Understanding the Causal Relationship of Lead Time on Material Cost Patterns with Machine Learning Models

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Abstract -

Supply-chain characteristics are known to influence material prices, however they are often overlooked when price forecasting and analysis is done. This study seeks to address this gap by creating a framework that links machine learning model performances with inference statistic methods to understand the influence of lead-time on material price patterns. Machine Learning (ML) implementation consisted on evaluate one-step-ahead price forecasts under small-sample conditions using 16 supervised learning methods to identify materials for which lead-time information consistently improves predictive accuracy. Then, a structural time-series intervention framework to estimate counterfactual price paths and quantify deviations following lead-time disruptions was applied. Results reveal heterogeneous responses across materials, for those materials such as steel joists and steel decking, economic increases in quarterly price growth (4–5 percentage points) were found after lead time shocks, while Heating, ventilation, and air conditioning (HVAC) and commercial refrigeration show minimal response. By linking ML-based material selection with causal time-series inference, the study provides micro-level evidence that lead-time shocks can generate short-run price pressures through supply-side constraints.

Keywords -

Lead-time, Price Forecasting, Machine Learning, Causal time-series

1 Introduction

Construction material price dynamics are deeply shaped by supply-chain characteristics, where the lead-time (LT) serves not only as a scheduling parameter but as a structural factor that enhances the investment planning and competitiveness of contractors [1]. While LT has been positively associated with higher unit prices and greater order sensitivity [2, 3], research on price forecasting continues to use machine learning (ML) methods that rely solely on macroeconomic indices, commonly using the Producer Price Index (PPI) and its lagged features [4, 5, 1, 6].

Moving from common econometric models used for forecasting construction costs and material prices that neglects the role of the LT series [7, 1, 8], this study creates a linkage between PPI and material category LT data by shifting the focus from forecasting performance to causal mechanism identification. Rather than asking whether lead time improves price forecasts, this study investigates under what conditions lead-time variations causally affect construction material prices, and how these causal pathways manifest in observed temporal dynamics.

By emphasizing causality over accuracy, this work contributes to a growing body of literature at the intersection of supply-chain analytics, time-series modeling, and causal inference. The analysis is focused on a selected subset of construction materials and a specific temporal window, a design choice based on data availability and methodological rigor. More broadly, this research underscores the necessity of embedding causal reasoning into predictive systems intended to inform real-world decisions in volatile and interdependent markets.

2 Background

Cost time-series analysis remains reliant on econometric models for material price forecasting [9]. The commonly used Vector Autoregression (VAR) and cointegration models use macroeconomic drivers that improve forecasts when the relationships hold in the long term [10], while Autoregressive Integrated Moving Average (ARIMA) type models use lagged prices when available [11]. Even advanced models using a multivariate setting rarely include direct measures of procurement frictions, such as lead times [12].

The relevance of including measures of procurement frictions is related to the understanding of volatility patterns that material price series exhibit and that are constantly challenging constant-variance models [13]. Some probabilistic and distributional forecasting methods address these challenges and extend the models to focus on predictive uncertainty for escalation and risk analysis [4]. However, these methods mainly used price history and macro covariates, limiting insights into procurement levers.

Advances in construction cost forecasting also include the use of ML models, which are able to capture nonlinear relationships between the response and predictor variables [14]. Early applications include the use of neural networks for cost prediction [15] and the comparison of ML algorithms to contrast the drivers influencing model performance [16].

Recent ML applications support procurement decisions by forecasting target material prices [17]. To represent uncertainty and manage training sensitivity, ensemble methods and interval forecasting have been used [8]. However, studies provide limited interpretability when an operational predictor such as lead time matters [18].

LT inclusion in material price analysis contributes to understanding whether delivery delays can be used as early signals of price pressures. Evidence at the industry level has linked delivery delays to higher PPI inflation during disruption periods [2]. This supports that the delivery delay measures are signals of price pressures when supply capacity tightens; however, it is needed to establish the relationship between material categories and LT influence, and when this improves price forecasts.

Connecting LT with material price forecasting is central to understanding which materials are sensitive to LT changes and thus, contributing to procurement decisions and policies [19]. Studies on forecasting show that to avoid distorting decision signals, temporal aggregation and update frequency should match lead time horizons [20]. However, material price forecasting literature has not separated the predictive value of LT levels versus LT changes under leakage-controlled evaluation.

3 Methods

This study adopts a causal time-series perspective to examine whether variations in lead time exert an influence on construction material price dynamics. The analysis focuses on a subset of materials previously identified as exhibiting forecast sensitivity to lead-time information.

Restricting attention to these materials allows the present study to interrogate causal mechanisms rather than predictive screening, consistent with recent recommendations in applied causal inference for time-dependent systems[21].

3.1 Data and Material Selection

The analysis uses quarterly data on producer prices and lead times for construction materials over the 2019–2024 period. Price information is measured using the end-of-quarter PPI series at the material level reported by the U.S. Bureau of Labor Statistics [22], while LT reflects reported delivery delays in quarters, collected from contractors. To focus the causal analysis on cases where lead time is economically relevant, materials are pre-selected using ML forecast performance metrics. Specifically, a pre-analysis was carried out comparing 16 supervised ML models, in which LT information was included or excluded from them to predict PPI.

The 2019-2024 observation window, while limited, encompasses one of the most recent supply chain disruption cycles, which includes the COVID-19 pandemic, the global logistics bottleneck of 2021-2022, and the subsequent normalization trajectory. This period is chosen because it contains multiple and identifiable lead-time shock events across materials that enable the observation of pre=treatment, treatment, and post-treatment dynamics on a 5 year term.

The forecasting models are estimated and evaluated using a rolling-origin scheme, allowing model parameters to be updated as the training window expands over time. Performance is assessed using standard out-of-sample accuracy metrics, including mean absolute error (MAE) and root mean squared error (RMSE). Models are estimated both with and without lead-time features, enabling a direct comparison of forecast accuracy across specifications.

To ensure that material selection is not driven by a single modeling paradigm, the forecasting exercise evaluates methods spanning a broad range of algorithmic classes. These include linear and regularized regression models, robust regression techniques, kernel-based methods, instance-based learning, decision-tree models, ensemble learners, and neural networks. By covering both parametric and highly flexible approaches, the model set reduces the risk that observed forecasting gains are artifacts of a specific functional form or estimation strategy.

This forecasting exercise is not intended to identify causal effects. Rather, it serves as a screening mechanism to determine whether lead-time information contributes meaningfully to predictive performance for a given material.

3.2 Lead-Time Influence Inference

Lead time is conceptualized as a supply-side treatment variable whose unexpected changes may induce downstream effects on material prices through production constraints, inventory adjustments, or market expectations [2].

Rather than modeling lead time as a continuous covariate, an approach that longer time series use to identify stable parameters, the analysis focuses on lead-time shocks, defined as deviations from recent historical patterns that are unlikely to be driven by contemporaneous price movements. With small sample-constrains as the ones in this study, the methodological approach employs a Bayesian structural time-series framework that is specifically developed for short time series, which avoids high-parameter models that would likely overfit. The deviation-based shock definition is theoretically grounded in causal impact literature and captures the core mechanism of interest without imposing a structural form that cannot be identified from the data. While this approach does not decompose the propagation channels of a disruption it provides average treatment effect on price growth in the quarters immediately following an anomalous lead-time shift.

The treatment is defined as an unexpected lead-time change calculated as:

$$\Delta \mathrm{LT}_t = \mathrm{LT}_t - \mathbb{E}[\mathrm{LT}_t | \mathrm{LT}_{t-1}, \mathrm{LT}_{t-k}] \quad (1)$$

Where $\mathbb{E}[\mathrm{LT}_t|\bullet]$ represents a short-memory expectation based on recent lead-time history. This formulation isolates unanticipated shifts rather than gradual trends, consistent with causal impact frameworks for time series with limited observations [21].

Treatment periods are identified when $\Delta\mathrm{LT}_t$ exceeds a material-specific threshold derived from historical variability, thereby approximating a quasi-exogenous supply disturbance.

The primary outcomes capture short-term price responses; in that sense, price growth ($\Delta\mathrm{P}_t$) is chosen to reflect both level adjustments and uncertainty responses, which are theoretically distinct channels through which supply-side shocks may propagate, which is calculated as:

$$\Delta \mathrm{P}_t = \log(\mathrm{P}_t) - \log(\mathrm{P}_{t-1}) \quad (2)$$

Given the small sample size, high-parameter models are avoided; instead, intervention-style causal analysis is used by comparing post-treatment price behavior to counterfactual trajectories inferred from pre-treatment dynamics. It is assessed whether observed price responses following lead-time shocks deviate systematically from patterns expected under no intervention. In that sense, estimated effects are interpreted as local average causal responses rather than universal structural parameters.

Causal interpretation relies on three core assumptions, which are explicitly stated. Temporal ordering where LT shocks precede observed price responses, so contemporaneous price movements cannot retroactively influence lead times within the same quarter. No reverse causality assumes that quarterly price changes do not directly affect lead times within the same period. Limited Confounding: While demand fluctuations may affect both prices and lead times, focusing on unexpected lead-time deviations mitigates confounding from slow-moving demand trends.

4 Results

The empirical analysis focuses on four construction materials, as shown in Table 1. The results from prior machine-learning experiments as cases where the inclusion of lead-time information systematically improves price forecast accuracy, showed that these materials exhibit improvement in out-of-sample error metrics (MAE and RMSE) when lead-time features are incorporated relative to baseline models excluding supply-chain signals. Rather than re-evaluating predictive performance, this study uses the ML results as a screening mechanism to isolate materials for which lead time is plausibly economically relevant, thereby narrowing the causal analysis to contexts where a supply-side channel is most likely to operate.

Table 1. Material selected based on improvement performance metric of LT in ML models

Material	# Obs	ML improvement
Copper Wire	14	5.73%
HVAC	13	6.57%
Steel Decking	15	1.76%
Steel Joist	14	8.08%

Across the four selected materials, both producer prices and lead times display a diverse set of temporal variation patterns (Figure 1). Lead times exhibit episodic increases or decreases rather than smooth trends, supporting their interpretation as shock-like events rather than slow-moving covariates.

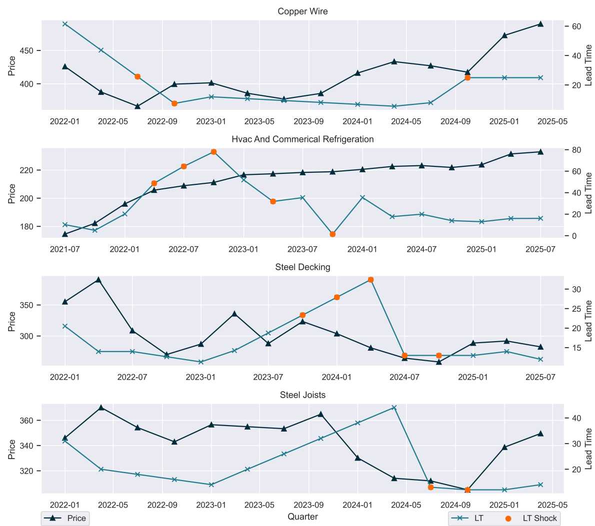

Figure 1. Material price behavior in contrast to lead time trends and lead time disturbances over the period of analysis

Effects of LT shocks on quarterly price growth are shown in Figure 2. For copper wire, the lead-time shock dated October 2024 generates an estimated average treatment effect of 0.0337, corresponding to a 3.37 percentage-point increase in quarterly price growth relative to the counterfactual. In contrast, HVAC and commercial refrigeration equipment exhibit a markedly smaller response. The estimated effect of 0.0034 implies an increase in quarterly price growth of only 0.34 percentage points, indicating minimal sensitivity to lead-time disruptions. Steel decking shows a strong and economically meaningful response to lead-time shocks. The estimated effect of 0.0462 corresponds to a 4.62 percentage-point increase in quarterly price growth following the October 2024 disruption. This result aligns with the production characteristics of steel decking, which often involves made-to-order fabrication and limited short-run flexibility. Steel joists exhibit the largest estimated response among the analyzed materials. The average treatment effect of 0.0515 implies a 5.15 percentage-point increase in quarterly price growth relative to the counterfactual. This pronounced effect is consistent with the highly customized nature of joist production, long fabrication lead times, and backlog-driven pricing.

Figure 2. Material price behavior in contrast to lead time trends and lead time disturbances over the period of analysis

The results reveal substantial heterogeneity in price responses to lead-time shocks, with effect sizes ranging from negligible (HVAC) to large (steel joists). This heterogeneity closely mirrors the ranking implied by the machine-learning forecast sensitivity analysis, providing external validation for the ML-based material selection approach.

It is important to note that the small number of observations per material (13-15 quarters) means that the estimated effects should be interpreted in context as bounded responses specific to the 2019-2024 disruption cycle. Nonetheless, the consistency between the ML-based sensitivity rankings and the causal effect magnitudes across the four analyzed materials provides cross-material evidence that strengthens the internal validity of the findings despite the limited temporal span

5 Discussion

This study challenges the commonly used baseline models for price forecasting and add an additional element of lead time relationship with material prices. From a practical perspective, LT results are relevant due to their influence on procurement decisions. The empirical analysis linking ML with inference statistical methods suggest that unexpected lead-time disruptions in selected construction materials are associated with deviations in price growth, with effects ranging from negligible (HVAC and commercial refrigeration) to significant increases of 3–5 percentage points in quarterly producer price growth (copper wire, steel decking, and steel joists). This pattern of heterogeneous responses aligns with economic theory and recent empirical work that identifies supply chain pressures as a significant driver of price dynamics, particularly in contexts where supply constraints are binding and replacement is limited.

At a broad macroeconomic level, a growing body of literature documents the importance of supply chain disruptions for inflation dynamics. Studies using time-varying causality and structural models find that supply chain pressures exert significant causal influence on consumer and producer price indices, especially during periods of acute stress such as the global financial crisis and the COVID-19 pandemic [23]. In addition, empirical work using structural vector autoregressive approaches shows that shocks to global supply chain pressures have positive and persistent effects on inflation metrics in the euro area and other advanced economies, suggesting that disruptions to delivery times and bottlenecks can feed into broad price trends beyond individual commodities [24]. These macroeconomic patterns support the intuition behind our more granular analysis: supply constraints, as proxied by lead-time shocks, can transmit into higher short-run price changes along affected production chains.

The results showed in this study intersect with the broader literature on supply shocks and inflation mechanisms. Recent frameworks emphasize that supply disruptions can amplify inflationary pressures through cost-push channels and feedback into price expectations and firm pricing decisions. For example, research that decomposes inflation into demand and supply contributions finds that supply shocks, including those that lengthen supplier delivery times, have historically played a sizable role in inflationary episodes, sometimes exceeding the contribution of conventional demand shocks [25]. The findings that that lead-time disruptions coincide with abrupt deviations from counterfactual price growth trajectories lend microeconomic evidence to these broader patterns.

The analysis restricts causal inference to materials prescreened with sensitivity to lead-time information. This design choice avoids applying a causal framework to materials where the supply-side channel has not been empirically validated, thereby improving interpretability. However, the heterogeneous response pattern observed across the four materials can be mapped to broader structural typologies applicable to the wider industry. Materials exhibiting strong lead-time sensitivity (e.g., steel joists, steel decking) share characteristics of fabrication-intensive, order-driven production with limited short-run capacity flexibility. In contrast, HVAC equipment, which shows minimal response, reflects a more inventory-buffered supply structure. These typological distinctions suggest a framework for extrapolating findings on construction materials with make-to-order production processes, long fabrication cycles, and low inventory buffering and materials with large-batch, inventory-held supply chains. Future research should test this typological mapping across a broader range of materials, potentially using the ML-based screening procedure as a scalable pre-selection mechanism.

The linkage between ML-based selection of sensitive materials and causal inference opens new paths for future research. First, extending the temporal scope beyond 2019–2024 would allow estimation of longer-run structural parameters and disentangle disruption-cycle effects from secular trends in construction material markets. Second, while the deviation-based shock definition adopted here is appropriate under small-sample constraints, future work with monthly or weekly data could implement more structurally explicit shock identification strategies (e.g., VAR) to decompose the channels through which lead-time disruptions propagate into prices. Such integration is increasingly feasible given recent developments in time-varying causality testing and machine-learning interpretability in macroeconomic contexts [23]. In that sense, these findings add to a growing body of evidence that supply chain disruptions, especially delivery time shocks, have meaningful impacts on price dynamics at both micro and macro levels.

6 Conclusions

Materials with fabrication-intensive and order-based supply chains such as steel joists and steel decking exhibit large deviations from their counterfactual price paths, with average increases in quarterly price growth of 4.6–5.2 percentage points. In contrast, HVAC and commercial refrigeration show a negligible response (0.3 percentage points), suggesting limited price sensitivity to lead-time disruptions.

Lead-time shocks generate economically large and heterogeneous price responses, particularly for fabrication-intensive construction materials, supporting a supply-side causal channel linking delivery delays to short-run price inflation.

Three boundary conditions govern the interpretation of these findings. First, the 2019-2024 time frame, while analytically rich, limits the ability to identify long-run trends or market dynamics within this period. Second, the small number of observations means that estimated effects represent local average causal responses rather than universal structural parameters. Third, the analysis focuses on four pre-screened materials; generalization to the broader construction material universe requires validation across a wider set of material categories using the same ML-based screening procedure. The goal is not precise effect size estimation, but mechanism validation that determines whether lead time operates as a causal driver of price dynamics for specific materials under observed market conditions.

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