulative estimating coefficient implies a herd reduction of $\approx -0.356\%$ over the next six months ($\approx -3.5\%$ for a 10-unit increase) associated with a monthly feed price increase. This can translate minor stock drops and short-term income decreases on smallholder operations during rising feed cost periods. Households' weakness during periods of rising feed costs is likely due to limited funding options. Targeted assistance or risk-sharing mechanisms with small producers will probably prevent herd depletion optimally. Basic forward contracts, cooperatively organized bulk purchasing arrangements, and index-based risk instruments can dampen the direct effects of feed price increases on small producers' cash flows and downstream prices.

Larger producers (enterprises) seem to be resilient at the monthly reporting frequency. We are proposing two possible explanations: either enterprise managers smooth adjustments over time scales using inventories, contracts or different horizon lengths; or enterprise adjustments are small in relation to sample variance and fell below the detection threshold.

The assistance of capacity building, aggregator access and training that allows smallholders to engage in cooperative procurement should alleviate forced destocking by lowering per-unit costs. Consequently, the absence of detectable herd adjustments at weekly intervals is most likely a function of monthly reporting. The implementation of herd monitoring at weekly or biweekly intervals and remote sensing proxies, administrative records, or surveys would allow for more effective capturing of short-run adjustments and would refine the problem of timing and magnitude. Joint modeling of prices and herd dynamics through implementation of hierarchical state-space or structural models that simultaneously estimate price formation and herd adjustment processes; this allows to test feedbacks (price - herd - price) relations.

Further analysis may involve mixed-frequency models (for instance, MIDAS), where feed prices are weekly and herds are monthly without strong aggregation to mitigate information loss due to intertemporal aggregation. Using weekly price data with monthly herd counts introduces potential measurement dilution. Rapid responses within a month can be obscured by monthly aggregation. Enterprise null results may reflect true resilience or limited power to detect small effects given observed variance and sample size.

There is a clear pattern shown by the analysis: shocks to feed costs are captured and pass through the system rapidly, there are modest reductions in household herd size over a few months, and enterprise herds, in this data set, show no response. From a policy and business perspective, protecting small producers from short-term feed cost volatility and improving risk-management capacity across the value chain should be priorities. Methodologically, the path forward is to improve temporal resolution of herd data, exploit exogenous variation for causal claims, and adopt joint modeling approaches that capture the dynamic feedbacks between prices adaption herd decisions. These steps will both sharpen inference and increase the practical relevance of future findings for stakeholders in the livestock sector.

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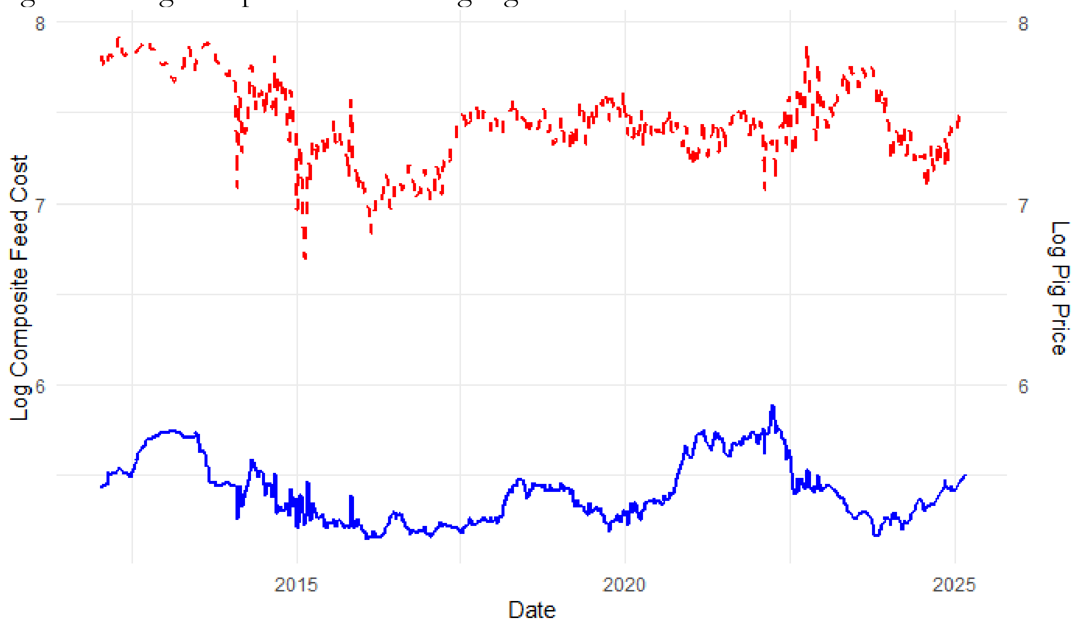
APPENDIX A
ADDITIONAL FIGURES

Figure 12. Log Composite Feed vs Log Pig Price



Red-dashed – pigs, blue – composite feeds.

Figure 13. Pearson correlation (weekly log-returns): Ukraine and EU