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Modeling Inflation Transmission among Different Construction Materials

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Abstract: Cost estimating in the construction industry is challenging due to the high uncertainty associated with the supply chain, especially after the COVID-19 pandemic. Some research studies have addressed such problems by developing models that predict material cost. In fact, all material can be interconnected and interrelated with lead-lag relationships such that any inflation in one material's price can be associated with inflation in other materials' prices, referred to as transmission of inflation. Despite the latter, none of the existing studies have investigated inflation transmission among all construction materials. This paper fills this knowledge gap. The authors used a multistep research methodology. First, Producer Price Index (PPI) data for 16 construction materials were collected and sorted. Second, the vector autoregression technique was used to model the relationships between each pair of material and subsequently validate the associations using the Granger causality test. Third, network analysis was performed to identify the inflation transmission capacity (out-degree centrality), inflation susceptibility (in-degree centrality), and inflation intermediatory capacity (betweenness centrality) for each material. Finally, modularity-based clustering was conducted to categorize the materials based on their price indices' interconnections and examine inflation transmission path among different sectors of construction-related material. The results show that metals and plastic products are generally the highest transmitters of inflation to other construction material including "Fabricated structural metal products" and "Plastic construction products." Furthermore, the results show that "Concrete products," "Flat glass," "Brick and structural clay tile," and "Architectural coatings" are also high transmitters of inflation and thus can be key indicators of increase in the overall construction cost. This paper provides the industry stakeholders with leading indicators and early warning signs for the inflated material prices. Contractors and owners can utilize those warning signs to enhance their procurement plans and budgeting decisions. **DOI: 10.1061/JCEMD4.COENG-13893.** © *2024 American Society of Civil Engineers.*

Introduction

Procurement strategies play a crucial role in construction projects and are heavily influenced by changes in the supply chain. However, the supply chain is susceptible to various price fluctuations as well as operational and disruption risks (Fahimnia et al. 2018; Sawik 2011; Tomlin 2006). For instance, in 2018, major disruptions occurred in the construction supply chain due to the implementation of new steel and aluminum import tariffs into the US, resulting in a 25% tariff on imported steel and a 10% levy on imported aluminum (BIS 2018). The increased input costs and retaliatory tariffs led to rises in producer pricing (Flaaen and Pierce 2019). As a result, the tariffs and supply chain disruptions increased the cost of construction material supplies, impacting construction enterprises by increasing the overall cost of construction projects.

Another example is the current global supply chain disruptions experienced after the outbreak of the COVID-19/Coronavirus pandemic that started in 2019–2020. The pandemic disrupted normal business operations in all industry sectors, including the construction industry. Despite being deemed essential businesses and exempt from certain restrictions (Conerly 2020), the construction industry was still affected by material and labor shortages, reductions in material production, and shipping interruptions. As a result, the construction industry faced increased risks due to the pandemic (Khalef et al. 2022).

Public agencies and private project owners often rely on cost indexes and material prices to support their budgeting decision-making (Swei 2020). One commonly utilized measure to gauge the current price levels of construction materials by the industry practitioners is the Producer Price Index (PPI). The US Bureau of Labor Statistics (BLS) publishes several industry-level and commodity-level PPIs of the construction material prices monthly. Although the inflation observed in the industry-level PPI for construction materials has slowed, the inflation observed in the commodity-level PPI for several construction materials has moved in divergent directions, and the actual increase varies a lot by type of material (AGC 2022).

The Associated Builders and Contractors (ABC) has recently reported that several contractors' short-term confidence in sales, profit, and staffing is severely affected by the inflated material prices (ABC 2023). Presented with inflated material prices, contractors cannot always pass on this inflation to project owners, especially in times and regions with reduced construction demand. In fact, the Associated General Contractors of America (AGC) has reported that the inflation in construction materials outpaced the

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increase in bid prices for a consecutive 19 months between December 2020 and June 2022 (AGC 2022). Accordingly, the inflated material prices present a challenge for owners and contractors. Whereas contractors may lose bids or profits due to inaccurate cost estimates, owners may be presented with inflated bids during periods with increased construction demand, very short-term price guarantees, and too few bidders for their projects (Ashuri and Lu 2010; Ilbeigi et al. 2017). Hence, providing construction contractors and project owners with insights and outlooks into the inflation mechanism of the various material prices is of paramount importance.

Based on the aforementioned, it is perceived that cost estimating in the construction industry is challenging due to the high uncertainty associated with the supply chain. The industry practitioners' need for accurate estimates of construction costs has been reflected in the plethora of studies attempting to propose forecasting models for various construction inputs. Some papers focused on the relationship between construction costs and the associated influencing factors (Trost and Oberlender 2003; Attalla and Hegazy 2003; Doğan et al. 2006). Other papers focused on developing models to capture and identify the behavior of construction costs in markets over time. These papers often use cost indexes that are either directly related to, or closely reflect, the prices of labor, materials, and equipment used in construction (Hwang 2011).

In the construction industry, estimating costs based on such indexes has been widely adopted (Diekman 1983). Estimating construction costs based on composite cost indexes involves analyzing and capturing the trend of indexes relevant to construction costs over time (Wilmot and Cheng 2003). An example of that includes the work of Ashuri and Lu (2010), Ashuri and Shahandashti (2012), Shahandashti and Ashuri (2013), Hwang (2011), Choi et al. (2021), and Kim et al. (2021), among many others. The literature already provided ample knowledge and tools for better prediction and forecasting of construction cost indexes. Although many studies have focused on developing forecasting models to better estimate construction cost indexes based on macroeconomic and microeconomic variables such as leading indicators, instances of those models' underperformance may be attributed to (1) ignoring other relevant leading indicators, and (2) the inaccurate assessment of the associations between the target variable (i.e., construction costs) and the identified leading indicators (Swei 2020). Although the interpretation of construction cost indexes provides an indication of industry-level trends of costs, a closer look into the individual cost inputs (i.e., individual materials' prices) is also of great value.

Generally, the price of each commodity is related to others due to different reasons including substitution effect and supply–demand relationships (Acemoglu et al. 2012). Inflation in construction costs is often associated with inflation in several inputs to those costs. The contribution of those inputs to costs in different construction projects varies significantly. Furthermore, although a macro-view of construction input prices revealed a 17% inflation in 2022 compared with 2021, the monthly variations of each input's prices do not follow similar trends (ABC 2022). The monthly variations in construction material prices can be interconnected and interrelated such that inflation in one material's prices be associated with inflation of another material's prices at a prior point in time, referred to as transmission of inflation. Thus, it is of crucial importance to further understand the transmission of price fluctuations among the different commodities or materials associated with the construction industry.

In fact, according to Sun et al. (2018), the identification of vital price indices and the transmission path of price fluctuations allows for better control and understanding of price inflation as well as easier market regulation. Furthermore, Zheng and Pan (2022) highlighted that understanding price transmission is crucial in creating efficient policies to manage inflation in prices as well as supporting vulnerable producers (i.e., contractors and subcontractors) and consumers (i.e., project owners). Generally, investigating the price transmission path among the different commodities and materials allows for a better understanding of inflation transmission mechanisms, and more specifically the different roles of construction materials in transmitting inflation (Sun et al. 2018).

Hence, this paper will focus on commodity-level prices rather than industry-level assessments to investigate the inflation transmission among various construction materials as a more efficient and effective way of supporting the supply chain associated with construction activities. The ability to quantify the inflation transmissions between the different material prices equips industry's stakeholders with early warning signs of inflationary volatility in certain material prices and enables them to prepare better-informed mitigation measures consequently. This would aid construction contractors, public agencies, and private-sector owners by providing a better understanding of inflation transmission among the various construction materials. Thus, this paper paves the way for enhanced procurement and risk management strategies in the event of inflated material prices.

Previous Studies for Investigating Construction Costs

Historical data of several construction cost inputs including material prices are considered time series in nature (Faghih and Kashani 2018; Ilbeigi et al. 2017; Ma et al. 2023). A review of the literature showed that many papers developed time-series models to either study different economic relationships in the construction sector or to promote accurate cost estimation in construction projects. An example of the former is the work of El-adaway et al. (2020), who examined the link between the stock prices of publicly traded US companies and Gross Domestic Product (GDP) in a way that actually showed how the 2008 economic collapse could have been proactively forecasted way ahead of time. Also, Zheng and Liu (2004) investigated the interplay between construction investment and GDP in China, and Anaman and Osei-Amponsah (2007) studied the same relationship in Ghana. In Hong Kong, Chiang et al. (2015) conducted research on the causal relationship among construction activity, employment, and GDP.

Further, Priya and Arabinda (2019) analyzed the stock prices of three Indian construction companies to provide guidance for investors in making informed decisions on holding, buying, or selling stocks based on economic signals. Barber and El-adaway (2015) examined the performance of construction activity in the southeastern US, focusing on its contribution to state GDP. In China, Chen et al. (2017) researched the correlation between price fluctuations in the stock market and the real estate market, and Lin et al. (2018) employed time-series analysis to uncover correlations between intellectual capital and business performance.

In relation to construction cost inputs, various studies focused on modeling the relationships between various macroeconomic indicators and the *Engineering News-Record* (ENR) construction cost index (CCI), such as the works of Ashuri and Lu (2010), Shahandashti and Ashuri (2013), Ashuri and Shahandashti (2012), and Ashuri et al. (2012a, b). The ENR's CCI is a composite index measuring changes in four inputs (cement, lumber, structural steel, and common labor). Ashuri and Lu (2010) developed univariate time-series models to model the autocorrelation relationship between current and lagged values of ENR's CCI and recommended the inclusion of economic and market-related factors to improve the modeling of the inputs' price movements.

Investigating the association relationships between 16 macroeconomic indicators and ENR's CCI, Ashuri et al. (2012a) identified the leading indicators of ENR's CCI through Granger causality tests and bivariate vector autoregression (VAR) models. Xu and Moon (2013) proposed bivariate VAR model of ENR's CCI using the Consumer Price Index (CPI) as a leading indicator in addition to lagged values of the ENR'S CCI itself. Although the VAR successfully modeled the associations between CPI and the ENR's CCI, Xu and Moon (2013) recommended the utilization of bivariate VAR for enhancing the modeling of the associations between various leading indicators and the individual construction materials.

Shahandashti and Ashuri (2013) further developed multivariate time-series models to predict ENR's CCI. Their study found that the crude oil price and the overall PPI are leading indicators of ENR's CCI and that modeling relationships between those indicators and the CCI enhance the interpretation of escalations in the CCI. The authors recommended applying similar approaches to other inputs to construction costs because the ENR's CCI does not capture all movements of costs in the US construction industry.

Some other papers implemented similar time-series techniques but focused on certain construction sectors. Using time-series analysis methods, such as the Granger causality test, Shahandashti and Ashuri (2016) found that crude oil prices and average hourly earnings are the leading indicators of national highway construction costs. From a pool of macroeconomic indicators, Choi et al. (2021) utilized the Granger causality and heteroskedasticity-adjusted correlation analysis to identify the leading indicators of city-level construction cost indexes. The conclusions highlighted by Choi et al. (2021) demonstrated that the significant cross-city variations in construction cost indexes were reflected in the different leading indicators of those indexes in different cities. Furthermore, due to the limitations inherited in the development of cost indexes that are composed of both material and labor components, the leading indicators of each component of those indexes might be different and the interpretation of multivariate forecasting models can yield erroneous conclusions (Faghih and Kashani 2018). To tackle this limitation, research efforts attempted to identify the leading indicators of the individual components of those indexes (i.e., individual material or labor components).

Ilbeigi et al. (2017) identified the short-term variations in asphalt cement using univariate models. The authors concluded that the univariate autoregressive integrated moving average (ARIMA) and Holt exponential smoothing demonstrated acceptable capabilities to model short-term variations of asphalt-cement prices when compared with Monte Carlo simulation. Alternatively, Faghih and Kashani (2018) proposed multivariate models of asphalt, cement, and steel prices in the US construction industry. The work done by Faghih and Kashani (2018) identified the leading indicators of asphalt, cement, and steel separately through Granger causality, then developed models that relied on vector error correction to forecast short- and long-term prices of those materials. The study not only concluded that multivariate forecasting models outperformed univariate models for each of the three investigated materials, but also highlighted that the identified leading indicators of each material were different.

Kim et al. (2021) used Granger causality, vector autoregression models, and vector error correction models to identify the leading indicators of different cost inputs to pipeline construction costs and propose forecasting models accordingly. The time-series analysis yielded different leading indicators for the various cost inputs (i.e., pipe material costs and labor costs).

Although the construction materials cost indexes can provide a general overview of the market conditions, assessment of escalation of the individual material prices can offer valuable insights to the industry's stakeholders (Baek and Ashuri 2019; Joukar and Nahmens 2016; Shiha et al. 2020). Furthermore, the reliance on specific resources can vary between several projects. Hence, the identification of the leading indicators of the individual price inputs can provide more relevant benefits to cost estimators of those specific projects (Xu and Moon 2013). The findings reported by Kim et al. (2021) echoed the ones by Faghih and Kashani (2018): the leading indicators of each input to the construction costs may vary and each material or labor cost shall be investigated separately if historical data are available.

Review of the literature showed that bivariate and multivariate time-series techniques can outperform univariate approaches in many instances. Based on the aforementioned research, to the best knowledge of the authors, although several macroeconomic indicators were investigated as leading indicators of construction cost indexes or prices of individual materials, no previous study investigated whether one price index of a construction material can be a leading indicator of another construction material's price index. Accordingly, this paper fills this knowledge gap.

Goal and Objectives

The goal of this paper is to investigate the inflation transmission mechanisms among the price indices of materials associated with the construction industry. The associated objectives include (1) determining the significant unidirectional and/or bidirectional causal relationships between each pair of construction materials that reflect inflation transmission among the materials; (2) identifying key construction materials in terms of their higher inflation transmission (i.e., the materials that can be utilized as early warning signs of other materials' inflation), their higher inflation susceptibility (i.e., the materials requiring further attention to their frequently escalated prices), and their intermediatory capacity (i.e., the materials that shall help facilitate the understanding of the causal relationships between those with higher inflation transmission and those with higher inflation susceptibility); and (3) clustering the materials based on their price indices' interconnections to examine inflation transmission path among broader materials' sectors.

Research Methodology

The authors utilized a research methodology comprised of four primary stages: (1) data collection; (2) identification of relationships among materials' price indices using VAR modeling and Granger causality; (3) network analysis; and (4) modularity-based clustering. A summary of the methodology and its connection to the research goal and objectives is provided in Fig. 1.

Overview and Justification of the General Methodological Approach

In the context of this paper, the construction industry depends on a set of materials whose prices can impact each other through causal relationships. Additionally, any inflation in one of the materials' prices may propagate to others, resulting in a domino effect, thus affecting contractors and subcontractors in terms of estimation, and project owners in terms of their budgeting decisions.

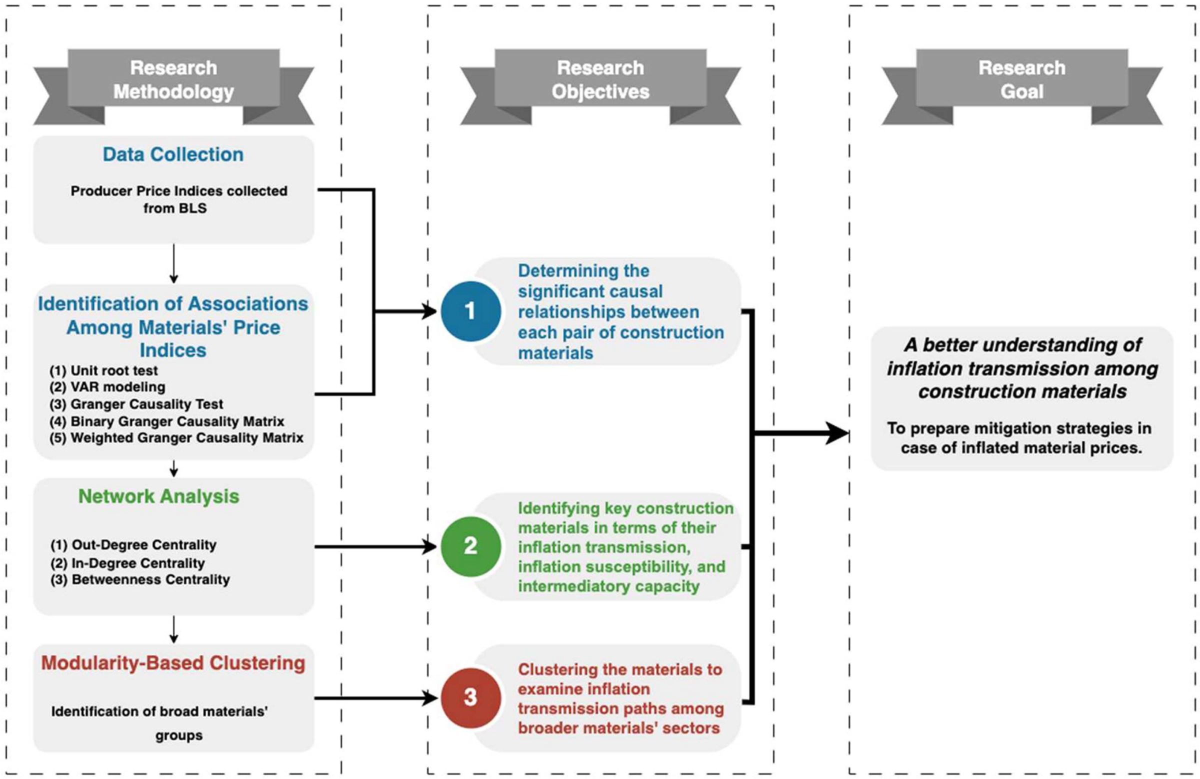

Fig. 1. Research goal, objectives, and methodology.

Understanding the inflation transmission mechanisms among commodity-level price indexes can be of higher value to contractors and subcontractors performing the cost estimates of items involving those individual materials. Furthermore, understanding those mechanisms on a broader cluster of materials level can provide additional value to project owners. As such, a robust methodological approach has to be used.

Whether one material's price index can be utilized as a leading indicator of another material's price index is to be explored by conducting time-series tests where VAR modeling can be accompanied by the Granger causality test. VAR modeling is a commonly utilized approach in studying whether lagged values of one time series can help in forecasting the current values of another time series. A useful capability of a VAR model is that it investigates the existence of two types of relationships between two time series: unidirectional and bidirectional (Ashuri and Shahandashti 2012). A unidirectional relationship exists when lagged values of one time series can help in forecasting the current values of the other time series, but not vice versa. A bidirectional relationship exists when lagged values of each time series can help in forecasting the current values of the other. Accordingly, VAR modeling can capture the internal structure of data sets and present highly accurate forecasts in the short-term forecasts.

In addition, the Granger causality test—developed by Granger (1969)—has been extensively utilized by researchers in the construction engineering and management domain to identify the associations between various explanatory variables and material prices (Ashuri and Shahandashti 2012; Choi et al. 2021; Faghih and Kashani 2018; Kim et al. 2021; Shahandashti and Ashuri 2013, 2016; Swei 2020). It is worth noting that the relationships inferred from VAR models and Granger causality tests are suitable to be utilized for short-term forecasting but not long-term forecasting (Assaad and El-adaway 2021b).

One notable drawback of VAR modeling is that its implementation and results' interpretation may be difficult for practitioners (Joukar and Nahmens 2016). To exploit the capabilities of VAR modeling while attempting to overcome this drawback, this paper utilizes network analysis and modularity-based clustering techniques to enhance the interpretation and to clarify the practical value of the identified causal relationships. Thus, in this paper, the results of the VAR modeling and Granger causality tests are used as inputs to the network analysis.

Network theory, which is a branch of graph theory, is a suitable approach for analyzing the interdependency between system elements and investigating their cause–effect relationships (Yang and Zou 2014). This method is particularly useful for complex systems with relational structures where individual elements can have an impact on or be affected by other elements within the system (Fang et al. 2012; Dogan et al. 2015; Mok et al. 2017; Chen et al. 2017). To further facilitate the understanding of the results of network analysis of the commodity-level material price indexes, modularity-based clustering is used to examine the inflation transmission among a broader level of materials.

Data Collection

For the analysis of this paper, it is important to identify the metric to be used that reflects price fluctuations of the materials on the one hand and a comprehensive—yet simplified—list of materials relevant to the construction sector on the other. To this end, the authors adopted the PPI as a measure of price inflation in the materials relevant to the construction sector. The PPI is defined as "the average change over time in the selling prices received by domestic producers for their output" (BLS 2023). In fact, PPI has been extensively used to reflect price inflation in general or in relation to specific products and materials (Shandashti and Ashuri 2013; Baek and Ashuri 2019;

Li et al. 2021; Shiha et al. 2020; Joseph Shrestha et al. 2016). To that end, the authors adopted the PPI as a measure of price inflation in relation to the various construction materials.

However, the authors still need to identify the list of the materials relevant to the construction sector. This paper retrieved PPI historical data from the publications of the producer price index program of the BLS. Two types of data are available to be collected: industry-level indexes, and commodity-level indexes. Following the recommendations provided by previous studies and the limitations of industry-level indexes highlighted therein (Faghih and Kashani 2018; Kim et al. 2021; Choi et al. 2021), this paper focused on individual material prices (i.e., commodity-level indexes). The BLS publishes 3,700 commodity-level producer price indexes that are not grouped by industry, and their commodity classification structure do not follow any standard coding structure (BLS 2023). Thus, the authors adopted the list of construction materials presented in the annual *Producer Prices and Employment Costs* report published by the AGC (2020). In their efforts to develop this report, the AGC attempted to pinpoint the commodities that are most relevant to the construction sector from the 3,700 and identified 34 commodities accordingly. However, to avoid redundancy on one hand and ensure conciseness on the other, the authors shortlisted the materials and considered 16 types of materials, which are inclusive and representative of all of the 34 types of materials. Table 1 presents the 16 types of materials adopted for the analysis of this paper along with the associated subtypes of materials.

For instance, Table 1 reflects that "concrete products" include concrete block and brick, concrete pipe, ready-mixed concrete, precast concrete products, and prestressed concrete products. Thus, instead of including the PPI of all the aforementioned subtypes, only the PPI of concrete products was included in the analysis of this paper. The same applies to "asphalt felts and coatings," "iron and steel," "nonferrous metals," and "fabricated structural metal products." Ultimately, the collected data of this paper include the monthly PPI for each of the 16 types of construction materials presented in Table 1. The time-series data were collected from 1991 to 2022, inclusive.

Identification of the Lead-Lag Associations among Materials' Price Indices

Unit Root Test

To ensure the reliability of the interpreted lead-lag associations between investigated material prices, the Granger causality test shall be conducted only on stationary time series with constant mean and variance (Ashuri and Shahandashti 2012). In addition, according to Shahandashti and Ashuri (2016), VAR statistical models are intended for analyzing time -series data that display stationarity. As a result, it is necessary to verify that the time-series data is stationary prior to developing the VAR model and carrying out the Granger causality test, which identifies causal relationships triggering fluctuations among the price of materials (Qiao and Guo 2014). If the time-series data are nonstationary, it should be made stationary by employing differencing, which involves subtracting a previous value from a subsequent value, and this process is also referred to as a unit root test (Faghih and Kashani 2018). Thus, the widely used Augmented Dickey-Fuller (ADF) test proposed by Dickey and Fuller (1979) was adopted in this study, and it is shown in Eq. (1)

$$\Delta \mathrm{PPI}(m)_t = \propto + \beta t + \gamma \mathrm{PPI}(m)_{t-1} + \sum_{i=1}^{k-1} \delta_i \Delta \mathrm{PPI}(m)_{t-i} + \varepsilon_t \quad (1)$$

where $\mathrm{PPI}(m)_t$ = PPI value of material m at time t; $\Delta\mathrm{PPI}(m)_t$ = first-order difference, i.e., $\mathrm{PPI}(m)_t - \mathrm{PPI}(m)_{t-1}$; α = drift term or intercept constant; β = coefficient for time trend; δ = coefficient used to examine whether it is necessary to apply differencing to the gathered data to achieve stationarity; and ε_t = error term.

The ADF test's null hypothesis (H0) is that the collected time-series data contain a unit root, meaning it is nonstationary (Assaad and El-adaway 2021a). To determine whether to reject this null hypothesis or not, the ADF test produces a p-value that is compared with a predefined significance level, which is assumed to be 0.05 in this paper. It is imperative to note that it is necessary to apply differencing to each time-series data until all of them become

Table 1. Materials included in the analysis of this paper

Construction material	Material's subtype	Material code[a]
Paving mixtures and blocks	—	WPU1394
Asphalt felts and coatings	Prepared asphalt, tar roofing, siding products	WPU136
Cement	—	WPU1322
Concrete products	Concrete block and brick; concrete pipe; ready-mixed concrete; precast concrete products; and prestressed concrete products	WPU133
Brick and structural clay tile	—	WPU1342
Plastic construction products	—	WPU0721
Flat glass	—	WPU1311
Gypsum products	—	WPU137
Insulation materials	—	WPU1392
Lumber and plywood	—	WPUSI004011
Architectural coatings	—	WPU062101
Iron and Steel	Steel mill products; steel pipe and tube; iron and steel scrap; and stainless and alloy steel scrap	WPU101
Nonferrous metals	Copper and brass mill shapes; aluminum mill shapes; and copper base scrap	WPU102
Fabricated structural metal products	Fabricated structural metal; fabricated structural metal bar joists and rebar; fabricated structural metal for nonindustrial buildings; fabricated structural metal for bridges; ornamental and architectural metal work; fabricated steel plate; and prefabricated metal buildings	WPU107
Asphalt	—	WPU058102
Construction sand, gravel, crushed stone	—	WPU1321

Source: Data from AGC (2020).
[a]Source code of each material from the Bureau of Labor Statistics (BLS) database.

stationary (Faghih and Kashani 2018). After achieving stationarity, the VAR statistical model can be developed and thus the Granger causality test can be conducted to explore any causal relationship or price fluctuation transmission between the different construction materials.

Vector Autoregression Modeling

Ganger causality is employed to analyze the relationships between the materials' PPI data. However, in order to perform the Granger causality test, VAR models should be developed to represent the relationship among each pair of construction materials' price indices. A 1-month-lagged VAR model between each pair of materials' PPI was developed as shown in Eq. (2)

$$\begin{bmatrix} \mathrm{PPI}(m_1)_t \\ \mathrm{PPI}(m_2)_t \end{bmatrix} = \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix} \begin{bmatrix} \mathrm{PPI}(m_1)_{t-1} \\ \mathrm{PPI}(m_2)_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \quad (2)$$

where $\mathrm{PPI}(m_1)_t$ and $\mathrm{PPI}(m_2)_t$ = PPI value of materials m_1 and m_2 at time t, respectively; α is the coefficient matrix; and ε is the error term vector. Ultimately, a VAR model was developed between each pair of the 16 materials considered in this paper to test for causal relationships among them. Thus, because there are 16 different types of construction materials, a total of 120 VAR models were developed on the PPI data.

Granger Causality Test

Upon the development of the VAR models, the Granger causality test was performed on each of the 120 VAR models where the null hypothesis reflects that there is no association between $\mathrm{PPI}(m_1)_t$ and $\mathrm{PPI}(m_2)_t$ (Assaad and El-adaway 2021b). The null hypothesis of the Granger test is that lagged values of $\mathrm{PPI}(m_2)$ with lag order of p are not useful in predicting the current values of $\mathrm{PPI}(m_1)$ [i.e., $\mathrm{PPI}(m_2)_{t-p}$ does not Granger-cause $\mathrm{PPI}(m_1)$ at the investigated lag length p]. Accordingly, it is worth mentioning that rejection of the Granger test's null hypothesis at a certain lag length p does not indicate that $\mathrm{PPI}(m_2)_{t-p}$ causes $\mathrm{PPI}(m_1)_t$ but rather that $\mathrm{PPI}(m_2)_{t-p}$ can be helpful in predicting $\mathrm{PPI}(m_1)_t$ [i.e., $\mathrm{PPI}(m_2)_{t-p}$ can be utilized as a leading indicator of $\mathrm{PPI}(m_1)_t$. Hence, the identified association relationships are referred to hereafter as one time-series Granger-causes the other rather than that one time series causes the other.

Each VAR model can be tested for two null hypotheses: (1) $\mathrm{PPI}(m_2)_{t-1}$ does not Granger-cause $\mathrm{PPI}(m_1)_t$, i.e., $(\alpha_{12} = 0)$; and (2) $\mathrm{PPI}(m_1)_{t-1}$ does not Granger-cause $\mathrm{PPI}(m_2)_t$, i.e., $(\alpha_{21} = 0 = 0)$ (Sun et al. 2018).

Finally, based on the VAR model and Granger causality test, two types of causal relationships (if any) are captured as follows: (1) unidirectional causality where either of the two hypotheses is rejected [i.e., either $\mathrm{PPI}(m_1)_{t-1}$ does Granger-cause $\mathrm{PPI}(m_2)_t$ or $\mathrm{PPI}(m_2)_{t-1}$ does Granger-cause $\mathrm{PPI}(m_1)_t$ but not both]; or (2) bidirectional causality where both hypotheses are rejected [i.e., $\mathrm{PPI}(m_1)_{t-1}$ and $\mathrm{PPI}(m_2)_{t-1}$ Granger-cause $\mathrm{PPI}(m_2)_t$ and $\mathrm{PPI}(m_1)_t$, respectively]. The Granger causality test was performed with the commonly used 0.05 significance level.

Granger Causality Matrices

To enhance the interpretation of the inferred causal relationships between material prices, two types of matrices are developed from the time-series tests results. Once the VAR models and causal relationships were identified, there is need to construct a matrix that enables to perform network analysis (Hummon and Dorein 1990). Thus, a binary Granger causality matrix (also called an adjacency matrix) was constructed as suggested by Sun et al. (2018). The binary Granger causality (BGC) matrix was constructed such that the rows and columns reflect the construction materials, and the cell entries reflect the existence of a causal relationship. Ultimately, the entries bgc_{ij} of the BGC matrix can be either one, indicating that the construction material in row i does Granger-cause construction material in column j, or zero, indicating that construction material in row i does not Granger-cause construction material in column j. Ultimately a 16×16 BGC matrix was constructed, reflecting all causal relationships among the construction materials' PPI.

Although BGC reflects all causal relationships, it does not actually reflect the degree of influence. To this end, another matrix was developed based on the BGC matrix, and it is called the weighted Granger causality (WGC) matrix (or weighted adjacency matrix in network theory). It is important to note that the scope of this paper is strictly focusing on inflation transmission rather than price fluctuations in general. To this end, the authors have only considered the causalities that are directly proportional (i.e., having positive coefficient in the VAR model). For instance, in case $\mathrm{PPI}(m_2)_t$ Granger-causes $\mathrm{PPI}(m_2)_t$ and the corresponding VAR coefficient is negative, the causal relationship was not included in the WGC matrix because they are not directly proportional to each other, and thus do not affect the inflation transmission mechanism. To this end, the entries of WGC were derived such based on Eq. (3)

$$\mathrm{wgc}_{ij} = \begin{cases} 0 & if\ \mathrm{bgc}_{ij} = 0 \text{ or } \alpha_{ij} < 0 \\ \alpha_{ij} & if\ \mathrm{bgc}_{ij} = 1 \text{ and } \alpha_{ij} > 0 \end{cases} \quad (3)$$

where wgc_{ij} = entry of the ith row and jth column in the WGC matrix; bcg_{ij} = entry of the BGC matrix in the ith row and jth column in the WGC matrix; and α_{ij} = coefficient value of the VAR model depicting the effect degree of construction materials' price i on construction materials' price j. Ultimately, a 16×16 WGC was constructed such that the entries wgc_{ij} that are (1) equal to zero depict that material price in row i does not Granger-cause material price in column j or material price in row i has a negative effect on material price in column j; and (2) greater than zero depict that material price in row i does Granger-cause material price in column j with weight α_{ij}.

Network Analysis

Network Building

Before conducting network analysis, it is necessary to construct a network that includes all the construction materials and their causal relationships. Networks can be categorized as either directed or undirected, as noted by Ahmat (2009). Caliandro (2022) explained that directed networks allow for nonreciprocal relationships among factors or nodes, whereas undirected networks assume that relationships are mutual. In other words, directed networks are better suited for capturing causal relationships compared with undirected networks, which are mainly useful for identifying mutual relationships (Lee and Stohr 1985). As a result, a directed network is more appropriate for the scope of this study.

In order to construct the network, the causal relationships obtained from the VAR model and Granger causality test have to be converted into a weighted adjacency matrix, as explained by Hummon and Doreian (1990). An unweighted adjacency matrix is a binary representation of the causal relationships between factors, where a value of one indicates the presence of a link between any two factors, and a value of zero indicates no link between them, according to Ramirez et al. (2016).

To achieve this, the authors created an unweighted adjacency matrix. This matrix has rows and columns that represent the materials, and its entries indicate whether there is a link between the corresponding factors. To this end, the authors developed the BGC

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matrix as explained in the previous subsection. However, Parker and McEachen (2016) noted that the unweighted adjacency matrix only indicates the presence or absence of links without providing any information about their quality or influence. Therefore, to gain a better understanding of inflation transmission among the construction materials, it is necessary to consider the number of associated positive causal relationships and the strength or quality of these materials in transmitting inflation. To achieve this, the authors developed the WGC matrix as explained in the previous subsection.

Centrality Measures

The development of WGC enables the weighted network to be visualized and analyzed, which could be implemented using the Gephi software version 0.10.1 package, which is a software program that is open-source and commonly employed for visualizing and analyzing graph networks (Gephi 2014). There are various measures of centrality that can be utilized for network analysis, such as degree centrality, in-degree and out-degree centralities, betweenness centrality, and network density, among others (Lee et al. 2018). However, for this study, the primary interest is to examine inflation transmission capacity, susceptibility, and intermediation capacity of each material. Therefore, the following three centrality measures were considered: in-degree, out-degree, and betweenness centralities.

Out-Degree Centrality. Out-degree centrality is determined by the sum of the outward weighted edges, as shown in Eq. (4) (Hassan et al. 2022). In the context of this paper, a higher out-degree of a material implies a greater capacity or range of transmission of its price inflation (Sun et al. 2018)

$$D_{\text{out}} = \text{WGC}_i = \sum_j \text{wgc}_{ij} \tag{4}$$

where D_{out} = out-degree centrality; and WGC_i = summation of the entries of the ith row of WGC.

In-Degree Centrality. In directed networks, in-degree centrality is determined by the sum of the inward weighted edges, as shown in Eq. (4). In the context of this paper, a construction material with a higher in-degree centrality will have a wider range of susceptibility to price changes in other materials (Sun et al. 2018)

$$D_{\text{in}} = \text{WGC}_j = \sum_i \text{wgc}_{ij} \tag{5}$$

where D_{in} = in-degree centralities; and WGC_j = summation of the entries of the jth column of WGC.

Betweenness Centrality. Betweenness centrality is a metric used to assess the extent to which a particular node serves as a mediator in a network (Zhang and Luo 2017). If a node is situated in a position where other nodes must pass through it to communicate, connect, transport, or conduct transactions, then that node is considered significant and is likely to have a high betweenness centrality score (Freeman 1997). In the context of this paper, the capacity of a material price to regulate the spread of price inflation among other materials is referred to as its intermediation capacity (Sun et al. 2018). The betweenness centrality for each material is computed as shown in Eq. (6)

$$B = \sum_j^n \sum_k^n \frac{g_{jk}(i)}{g_{jk}} \quad \text{for } i \neq j \text{ and } j < k \tag{6}$$

where i, j, and k = different materials; g_{jk} = number of shortest paths between node j and node k; and $g_{jk}(i)$ = number of shortest paths between nodes j and k passing through node i.

Modularity-Based Clustering

Upon constructing and analyzing the network, it is crucial to identify what are the types of materials that influence each other the most in terms of price inflation. To this end, there is a need for a clustering method that clusters the construction materials by maximizing the internal edges (i.e., the causal relationships among the materials' prices within the same cluster) while minimizing the external edges (i.e., the causal relationships between the materials prices within a cluster and prices of material in other clusters). Thus, the authors adopted modularity-based method for network clustering due to its capability to efficiently and reliably handle different types of large and complex networks (Muhammed et al. 2017).

The use of modularity-based method for network clustering aims to identify highly interconnected groups of nodes that are more closely linked to each other compared with the rest of the network (Clauset et al. 2004; Newman 2006). The approach involves optimizing/maximizing the modularity quality function, which assesses the extent to which the network can be partitioned into distinct communities by maximizing the modularity quality function (Rahmani et al. 2018), as shown in Eq. (7). Ultimately, the number of clusters should be set prior to the implementation of the algorithm to clusters the nodes by maximizing the modularity index shown in Eq. (7) (Muhammed et al. 2017)

$$Q = \frac{1}{2m} \sum_{ij} \left[\text{wgc}_{ij} - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j) \tag{7}$$

where wgc_{ij} = edge weight between material price i and material price j; k_i and k_j = number of edges connected to material prices i and j, respectively; c_i = cluster of material price i; c_j = cluster of material price j; $\delta(c_i, c_j)$ = binary number, which is equal to one if i and j are in the same cluster, i.e., $c_i = c_j$, and equal to zero otherwise, i.e., $c_i \neq c_j$; and m = total number of edges in the graph.

The authors implemented the clustering technique using Gephi, where the resolution parameter in the modularity settings indicates the desired number of clusters. By default, the resolution value is set to one, and higher values result in fewer clusters, whereas lower values lead to more clusters (Rahmani et al. 2018). For this study, the authors opted to use the default resolution value of Gephi, which is equal to one.

Results and Analysis

Data Visualization and Descriptive Analysis

As mentioned in the "Methodology," the authors collected PPI data for 16 different types of construction materials from BLS with a monthly time interval. Fig. 2 presents the collected PPI data for the materials. Fig. 2 shows that "Asphalt," "Iron and steel," and "Nonferrous metals," as well as "Lumber and plywood," reflect high fluctuations when compared with, for example, "Construction sand, gravel, and crushed stone" and "Concrete products." Furthermore, the graphs of the PPI show that the data are nonstationary, thus necessitating the performance of unit root test prior to the VAR modeling and Granger causality testing.

Although data visualization is crucial for the identification and better understanding of potential patterns and trends in the data, it is still necessary to conduct descriptive statistics on the data as to allow better numerical investigation and interpretation. Therefore, Table 2 presents the descriptive statistics of each of the 16 collected PPI data. As indicated in Table 2, different types of materials are associated with different ranges and volatilities.

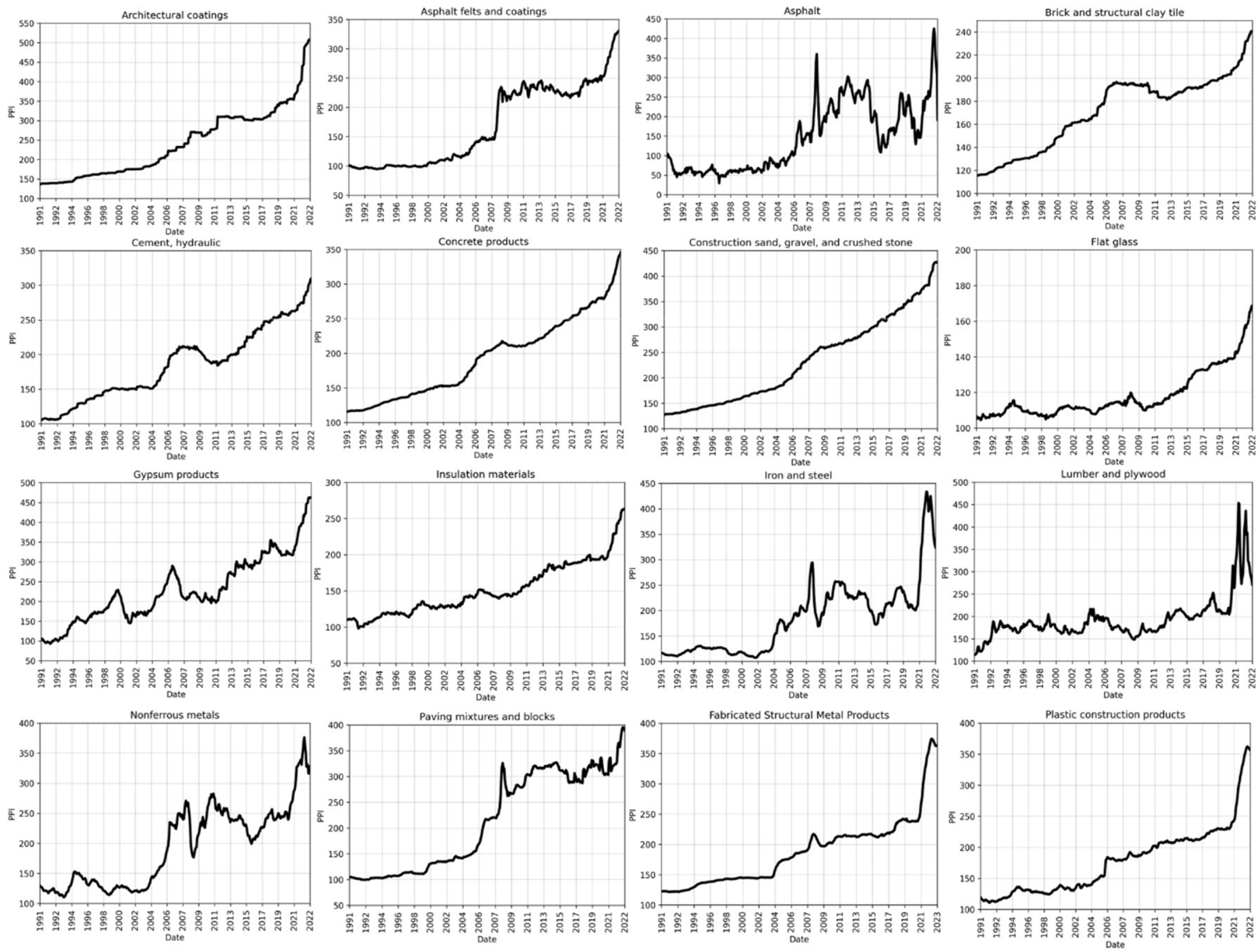

Fig. 2. Collected PPI data.

Table 2. Descriptive statistics of the producer price indexes of the 16 construction materials

Construction materials	Mean	Standard deviation	Minimum	25%	50%	75%	Maximum
Architectural coatings	240.09	85.63	136.10	165.03	222.75	307.23	508.89
Asphalt felts and coatings	168.92	67.85	94.50	100.50	145.00	230.15	330.59
Asphalt	144.37	86.38	29.50	63.40	128.65	211.70	425.06
Brick and structural clay tile	170.94	31.75	115.30	137.23	183.45	194.50	240.60
Cement	184.72	51.16	104.80	148.00	189.00	212.10	309.99
Concrete products	192.95	57.34	115.00	141.40	198.10	234.18	345.58
Construction sand, gravel, and crushed stone	232.50	83.10	126.70	155.03	222.50	292.35	427.79
Flat glass	118.29	13.44	104.50	109.48	112.55	122.13	168.57
Gypsum products	227.66	82.15	92.80	169.23	211.55	290.60	463.01
Insulation materials	151.52	35.87	98.00	125.48	142.85	182.25	263.48
Iron and steel	183.46	70.00	107.10	120.70	180.95	224.28	433.53
Lumber and plywood	193.12	48.67	114.30	167.80	179.75	203.65	453.40
Nonferrous metals	193.32	65.79	110.20	127.20	199.00	244.13	376.17
Fabricated structural metal products	186.60	54.46	121.70	142.98	185.55	215.33	374.51
Paving mixtures and blocks	213.44	93.97	99.30	113.45	216.25	310.18	395.38
Plastic construction products	177.48	54.28	111.10	131.48	180.30	211.40	362.15

For instance, "Architectural coatings," "Gypsum products," "Paving mixtures and blocks," and "Construction sand, gravel, and crushed stone" showed high PPI averages when compared with "Asphalt," "Flat glass," and "Insulation materials." However, in order to capture the inflation intensity during the 1991–2022 period, the standard deviation should be considered. Ultimately, the descriptive statistics showed the highest standard deviation in relation to "Architectural coatings," "Asphalt," "Construction

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sand, gravel, and crushed stone," "Gypsum products," and "Paving mixtures and blocks." Thus, the aforementioned materials are the ones that witnessed the highest price inflations. On the other hand, the lowest price inflation was associated with "Brick and structural clay tile," "Flat glass," "Insulation materials," and "Lumber and plywood." The observed descriptive statistics presented in Table 2 further confirm the findings of Faghih and Kashani (2018) and Kim et al. (2021) that the different material prices do not vary at the same rate.

Causal Relationships among Materials' Price Indices: VAR and Granger Causality

Following the visualization and presentation of the descriptive statistics of the gathered materials' PPIs, the authors investigated the stationarity of each data series by performing a unit root test. The outcomes of this test are displayed in Table 3.

The results in Table 3 indicate that 10 out of the 16 materials' PPI are stationary (Column 2 of Table 3). Therefore, all PPI data need to be differenced as to ensure that all time series are stationary prior to the construction of the VAR models. Ultimately, Column 3 of Table 3 indicates that all PPI data are stationary after the first-order difference. Thus, VAR models will be developed based on the differenced data rather than on the original data.

Afterward, a total of 120 VAR models were developed to test the Granger causality among the 16 construction materials' PPI. By performing Granger causality, the authors were able to identify the causal relationships whenever a p-value was found to be less than 0.05. Fig. 3 shows the obtained p-values for all Granger causality tests performed on the construction materials.

It should be noted that causality in Fig. 3 is directed from rows to columns. For instance, "Cement" was found to Granger-cause "Architectural coatings," "Brick and structural clay tile," "Construction sand, gravel, and crushed stone," "Flat glass," "Gypsum products," and "Insulation materials." The same applies for all other construction materials analyzed in this paper. Finally, based on the p-values in Fig. 3, the BGC matrix is developed by replacing the p-values that are less than 0.05 by one, and those that are greater than 0.05 by zero. The BGC matrix is shown in Fig. 4.

As reflected in Figs. 3 and 4, there is a total of 110 causal relationships between the various construction materials. Furthermore, the BGC matrix is not symmetrical, indicating the presence of unidirectional causalities. In other words, although price fluctuations in one material affect another, the opposite does not hold true. An example of that is the PPI of "Cement," which was found to Granger-cause the PPI "Brick and structural clay tiles"; however, the PPI "Brick and structural clay tiles" had no effect on the PPI of "Cement." Furthermore, some materials were found to have bidirectional causalities, indicating that a change in price in any one of the material transmits into the other material, and vice versa. An example of that is "Concrete products" and "Construction sand, gravel, and crushed stone." Finally, some materials showed no causalities at all, indicating that there is no transmission of price fluctuations among the pair of materials. An examples is "Asphalt felts and coatings" and "Construction sand, gravel, and crushed stone.

Upon constructing the BGC matrix, the authors derived the WGC matrix as depicted in Eq. (3). Thus, the authors replaced the binary values with the coefficients obtained from the VAR models. In order to ensure that the analysis only reflects inflation transmission rather than price fluctuation in general, causal relationships associated with negative VAR coefficients were set to zero. The BGC matrix is shown in Fig. 5.

Table 3. Unit root test results

Construction materials	p-value (PPI)	p-value (ΔPPI).
Architectural coatings	0.010^*	0.01^*
Asphalt felts and coatings	0.595	0.01^*
Asphalt	0.010^*	0.01^*
Brick and structural clay tile	0.669	0.01^*
Cement	0.076	0.01^*
Concrete products	0.010^*	0.01^*
Construction sand, gravel, and crushed stone	0.253	0.01^*
Flat glass	0.010^*	0.01^*
Gypsum products	0.039^*	0.01^*
Insulation materials	0.010^*	0.01^*
Iron and steel	0.018^*	0.01^*
Lumber and plywood	0.010^*	0.01^*
Nonferrous metals	0.375	0.01^*
Fabricated structural metal products	0.010^*	0.01^*
Paving mixtures and blocks	0.485	0.01^*
Plastic construction products	0.010^*	0.01^*

Note: $^*p$-value less than 0.05, and thus, null hypothesis is rejected, indicating that the time-series data are stationary.

Code	Construction Materials	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14	M15	M16
M1	Architectural coatings	-	0.009	0.920	0.041	0.454	0.000	0.049	0.027	0.490	0.688	0.310	0.000	0.413	0.006	0.325	0.013
M2	Asphalt felts and coatings	0.119	-	0.000	0.874	0.165	0.787	0.060	0.113	0.947	0.212	0.001	0.929	0.802	0.000	0.000	0.001
M3	Asphalt	0.024	0.918	-	0.704	0.922	0.503	0.000	0.322	0.416	0.771	0.000	0.079	0.000	0.033	0.025	0.810
M4	Brick and structural clay tile	0.004	0.018	0.770	-	0.398	0.009	0.008	0.119	0.019	0.037	0.026	0.055	0.258	0.154	0.578	0.090
M5	Cement	0.000	0.081	0.494	0.000	-	0.359	0.00	0.000	0.000	0.000	0.318	0.854	0.962	0.264	0.319	0.099
M6	Concrete products	0.000	0.184	0.057	0.000	0.001	-	0.00	0.000	0.000	0.000	0.082	0.110	0.695	0.000	0.011	0.000
M7	Construction sand, gravel, and crushed stone	0.011	0.269	0.150	0.365	0.755	0.000	-	0.014	0.200	0.520	0.025	0.037	0.028	0.764	0.290	0.095
M8	Flat glass	0.026	0.021	0.793	0.658	0.411	0.007	0.080	-	0.016	0.018	0.309	0.263	0.284	0.016	0.711	0.016
M9	Gypsum products	0.004	0.708	0.423	0.137	0.606	0.402	0.237	0.008	-	0.004	0.067	0.981	0.408	0.403	0.801	0.992
M10	Insulation materials	0.010	0.039	0.284	0.137	0.765	0.300	0.000	0.000	0.001	-	0.020	0.280	0.519	0.062	0.621	0.000
M11	Iron and steel	0.610	0.013	0.191	0.358	0.517	0.597	0.028	0.165	0.726	0.933	-	0.732	0.000	0.424	0.404	0.571
M12	Lumber and plywood	0.793	0.172	0.890	0.429	0.175	0.057	0.748	0.806	0.054	0.432	0.653	-	0.218	0.001	0.626	0.109
M13	Nonferrous metals	0.491	0.001	0.921	0.110	0.739	0.867	0.786	0.964	0.765	0.572	0.369	0.001	-	0.000	0.087	0.527
M14	Fabricated structural metal products	0.000	0.012	0.000	0.002	0.081	0.000	0.001	0.003	0.000	0.000	0.000	0.008	0.000	-	0.028	0.000
M15	Paving mixtures and blocks	0.009	0.000	0.000	0.033	0.400	0.308	0.000	0.002	0.001	0.002	0.000	0.005	0.029	0.086	-	0.835
M16	Plastic construction products	0.000	0.019	0.002	0.024	0.259	0.000	0.001	0.004	0.000	0.000	0.000	0.003	0.000	0.000	0.087	-

Fig. 3. Granger causality test results.

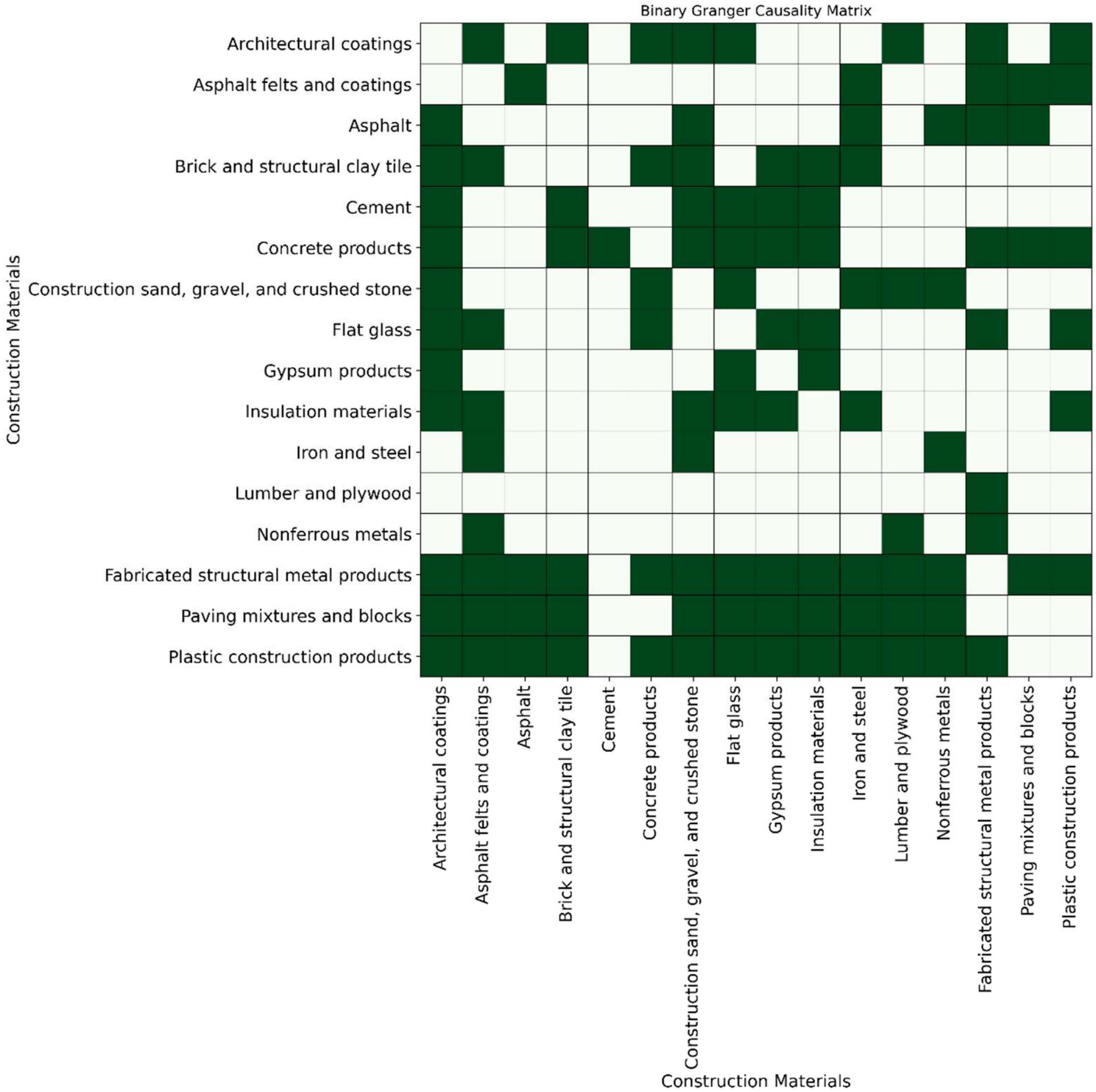


Fig. 4. Constructed BGC matrix. Dark-colored cells = 1 and light-colored cells = 0.

The WGC matrix consists of a total of 103 positive causal relationships. Thus, 7 out of the 110 relationships were to have a negative causal relationships (i.e., a price increase in one material leads to a price decrease in the other) including (1) "Iron and steel" with "Asphalt felts and coatings"; (2) "Iron and steel" with "Construction sand, gravel, and crushed stone"; (3) "Lumber and plywood" with "Fabricated structural metal products"; (4) "Nonferrous materials" with "Fabricated structural metal products"; (5) "Construction sand, gravel, and crushed stone" with "Nonferrous materials"; (6) "Nonferrous materials" with "Asphalt felts and coatings"; and (7) "Asphalt" with "Paving mixtures and blocks."

Ultimately, the WGC matrix consists only of positive causal relationships reflecting inflation transmission among the 16 different types of construction materials. Furthermore, as shown in Fig. 5, the causal relationships differed in strength depending on the corresponding VAR coefficients. For instance, the strongest causal relationships were those of (1) "Concrete products" on "Architectural coatings" and "Gypsum products"; (2) "Fabricated structural metal products" on "Asphalt" and "Iron and steel"; and (3) "Plastic construction products" on "Asphalt."

Inflation Transmission: Network Analysis

Based on the causal relationships on the one hand and their corresponding strength on the other hand as reflected in WGC matrix, the authors were able to effectively perform network analysis to better interpret the causal relationships inferred from time-series techniques and understand inflation transmission mechanism in the construction materials supply chain. Fig. 6 shows the inflation transmission network associated with the WGC matrix consisting of the 16 nodes (construction materials) and directed edges. The intensity of the edges is directly proportional to their corresponding weight. Thus, the darker the edges' weight, the higher the degree of price inflation transmission the parent node has on the child node.

For a better understanding of the influential construction materials in terms of inflation transmission range or capacity, susceptibility, and intermediatory capacity, the authors presented the in-degree, out-degree, and betweenness centralities in a tabular form (Table 4).

As indicated in Table 4, the construction materials with the highest inflation susceptibility in the network (i.e., the ones with the highest in-degree centralities) include (1) "Gypsum products" with

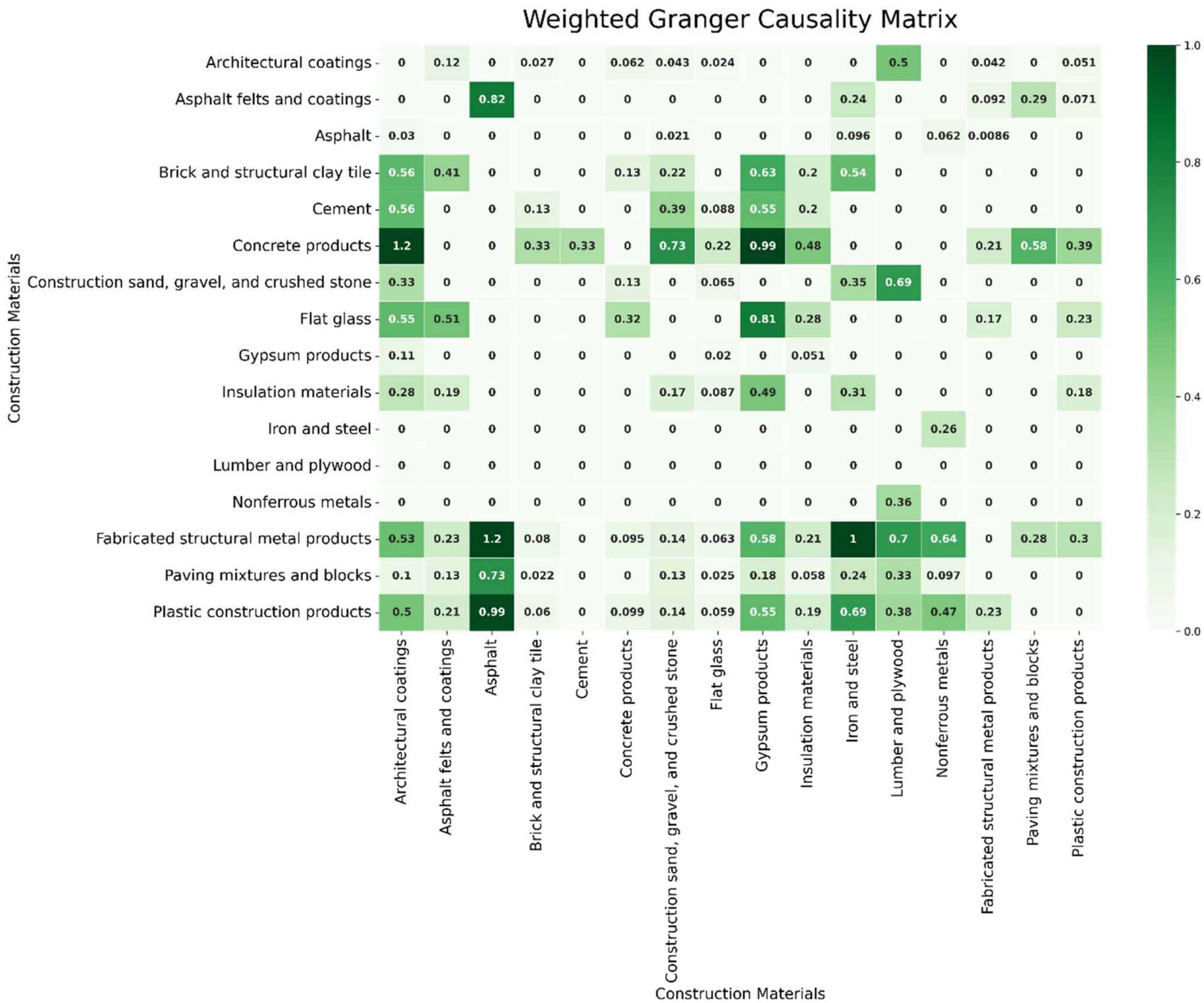


Fig. 5. Constructed weighted Granger causality matrix.

a value of 4.784; (2) "Architectural coatings" with a value of 4.780; and (3) "Asphalt" with a value of 3.726. In addition, the construction materials that have the highest inflation transmission capacity (i.e., the ones with the highest out-degree centralities) include (1) "Fabricated structural metal products" with a value of 6.034; (2) "Concrete products" with a value of 5.505; and (3) "Plastic construction products" with a value of 4.558. Finally, the construction materials with the highest intermediatory capacity (i.e., the ones with the highest betweenness centrality) include (1) "Concrete Products" with a value of 18.319; (2) "Architectural coatings" with a value of 18.263; and (3) "Fabricated structural metals products" with a value of 4.467.

Thus, the results show that "Gypsum products" is highly susceptible to price inflations in other construction materials, and it was found to be capable of significantly transmitting inflation to other materials. "Architectural coatings" was found to have also high susceptibility to construction materials inflation. However, it was also found to have high inflation intermediatory capacity, indicating that, although it does not have a high inflation transmission capacity, it can still affect the price of influential construction materials. "Asphalt" was found also to be susceptible to inflation; however, it was found to have low inflation transmission capacity as well as low inflation intermediatory capacity. "Fabricated structural metal products" and "Concrete products" were found to have high transmission and intermediatory capacity with a low inflation susceptibility, indicating that these two materials are critical in terms of inflation transmission and can be used as early warning signs of price inflations in construction materials. Furthermore, the aforementioned materials, in addition to "Architectural coatings," can also indicate that inflation has also been witnessed in some construction materials, and thus further transmission to new construction materials is expected. The same results were found for "Plastic construction products."

Modularity-Based Clustering: Construction Materials Clusters

Upon performing modularity-based clustering, the authors were able to cluster the materials based on their causal relationships as shown in Fig. 7. As shown in Fig. 7, the 16 construction materials were clustered into three different groups. The first cluster mainly consists of metals and plastic, the second cluster consists of concrete, wood, and finishing materials, and the third cluster consists of paving and asphalt materials.

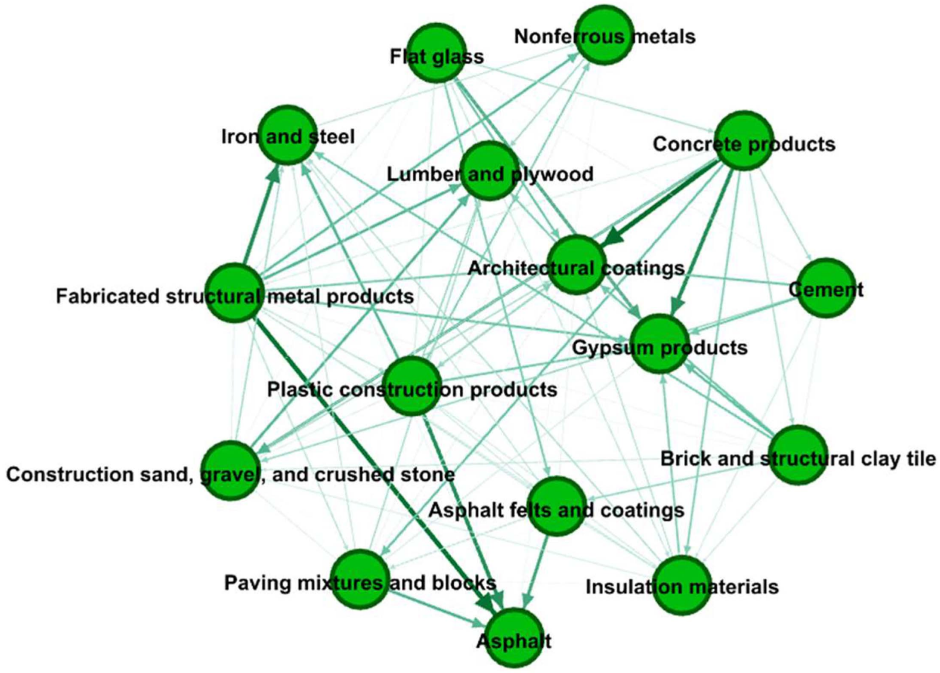


Fig. 6. Directed network depicting inflation transmission among construction material supply chain.

Table 4. Centrality measures

Construction materials	In-degree centrality Weight	In-degree centrality Rank	Out-degree centrality Weight	Out-degree centrality Rank	Betweenness centrality Weight	Betweenness centrality Rank
Architectural coatings	4.780	2	0.867	11	18.263	2
Asphalt felts and coatings	1.787	7	1.516	10	8.320	6
Brick and structural clay tile	0.649	15	2.688	5	2.679	11
Concrete products	0.846	12	5.505	2	18.319	1
Construction sand, gravel, and crushed stone	1.985	6	1.574	9	5.158	8
Flat glass	0.656	14	2.877	4	10.313	5
Lumber and plywood	2.968	5	0.000	16	0.000	16
Fabricated structural metal products	0.754	13	6.034	1	16.467	3
Plastic construction products	1.217	10	4.558	3	12.343	4
Asphalt	3.726	3	0.218	14	0.950	13
Iron and steel	3.472	4	0.260	13	3.242	10
Paving mixtures and blocks	1.155	11	2.046	6	3.654	9
Nonferrous metals	1.532	9	0.362	12	1.250	12
Gypsum products	4.784	1	0.178	15	0.200	14
Insulation materials	1.655	8	1.704	8	5.841	7
Cement	0.333	16	1.908	7	0.000	15

For a better understanding of the characteristics of the three identified clusters of construction materials, the authors present their average centralities in Table 5. Ultimately, the results show that metals and plastic have the highest inflation transmission as well as inflation intermediatory capacity indicating their importance as key indicator of price inflation in concrete, wood, and finishing materials as well as paving and asphalt materials. As for paving and asphalt materials, it has the highest in-degree centrality, indicating they are the most susceptible to inflation in materials' prices in other clusters.

To further understand the inflation transmission between each cluster, the authors developed a network matrix based on the WGC matrix where only the intercluster relationships were included, while excluding the intracluster ones. The network matrix and graph are shown in Fig. 8.

In Fig. 8(a), the nodes represent the clusters, and the edges represent the intercluster relationships. Furthermore, the in-degree centrality of each cluster is proportional to the nodes' colors. Thus, the darker the node color, the higher is its in-degree centrality. For the out-degree centrality, it is set to be proportional to the nodes' sizes, where the bigger the size of the nodes, the higher the associated out-degree centralities. It is important to note that betweenness centrality was not computed because all nodes are connected, and thus the metric is not applicable or useful. Ultimately, the graph shows that metals and plastic materials have the highest out-degree and the lowest in-degree centralities, indicating that they are in control of transmitting inflation while having low susceptibility to inflation by the other cluster of materials.

All the latter are also reflected in the network matrix of Fig. 8(b), where the highest weights are present in the directed edges from

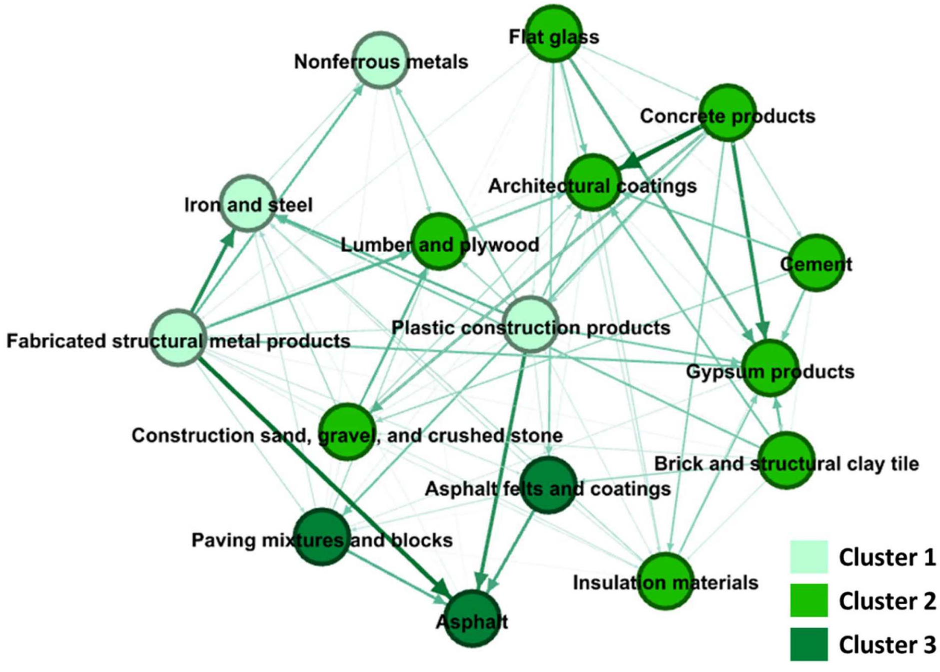


Fig. 7. Clustered materials' inflation transmission network.

Table 5. Cluster characteristics

Cluster	Average in-degree centrality	Average out-degree centrality	Average betweenness centrality
Metals and plastic	1.744	2.804	8.325
Concrete, wood, and finishing materials	2.073	1.922	6.753
Paving and asphalt materials	2.223	1.260	4.308

metals and plastics to concrete, wood, and finishing materials as well as to paving and asphalt mixtures. Furthermore, concrete, wood, and finishing materials have the highest in-degree, indicating that these materials are the most susceptible to inflation by the other clusters. The latter is mainly due to the high effect of metals and plastic materials on their prices. The next section presents detailed analysis on the findings of this paper in relation to each materials' cluster.

Discussion

This section presents a detailed discussion on the key findings and outcomes of this paper. The next subsections discuss the results in relation to each cluster of materials.

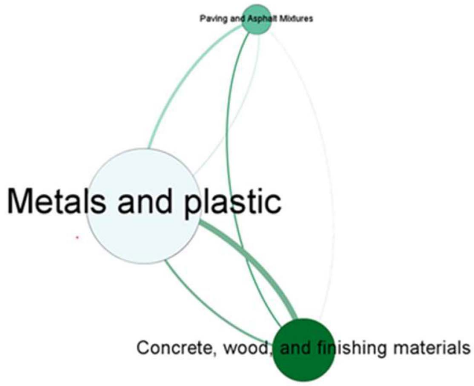
Cluster 1: Metals and Plastic Materials

Metals and plastic materials include the following: (1) "Nonferrous metals"; (2) "Iron and steel"; (3) "Fabricated structural metal products"; and (4) "Plastic construction products." Metals and plastic materials were found to be the most influential when it comes to transmitting inflation to other construction materials (i.e., high inflation transmission range or out-degree centrality). More specifically, it was found that inflation in metals and plastic prices can be critical indicators to potential price inflation in concrete, wood, and finishing materials as well as paving and asphalt mixtures (reflected by high intercluster causality weights in Fig. 8).

Such results can be further explained by having "Fabricated structural metal products" as well as "Plastic construction products" ranked as first and third, respectively, in terms of out-degree centrality (i.e., inflation transmission capacity). Furthermore, these two materials were also found to have high betweenness centralities (ranked third and fourth, respectively), indicating their inflation conductivity and transmission over the whole construction materials network. On the other hand, these two materials possess low in-degree centralities, indicating that they are actually more influential than susceptible to price inflation in construction materials.

As for "Iron and steel" and "Nonferrous metals," they were found to be highly susceptible to inflation rather than influential in the materials' construction supply chain. To further facilitate interpretation of the results, the authors present the difference between the out-degree and in-degree centralities as a measure of the materials inflation susceptibility or influence on the supply chain in Table 6.

Although it should be expected that primary materials (i.e., iron and steel and nonferrous metals) to be more influential in transmitting inflation to other construction materials, the insights showed contradicting results that "Fabricated structural metal products" have more transmission capacity. Another interesting finding is that "Fabricated structural metal products" was found to transmit inflation to "Iron and steel." In fact, inflation is commonly known to be transmitted from input materials to processed materials (Tang et al. 2010). However, in this case, the witnessed short-term inflation transmission seems to be reversely directed from "Fabricated



(a)

Clusters	Paving and Asphalt Mixtures	Concrete, wood, and finishing materials	Metals and plastic
Paving and Asphalt Mixtures	0	0.906	1.242
Concrete, wood, and finishing materials	1.807	0	2.471
Metals and plastic	2.893	4.725	0

(b)

Fig. 8. Clusters' network: (a) graph; and (b) matrix.

Table 6. Difference between out-degree and in-degree centralities of metals and plastic materials

Materials	Out-degree	In-degree	Difference	Conclusion
Iron and steel	0.26	3.472	−3.212	Inflation receiver
Nonferrous metals	0.362	1.532	−1.17	Inflation receiver
Fabricated structural metal products	6.034	0.754	5.28	Inflation transmitter
Plastic construction products	4.558	1.217	3.341	Inflation transmitter

structural metal products" (i.e., processed product) to iron and steel (i.e., input product).

According to Chen and Zhu (2018), inflation can be transmitted from the downstream to upstream of the supply chain due to a pull-demand inflation mechanism where there is imbalance in the demand and supply of the processed products, leading to increasing their prices by the fabricators, and subsequently increasing the prices of raw materials by the suppliers. Thus, the results show that the dominating inflation mechanism is from "Fabricated structural metal products" (i.e., downstream) to "Iron and steel" (i.e., upstream).

Ultimately, the results suggest that "Fabricated structural metal products" as well as "Plastic construction products" are inflation transmitters in the construction materials supply chain. On the other hand, "Iron and steel" and "Nonferrous materials" seem to be inflation receivers.

Cluster 2: Concrete, Wood, and Finishing Materials

Concrete, wood, and finishing materials were found to be the most susceptible materials to price inflation in the network (i.e., high in-degree centrality). Such results can be further explained by having "Gypsum products," "Architectural coatings," and "Lumber and plywood" ranked as first, second, and fifth, respectively, in terms of in-degree centrality (i.e., inflation susceptibility). As for "Architectural coatings," although it is more likely to be susceptible to inflation in other construction, it is ranked second in terms of betweenness centrality, indicating its inflation conductivity and intermediatory capacity across the whole construction materials network. Thus, despite being a low inflation transmitter relative to other materials, it has a critical propagation effect by having high spread over different materials within the network.

As for "Construction sand, gravel, and crushed stone," it is also considered to be an inflation receiver more than an inflation transmitter in the construction material network. To further facilitate interpretation of the results, the authors present the difference between the out-degree and indegree centralities as a measure of the materials inflation susceptibility or influence on the supply chain in Table 7.

Materials with higher out-degree than in-degree centralities include (1) "Brick and structural clay tile"; (2) "Concrete products"; (3) "Flat glass"; (4) "Insulation materials"; and (5) "Cement." More specifically, "Concrete products" and "Flat glass" were found to be among the top five materials in terms of out-degree centralities,

Table 7. Difference between out-degree and in-degree centralities of concrete, wood, and finishing materials

Construction materials	Out-degree centrality	In-degree centrality	Difference	Conclusion
Architectural coatings	0.867	4.780	−3.912	Inflation receiver
Brick and structural clay tile	2.688	0.649	2.040	Inflation transmitter
Concrete products	5.505	0.846	4.659	Inflation transmitter
Construction sand, gravel, and crushed stone	1.574	1.985	−0.410	Inflation receiver
Flat glass	2.877	0.656	2.220	Inflation transmitter
Lumber and plywood	0.000	2.968	−2.968	Inflation receiver
Gypsum products	0.178	4.784	−4.606	Inflation receiver
Insulation materials	1.704	1.655	0.049	Inflation transmitter
Cement	1.908	0.333	1.576	Inflation transmitter

Table 8. Difference between out-degree and in-degree centralities of paving and asphalt mixtures

Construction materials	Out-degree centrality	In-degree centrality	Difference	Conclusion
Asphalt felts and coatings	1.516	1.787	−0.270	Inflation receiver
Asphalt	0.218	3.726	−3.507	Inflation receiver
Paving mixtures and blocks	2.046	1.155	0.891	Inflation transmitter

indicating their importance as key warning signs of inflation propagation in the construction supply chain (ranked as second and fourth respectively). Furthermore, both of these materials seem to also have high criticality in terms of their intermediatory capacity, meaning that they possess high spread capabilities within the inflation transmission network.

Ultimately, the results suggest that "Concrete products" and "Flat glass" are inflation transmitters in the construction materials supply chain. On the other hand, "Gypsum products" and "Architectural coatings" seem to be inflation receivers, where the latter have further critical inflation intermediatory capacity. Thus, any inflation in "Concrete products," "Flat glass," and "Architectural products" is expected to be transmitted to other construction materials in the network.

Cluster 3: Paving and Asphalt Mixtures

Paving and asphalt mixtures were found to be the least in terms of inflation transmission capacity in the network (i.e. low out-degree centrality). In fact, only "Paving mixtures and blocks" was found to be an inflation transmitter, whereas both "Asphalt" and "Asphalt felts and coatings" were found to be inflation receivers (Table 8). The highest inflation transmission capacity was associated with "Paving mixtures and blocks" followed by "Asphalt felts and coatings," then by "Asphalt." However, when compared with the materials of Clusters 1 and 2, it can be noticed that inflation transmission capacity of paving and asphalt mixtures is not considered critical.

Furthermore, the causal relationship directed from "Asphalt felts and coatings" and "Paving mixtures and blocks" to "Asphalt" is similar to that between "Fabricated structural metal products" and "Iron and steel." Thus, "Asphalt felts and coatings" and "Paving mixtures and blocks" (downstream), being processed products extracted from "Asphalt," were found to transmit inflation to "Asphalt" (upstream). However in the "Paving mixtures and blocks"–"Asphalt" case, the causal relationship is reciprocal, indicating that any inflation in one material will lead to inflation to the other and subsequently turn into an inflationary loop.

This paper's findings present new leading indicators for individual material price indexes a well as broader material groups or clusters. Those findings complement the work done by existing studies that investigated individual materials' prices or composite indices. Faghih and Kashani (2018) identified (1) crude oil prices and consumer price index as leading indicators of asphalt prices, (2) gross domestic product, number of housings starts, and total construction spending as leading indicators of cement prices, and (3) consumer price index, number of housings starts, and global iron ore price as leading indicators of steel. On the other hand, several studies that investigated the ENR's CCI found consumer price index, number of housings starts, crude oil prices, and number of housings starts to be leading indicators of CCI (which is composed of cement, steel, lumber, and common labor costs) (Ashuri et al. 2012a; Shahandashti and Ashuri 2013; Xu and Moon 2013; Choi et al. 2021). The identified lead-lag relationships between material price indexes or material clusters further enhances the predictability of the main construction materials. For instance, forecasting models of concrete, wood, and asphalt and paving mixtures can be complemented by using metals and plastic prices as additional leading indicators to those models.

Addition to the Body of Knowledge

This paper makes significant contributions to the body of knowledge. As offering a first attempt toward the investigation of inflation transmission among the different construction materials, the practical implications of this paper's findings can be multifold. Construction contractors and subcontractors can adjust their procurement plans for the identified inflation-susceptible materials to mitigate the impact of their inflated prices. For example, contractors can utilize this paper's identified causal relationships in planning procurement strategies for "Architectural coatings" and "Gypsum products" using the prices of "Concrete products" as leading indicator. Similarly, project owners can benefit from this paper's findings to assist their budget-related decisions. For instance, inflated prices of "Fabricated structural metal products" and "Plastic construction products" would present Departments of Transportation with leading indicators and early warning signs of inflation in "Asphalt" prices.

Finally, researchers can use the findings of this paper in improving the accuracy of the forecasting models of material prices. Existing studies have not explored using one construction material's prices as a leading indicator of another construction material's prices bearing in mind that the time-series tests conducted in this paper indicate that current prices of construction materials can help forecasting short-term escalations in the prices of other construction prices.

Conclusion and Future Work

This paper investigated inflation transmission among the various materials associated with the construction industry. First, the authors collected data from BLS for the producer price indices of a total of 16 construction elements. Second, the causal relationships between the materials' PPI were modeled and then verified in terms of their significance using the Granger causality test. Ultimately, only directly proportional relationships were included in the analysis to strictly reflect inflation transmission rather than overall price fluctuations. The significant and positive causal relationships were then presented in the form of a binary matrix and a weighted matrix.

Third, network analysis was performed to identify the inflation transmission capacity, susceptibility to inflation, and inflation intermediatory capacity associated with each material. Fourth, modularity-based clustering was conducted to group the materials' PPI based on their interconnectivities and causal relationships to identify inflation transmission path among the various materials' sectors.

As such, the authors developed a total of 120 VAR models to analyze the mutual relationship for each pair of materials. A total of 103 directed causal relationships were found to contribute to inflation transmission among the materials. The network analysis showed that the materials with the highest inflation transmission

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capacities include (1) "Fabricated structural metal products"; (2) "Plastic construction products"; (3) "Concrete products"; (4) "Flat glass"; and (5) "Brick and structural clay tile." Ultimately, it is concluded that significant changes in the price of these materials can be utilized as leading indicators of price escalations in the supply chain and other construction materials.

In addition to the aforementioned materials, "Architectural coatings," despite having low inflation transmission capacity, has high inflation intermediatory capacity, indicating that any increase in its price may lead to cascading effect to the whole construction material network. Finally, metals and plastics materials were found to be highly transmitters of inflation to other materials, whereas concrete, wood, and finishing products were found to be the most susceptible. Ultimately, the findings of this paper provide clear insights on the key materials that may indicate overall inflation in construction cost. Furthermore, this study provides industry practitioners with the materials that can serve as early warning signs of overall inflation in the construction industry.

This paper's findings pave the way for more enhanced forecasting models of construction material prices. Inspired by the discussion and findings of this paper, future research studies can

- incorporate this paper's identified associations into short-term forecasting models to enhance the predictability of construction material prices;
- analyze inflation transmission between the construction sector and other important sectors;
- investigate the inflation transmission of each of the construction materials on the overall construction price;
- build hybrid prediction models that combine time-series and artificial intelligence techniques for construction materials by considering the causal relationships identified in this paper as well as other macroeconomic and market variables;
- assess whether the inclusion of this paper's identified relationships can enhance the accuracy of those models in case of the occurrence of special events;
- attempt to identify long-term inflation transmissions between materials in the construction supply chain; and
- develop a micro-level index for construction industry–related perturbations as related to labor, material, and equipment.

Data Availability Statement

All data, models, and code generated or used during the study appear in the published article.

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