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Measuring Agricultural Price Shocks in a Small Open Economy: Imported Crop in South Korea

by

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Measuring Agricultural Price Shocks in a Small Open Economy: Imported Crop in South Korea

This paper presents a novel approach to estimating the cost pass-through between imported crop prices and domestic food prices in a small open economy through firm markups. Our approach differentiates from the existing studies by enabling the estimation of firm-level pass-through elasticities for imported crop prices. Using proprietary firm-level financial data combined with public information on imports and subsector-specific usage of 8 major crops, we study firms in the 9 sectors comprising the South Korean food industry over the 2000-2021 period. Our findings include markup polarization across firms with a particular increase in higher markup firms. We also observe considerable heterogeneity in cost pass-through elasticity across sectors and markets: ranging from 0.085 to 0.510. Additionally, our measurements reveal a growing pass-through tendency in recent years, suggesting that global crop price shocks will likely have a more substantial impact on the food supply chain in South Korea.

Keywords: *Cost pass-through elasticity; Firm-level markups; Food industry; Grain import; Material inputs.*

1 Introduction

With escalating distrust among trade partners, deglobalization efforts have overshadowed the global supply chain in recent years (Zhang, 2021). Within the context of the food industry, the viability of reshoring, entailing the repatriation of farming operations, is constrained in many countries due to their low agricultural fertility. Thus, the heightened uncertainty and shocks in the global supply of agricultural commodities can be notably detrimental to these countries, many of which are small open economies in the international market. The challenges associated with maintaining food security in the face of import dependency have become a central concern for policymakers, particularly during periods characterized by sharp increases in agricultural commodity prices (De Schutter, 2017). Addressing these challenges and understanding the implications of deglobalization on the food industry are critical for informing policy discussions and developing strategies to mitigate risks and uncertainties in global agricultural markets.

Exploring the extent to which agricultural commodity price shocks move along the vertical food supply chain and are passed onto food prices, defined as the degree of pass-through, brings useful insights for the industry and policy establishments. In the existing literature, explanations of the effect of price shocks on importing economies are concentrated on vertical price transmission (Alghalith, 2010; Ibrahim, 2015; Guo and Tanaka, 2019). Although the previous studies have established evidence of market dynamics resulting from import price shocks, the focus has primarily been on the upstream firms, particularly state trading enterprises, and their monopsony power (McCorriston and MacLaren, 2005; 2008), leaving a gap in our understanding of pass-through at the firm-level in the downstream sector. Considering the consequence in the downstream following import price shocks are immediately related to household expenditure and welfare, investigating the pass-through dynamics with emphasis on downstream is especially important.

This paper introduces a novel approach to quantifying the cost pass-through by utilizing firm-level markups – the ratio of price to marginal cost, allowing for the establishment of comprehensive pass-through dynamics through the uncovering of firm-level cost pass-throughs. To be specific, our approach builds on the pioneer work by De Loecker and Warzynski (2012, *DLW henceforth*) for the firm-level markup estimation. Inspired by Hall (1988), DLW suggest an empirical framework to estimate the firm-level markups by leveraging the modern advancements in the production function estimation represented by, *inter alia*, Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg, Caves, and Frazer (2015, *ACF hereafter*). In general, food processing firms are critically constrained by the availability of material inputs, thus we adopt the Leontief production structure as considered in previous studies (ACF; De Loecker et al., 2020; De Loecker and Scott, 2022). Relying on the Leontief-driven fixed proportion rule, we demonstrate that the pass-through elasticity can be formulated as an equation, which consists of the markup elasticity of material input price, firm-level markup, expenditure share of the material input, and the portion of import product within the material cost. Thus, in empirics, given the firm-level markups obtained from the DLW procedure, we can estimate the markup elasticity with respect to the import price, which in turn permits us to calculate the firm-level pass-through elasticity.

This study employs the proposed method of pass-through estimation to investigate the impact of import crop price shocks on manufactured food prices in South Korea. Specifically, the scope of analysis encompasses 10,780 food and beverage producing firms in Korea, spanning the years from 2000 to 2021. There are two key reasons for selecting the Korean food industry as the subject of study. First, it is an active agricultural importer, producing less food than it consumes but easily meets domestic dietary needs through imports due to its high purchasing power (Clapp, 2017). Second, South Korea has witnessed dynamic changes in crop import sources over the past few decades, indicating that the impacts of evolving global market conditions are pronounced in its importing and related sectors. For example, while 91% of South Korean corn import was delivered from the U.S. in the 1990s, the share declined to 64% in the 2000s and further to 51% in the 2010s (FAO, 2023). The significant reduction in the U.S. share in South Korean corn imports is largely attributable to Brazil, whose production has increased substantially over the last two decades (Bustos, Caprettini, and Ponticelli, 2016).

The estimated firm-level markups disclose two prominent characteristics of the Korean food industry. The first distinctive feature is the polarization in the markup distribution during the study period. Although firm markups in the median or below in the markup distribution are found to remain steady, the markups at a higher percentile, such as 75th, 90th, or 95th, appear to have a continuous and significant increase over time. Indeed, the cross-sectional comparison between the kernel densities of markup in different years reveals the distribution has evolved with thicker tails. If we regard the markup as a proxy for market power, the observed polarization in the markup distribution suggests an increased concentration of market power in the food industry. The second characteristic of the industry we document is substantial heterogeneity in markup patterns between the sectors. However, the polarizing trend of markups is commonly found in all sectors, and the stable trend of markups below the 50th percentile is detected in all but beverage-related sectors.

In addition, based on the proposed pass-through elasticity measure, we discover three features in pass-through dynamics. First, the aggregate pass-through elasticity with respect to the eight import crops appears to remain relatively stable during the past two decades at around 0.197, whereas significant variations in pass-through elasticities across sectors and market stages are identified.

For instance, “Grain mills and Starches” sector is found to have the highest pass-through elasticity to the aggregate crop price, with values of 0.359 for wholesalers, 0.510 for retailers, and 0.406 for firms engage in both stages (mixed). By contrast, the “Alcoholic beverages” sector demonstrates the lowest pass-through elasticity for the average crop price, with values of 0.085 for wholesalers and 0.086 for mixed-category firms. Second, among the major commodities – corn, soybeans, and wheat, the crops with higher import dependency, such as wheat and corn, turn out to have higher pass-through elasticity, compared to soybeans that has a relatively low import dependency. Lastly, during the last six years of our study period, except for 2021, we find that, in all sectors, the pass-through elasticities have increased or little changed. This implies that the food system tends to become increasingly vulnerable to global supply shocks.

To examine our proposed pass-through measure, we carry out two exercises for model validation. First, following Berck et al (2009), we additionally estimate a pass-through measure using a dynamic GMM estimation, which can be seen as a benchmark of the conventional approach. The results report that the industry-level short-term pass-through elasticity with respect to the eight subject crops of our interest is 0.208, which is similar as what is obtained from the aggregate of our firm-level pass-through elasticities. The consistency between the two estimates from different methods supports the validity of our approach. Second, we extrapolate the estimates of pass-through elasticity in 2021 to calculate the potential inflationary pressure attributable to the increase in imported crop price in 2022. Our model predicts that around 8.97% of price increase in the food industry by import crop price shock in 2022; the observed change in the producer price index (PPI) in 2022 was 8.88%, which is reasonably close to our prediction. Comparisons in individual sectors also reaffirm the model predictions and PPI changes are considerably close each other.

The contribution of this research is twofold. First, we propose an alternative approach that enables estimating firm-level pass-through elasticities through firm-level markups. Considering that the two strands of literature in the international trade – pass-through-related studies and analyses using firm-level markups – are material yet separated to some extent, this paper suggests the nexus of the two can bring a step forward for the pass-through studies. Second, markup estimation studies on food sectors have been limitedly investigated (Curzi, Garrone, and Olper, 2021; De Loecker and Scott, 2022). To our best knowledge, this is the first study exploring the Korean food industry using the DLW framework. As stated above, since Korea is a good example of a small open economy in the international crop market, especially for corn, soybean, and wheat, this paper could deliver useful implications in a broader context of international trade as well as the Korean food industry.

2 Background and Data

While firms’ import decisions typically stem from an endogenous sorting process (Gibson and Graciano, 2011), agricultural imports tend to be very inelastic across all firms using the relevant inputs for food production, particularly when there are not enough domestic substitutes available. Moreover, in instances where a country does have little market power in the international trade of such inputs, a trade shock can be deemed an identifiable external shock to the supply chain of the importing country. In this section, we examine South Korea's grain import and food industry structure to ascertain its suitability for our research context, outlining the data sources used for our analysis.

2.1 Grain import of South Korea

Although South Korea has a solid domestic food manufacturing industry, its food supply chain heavily relies on agricultural imports, which, for example, accounted for 68 percent of total inputs used for food production in 2021[1]. The value of grain import has significantly increased during our study period, from $1.51 billion in 2000 to $5.02 billion in 2021 (Korea Customs Service, 2024). The rise is attributed to South Korea's constrained agricultural production capacity, which hampers the ability to replace imported grain with domestically grown alternatives in response to fluctuations in crop import prices. Importantly, nevertheless of its heavy reliance on imported grain, South Korea is arguably a small player in the global grain market. For instance, as of 2021, South Korea appears to take 5.5%, 2.0%, and 0.8% of global corn, wheat, and soybean imports, respectively (OEC, 2024).

Our study focuses on eight crops: corn, soybean, wheat, tapioca, centrifugal sugar cane, coffee bean, cacao bean, and sesame seed. To ensure the necessity of importing, when choosing the subject crops, we require crops to have the import share out of total usage in the food industry that exceeds 90% as of 2021 (Appendix Table S7)[2]. Additionally, we confirm through the detailed trade matrix of the Food and Agriculture Organization (FAO) that South Korea does not have significant global influence on the eight crops as their average export share in the global market is less than 0.1%.

Figure 1 illustrates the evolution of import prices and values for the eight crops, alongside the quantity-weighted average labeled as "All." Across all items, import prices surged significantly in the 2007-2008 period, remaining consistently elevated from 2010 to 2015. Although prices declined in the 2015-2020 period, they remained higher than those in the early 2000s. Notably, import values have generally fluctuated in the same direction as import prices (i.e., both increase and decrease) for most items, except for tapioca, whose import value has remained exceptionally low. For example, when the import price of most commodities peaked in 2008, the import value also experienced a significant increase. A similar pattern is observed in the post-2015 period, where both series exhibit a simultaneous decreasing trajectory. Given the implied inelastic responses in import quantity, we see South Korea as a small open economy suitable for measuring pass-through, where the import price shock is well captured.

The import price series are taken from the detailed trade matrix of the Food and Agriculture Organization (FAO)[3]. The dataset offers annual data on bilateral trade flows (import and export)

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[1] We source the relevant data from *the Survey of Raw Material Usage by Food Manufacturing in South Korea*, published by Ministry of Agriculture, Food and Rural Affairs and Korea Agro-Fisheries & Food Trade Corporation. As of 2021, the proportion of imported agricultural inputs in the total inputs used is 68.3% in terms of quantities and 48.2% in terms of expenditure in South Korea.

[2] Although having above 90% import dependency, pollack and peanut are not included since their import price information was not available.

[3] We align the crop items between the FAO detailed trade matrix and imported grain usage data as follows: "Tapioca of cassava" with "Tapioca," "Coffee, green" with "Coffee beans," "Raw cane or beet sugar (centrifugal only)" with "Raw cane sugar," and "Cocoa beans" with "Cocoa beans." The variables, such as soybeans, corn, wheat, cocoa beans, and sesame seed, show exact matches in both datasets.

for major agricultural and food commodities, broken down by origin and destination country. Specifically, the import price for each country and commodity is computed by dividing the import value by the corresponding import quantity. These individual price series are then aggregated, using the quantity share of imports from each trade partner in the total product for each year. Furthermore, we construct the quantity-weighted average price index for eight crops in the analysis by assigning weights based on the share of import quantity for each item relative to the total import quantity of the selected commodities.

2.2 KISVALUE data of firm financial statements

To explore the effect of imported crop prices on domestic food prices, we drew on firm-level financial statements from KISVALUE, a proprietary dataset compiled by NICE Information Services. This database provides detailed financial information, such as gross sales and total costs, from various South Korean firms of different sizes and types (privately held and publicly traded). With its comprehensive coverage of firms within South Korea that exhibit a significant reliance on imported crops over a sufficiently long period, the database should be well-suited to answer our research question. We extracted financial statements from food and beverage manufacturing firms that have operated in South Korea at least once between 2000 and 2021. Our focus is placed on the sectors with more than 100 firms in the sample, leading to the exclusion of the feed processing sector.

We have categorized all observed firms into nine sectors within the food industry, aligning them with both three-digit and five-digit Korean Standard Industrial Classification (KSIC) codes.[4] These KSIC codes are equivalent to the three-digit and five-digit North American Industry Classification System (NAICS) codes used in the United States. Specifically, our sample encompasses nine sectors defined by KSIC 3-digits and 48 subsectors defined by KSIC 5-digits. The dataset has 63,876 observations of 10,780 unique firms spanning 21 years from 2000 to 2021, covering around 89.8% of the aggregate sales within the local food and beverage manufacturing sector within South Korea (refer to Appendix Table S4 for details).

Following De Loecker, Eeckhout, and Unger (2020), we generate firm input variables based on the financial records. The output is defined as gross sales, while the key inputs encompass material, capital, and labor. We utilize four observable cost components – Cost of Goods Sold (hereafter COGS), Selling, General, and Administrative expense (hereafter SG&A), labor expenses, and total assets. Note that SG&A represents overhead costs and COGS is an aggregate of material costs and labor expenses, meaning that the material costs can be obtained by subtracting labor expenses from COGS. The capital expenses are approximated by multiplying the total asset by the rate of user

[4] The full names of the nine sectors are: *Slaughtering of livestock, processing and preserving of meat and meat products* (KSIC codes: 101; hereafter "Meat"), *Processing and preserving of fish, crustaceans, molluscs and seaweeds* (KSIC codes: 102; hereafter "Seafood"), *Processing and preserving of fruit and vegetables* (KSIC codes: 103; hereafter "Fruits and Vegetables"), *Manufacture of vegetable and animal oils and fats* (KSIC codes: 104; hereafter "Oils and Fats"), *Manufacture of dairy products and edible ice cakes* (KSIC codes: 105; hereafter "Dairy"), *Manufacture of grain mill products, starches and starch products* (KSIC codes: 106; hereafter "Grain mills and starch"), *Manufacture of other food products* (KSIC codes: 107; hereafter "Others"), *Manufacture of alcoholic beverages* (KSIC codes: 111; hereafter "Alcoholic beverage"), and *Manufacture of ice and non-alcoholic beverages; production of mineral waters* (KSIC codes: 112; hereafter "Non-alcoholic beverage"). Note that "Others" includes subsectors manufacturing food items that do not fall into the classifications of other sectors, such as rice cakes, bakery products, sugar confectioneries, sugar, noodles, food additives, lunch boxes, coffee, tea, etc.

cost of capital, of which the rate captures exogenous depreciation and risk premium proxied by adding 12% to the real interest rate as in De Loecker, Eeckhout, and Unger (2020). Additionally, we follow Asker, Collard-Wexler, and De Loecker (2013) to adjust for inflation distortions. All the monetary variables in input and output are deflated by the sector-specific producer price index (PPI) (or subsector-specific PPI if available), obtained from Bank of Korea (2023), and expressed in South Korean Won (KRW).

2.3 Description on summary statistics

Table 1 presents summary statistics for the key variables utilized in our analysis, which provides an outlook of industry dynamics. The number of firms in the sample has steadily increased over the study period, not only because of the enhanced inclusiveness of the KISVALUE dataset but also the gradual expansion of the food and beverage industry. This trend is evidenced by a different government survey, *The Mining and Manufacturing Survey*, by Statistics Korea, where the number of firms in the industry is documented to rise from 54,022 in 2000 to 64,365 in 2020.

To identify large firms, any firms with assets exceeding the annual average assets in our sample are classified as large corporations (Affrisy et al. 2011). As shown in **Table 1**, large firms constitute a small percentage of the total at around 6-7%. In addition, the KISVALUE dataset provides self-reported data on the business area of each firm, including details about the products manufactured and sold by firms as well as information about the specific market stage in which they operate. Using this information, we discern whether firms are exclusively involved in wholesale or retail markets or if they participate in both. If a firm explicitly specifies its exclusive engagement in wholesale activities, it is categorized as a wholesale firm. Likewise, if a firm exclusively engages in retail activities, it is classified as a retail firm. If a firm participates in either both stages or lacks information on the market stage, it is regarded as a firm engaged in mixed-stage activities. The average share of firms engaged in both market stages (i.e., “mixed”) is 90.4%, increasing from 84.0% in the 2000-2004 period to 93.2% in the 2016-2021 period. In contrast, the share of firms exclusively engaged in wholesale activities averages 8.5%, declining from 15.3% in the 2000-2004 period to 5.37% in the 2016-2021 period. Notably, the share of retailing firms in our sample remains consistently low, hovering around 0-1%. This pattern aligns with the traditional practice in the food and beverage industry, where manufacturers historically prioritize selling their products to the wholesale market. The observed scarcity of firms exclusively participating in the retail market in our dataset may be attributable to such industry practices.

Appendix Table S1 reveals interesting trends, exhibiting the summary statistics across different size categories and firm types. Both large and mid/small-sized firms show an overall upward trend in financial outcomes during the 2005-2010 period, followed by a slight decrease in the later years. Notably, large firms consistently exhibit a steadier trajectory in sales, while mid/small-sized firms do not. Large firms consistently report higher sales and costs across all categories compared to their mid/small-sized counterparts, with material costs constituting a substantial portion. Specifically, the overhead costs (SG&A) are considerably higher in large firms, indicative of their relatively higher operational scale. Additionally, Appendix Table S1 reports a consistent trend in financial outcomes for each firm types. The retailers and mixed are characterized by a temporary surge in both sales and costs during the 2005-2010 period, followed by a subsequent decline in later periods. In contrast, wholesalers demonstrate a gradual increase in both sales and costs over the study period. This contrast suggests that mixed category firms are likely to exhibit behavior more closely aligned with that of retailers when compared to wholesalers. Considering this trend, there is potential for comparing mixed category firms with the wholesale group to address our data limitation of insufficient retailers when conducting analyses across different market stages.

3 Model for Markup Measure

3.1 Production approach to markup estimation

This study examines the food-related sectors, where it is assumed that most firms heavily depend on material inputs (e.g., crops) for their production. Similar to De Loecker and Scott (2022), we postulate a Leontief production technology, critically constrained by the availability of material input. Consider a firm i in time t that uses material input M_{it} and whose production function is as follows:

$$Q_{it} = \min\left[\gamma_{it} M_{it}, F\left(X_{it}, K_{it}; \beta_{s[i]}\right) \exp(\omega_{it})\right] \tag{1}$$

, where X_{it} is a variable input capturing the labor use, K_{it} is a dynamic input such as capital stocks, and ω_{it} is a *Hicks-neutral* productivity shifter. We denote $F(X_{it}, K_{it}; \beta_{s[i]}) exp(\omega_{it})$ as an operational input Y_{it}, representing a composite input other than the material input. Following DLW, we assume that all firms in the same sector, denoted by $s[i]$, have a set of common technology parameters $\beta_{s[i]}$ in their production for the operational input. Note that γ_{it} indicates the effective unit of Y_{it} for the output, which varies by firm and time. If the firm's product does not require much material input, γ_{it} would be very large, and vice versa. The Leontief structure imposes a fixed proportional rule for the production efficiency: $\gamma_{it} M_{it} = F(\cdot) exp\,(\omega_{it})$.

Given the target outcome $\bar{Q}$ and the fixed proportion rule, the specified production function yields the cost-minimizing material input demand of $M_{it}^{*} = \bar{Q}/\gamma_{it}$. Also, the cost-minimizing operational input can be derived by solving

$$\min_{X_{it}, K_{it}} P_{it}^{X} X_{it} + P_{it}^{K} K_{it} \quad \text{subject to} \quad F\left(X_{it}, K_{it}; \beta_{s[i]}\right) \exp(\omega_{it}) \geq \bar{Q} \tag{2}$$

, where P_{it}^{X} and P_{it}^{K}, respectively, are input price for variable input X_{it} and capital K_{it}. The first order condition with respect to X_{it} is $P_{it}^{X} - \lambda_{it}(\partial F(\cdot) \exp(\omega_{it})/\partial X_{it}) = 0$, and the Lagrange multiplier λ_{it} stands for the marginal cost of the operational input. As shown in DLW, the first order condition can be expressed by

$$\mu_{it}^{F} = \theta_{it}^{X} \cdot (\alpha_{it}^{X})^{-1} \tag{3}$$

, where $\mu_{it}^{F} = P_{it}/\lambda_{it}$ is the operational markup, $\theta_{it}^{X} = (\partial Q_{it}/\partial X_{it})(Q_{it}/X_{it})^{-1}$ is the output elasticity with respect to X_{it}, and $\alpha_{it}^{X} = (P_{it}^{X} X_{it}/P_{it} Q_{it})$ is the expenditure share of X_{it}. Since the total cost consists of two components – material cost and operational cost, the marginal cost of firm i is $MC_{it} = P_{it}^{M}/\gamma_{it} + \lambda_{it}$. As a result, the markup of the firm is

$$\mu_{it} = \frac{P_{it}}{MC_{it}} = \frac{1}{\alpha_{it}^{M} + (\mu_{it}^{F})^{-1}} \tag{4}$$

, where $\alpha_{it}^{M} = (P_{it}^{M} Y_{it} / P_{it} Q_{it})$ is the expenditure share of M_{it}. As stated in the Data section, we can calculate α_{it}^{M} and α_{it}^{X} using the revenue and expenditure records of each firm. Thus, to measure the firm-level markup in (4), only the output elasticity θ_{it}^{X} needs to be identified, which requires the production estimation of $F(\cdot)\exp(\omega_{it})$. Note that, as emphasized in DLW, this approach permits us to identify firm-level markups without imposing an exact mode of competition. One restriction of this approach to markup estimation is the assumption of static pricing behavior, ruling out dynamic pricing. Namely, it is assumed that firms set prices in each period without considering costly adjustments in changing prices.

3.2 Estimation procedure for markups

Following DLW, we take advantage of ACF approach to estimate the production function and to obtain the output elasticity θ_{it}^{X}. Specifically, we take the two-step approach proposed by ACF, using a translog production function for $y_{it} = ln\, Y_{it} + \epsilon_{it}$, where

$$y_{it} = \beta_x x_{it} + \beta_k k_{it} + \beta_{xx} x_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{xk} x_{it} k_{it} + \omega_{it} + \epsilon_{it} \tag{5}$$

, and all the lower-case variables stand for the log of the corresponding upper-case variables. As a first step, we run an OLS of (5) to tease out the measurement ϵ_{it} and obtain a prediction of $\ln Y_{it}$.

To denote the sector-specific technological parameters, all β's are subscripted by $s[i]$. Including time fixed effects τ_t, the predicted $\ln Y_{it}$ is

$$\phi_{it} = \beta_{x,s[i]} x_{it} + \beta_{k,s[i]} k_{it} + \beta_{xx,s[i]} x_{it}^2 + \beta_{kk,s[i]} k_{it}^2 + \beta_{xk,s[i]} x_{it} k_{it} + \tau_t \tag{6}$$

The key challenge in identifying the parameters of interest arises from the potential correlation between a firm's input decision and unobserved productivity ω_{it}. We adopt the idea from the existing literature in production estimation that the innovation to productivity is orthogonal to both the lag of variable input and the contemporary dynamic input (Olley and Pakes, 1995; Levinsohn and Petrin, 2003; ACF; DLW). Here, the innovation is captured by the deviation of ω_{it} from the prediction by its lag, where the productivity is assumed to follow the law of motion: $\omega_{it} = g_t(\omega_{it-1}) + \xi_{it}$. For notational simplicity, let us omit the sector subscript $s[i]$ and denote $\mathbf{x}_{it} = (x_{it}, k_{it}, x_{it}^2, k_{it}^2, x_{it} k_{it})$ and $\boldsymbol{\beta} = (\beta_x, \beta_k, \beta_{xx}, \beta_{kk}, \beta_{xk})$. Given a set of parameters $\hat{\phi}_{it}$ from (6), we can calculate $\omega_{it}(\boldsymbol{\beta}) = \hat{\phi}_{it} - \mathbf{x}_{it}\boldsymbol{\beta}_{it}$, and we can measure the innovation ξ_{it} by regressing $\omega_{it}(\beta)$ on its lag and a constant term.

As a second step, we implement the GMM estimation using the moment conditions grounded on the assumption that the innovation is independent from already-determined input choices (i.e., past variable input and current capital stock):

$$E\left(\xi_{it}(\boldsymbol{\beta})\begin{pmatrix} x_{it-1} \\ k_{it} \\ x_{it-1}^2 \\ k_{it}^2 \\ x_{it-1}k_{it} \end{pmatrix}\right) = 0 \tag{7}$$

As shown in DLW, the estimated parameters yield output elasticity with respect to labor:

$$\hat{\theta}_{it}^X = \hat{\beta}_x + 2\hat{\beta}_{xx}x_{it} + \hat{\beta}_{xk}k_{it} \tag{8}$$

It is noteworthy that the output elasticity varies by firm and time in the translog specification. In contrast, should a Cobb-Douglas production be assumed, the output elasticity would be constant for all firms in the same sector as $\hat{\beta}_x$.

In addition, as noted by DLW, we should incorporate the measurement error ϵ_{it} in order to calculate the correct expenditure shares, α_{it}^M and α_{it}^X. The observed sales are equal to $P_{it}Q_{it} = P_{it}(Y_{it}\,exp(\epsilon_{it}))$. By dividing the observed sales, either $\tilde{\alpha}_{it}^M$ or $\tilde{\alpha}_{it}^X$, into $\exp(\hat{\epsilon}_{it}) = \exp\big(y_{it} - \hat{\phi}_{it}\big)$, the corrected expenditure shares can be obtained:

$$\hat{\alpha}_{it}^j = \tilde{\alpha}_{it}^j \cdot \exp(\hat{\epsilon}_{it}) \quad \text{for} \quad j = X, M \tag{9}$$

The estimates from (8) and (9) enable us to measure the firm-level markups of (4).

4 Estimated Markups and Industry Dynamics

The estimated markups provide useful insight for the industry dynamics. **Figure 2** presents the estimated markup for different percentiles in the markup distribution over time. Two notable observations emerge. First, in Fig2-(a), markups for higher percentiles have increased to a greater extent. For example, the markups for the 95th, 90th, and 75th percentiles have largely risen throughout the study period, while the markup of the median (50th) and the 25th percentiles remained relatively stable. Additionally, higher percentiles exhibited a greater fluctuation, and for the high percentiles, the magnitude of fluctuation increased after 2010. The disparity in markup across percentiles has widened over time, with the markup gap between median and high percentile firms growing more than that between median and low percentile firms. Second, Fig2-(b) illustrates the distribution of markups across several different years. It is clear that the markup distribution has evolved to have a thicker tail over the last two decades. If we consider the markup as a proxy for market power, the observed polarization in the markup distribution indicates an increased concentration of market power in the food industry.

Figure 3 depicts the sector-specific markup trends. The beverage-related sectors turn out to have relatively high markups compared to others, while the meat sector is identified to have relatively low markups. Similar to the pattern observed in Fig 2-(a), we identify the disproportionate markup increase in the high percentile groups after 2015 in most sectors. Moreover, we find that markups below the 50$^{\text{th}}$ percentile have remained almost constant over time in sectors other than the beverage-related sectors. In **Table 2**, we further explore the heterogeneity of markups across sectors. The percentage difference from the median is displayed in parentheses. Although the polarization of markup distribution is detected in Fig 2-(b), **Table 2** reaffirms that the markup-polarizing pattern is commonly observed in all sectors. Thus, the prevalence of polarization in markups can be concluded as a prominent trend in the Korean food industry.

5 Procurement of Cost Pass-through Elasticity Using Markups

5.1 Connection between markup and cost pass-through elasticity

The estimated markups can be used to reveal the extent to which changes in imported crop prices are passed on to manufacturing prices. To capture the cost pass-through of imported crop prices, we further separate the material input into crop and other raw materials. Considering that raw materials are usually complementary each other, we can extend the Leontief structure in (1) to explicitly include two different types of material inputs.

$$Q_{it} = \min\left[\gamma_{it}^{\widetilde{M}} \widetilde{M}_{it}, \gamma_{it}^{G} G_{it}, F\left(X_{it}, K_{it}; \beta_{s[i]}\right) \exp(\omega_{it})\right] \tag{10}$$

, where G_{it} is the imported crop input and $\widetilde{M}_{it}$ is all material inputs other than G_{it}. With the two components of material inputs, the markup in (4) can be rewritten as

$$\mu_{it} = \frac{1}{\alpha_{it}^{G} + \alpha_{it}^{\widetilde{M}} + (\mu_{it}^{F})^{-1}} \tag{11}$$

Similar to (4), α_{it}^{G} and $\alpha_{it}^{\widetilde{M}}$ indicate the expenditure share of G_{it} and $\widetilde{M}_{it}$ in sales, respectively. If we denote κ_{it} as the expenditure share of imported crop in material expenses, the above two variables could be defined as a function of κ_{it} and α_{it}^{M} as follows: $\alpha_{it}^{G} = \kappa_{it}\alpha_{it}^{M}$ and $\alpha_{it}^{\widetilde{M}} = (1-\kappa_{it})\alpha_{it}^{M}$.

Contemplating the relatively homogeneous product characteristics within a specific crop type, we make an assumption that all firms in the industry have access to the same price information regarding the imported crop, which is denoted by P_{it}^{G} (e.g., the same import corn price for all firms in year t). Differentiating the markup in (11) by the import crop price P_{t}^{G},

$$\frac{\partial \mu_{it}}{\partial P_{it}^{G}} = -\mu_{it}^{2}\left[\frac{G_{it}}{P_{it}Q_{it}} - \frac{P_{it}^{G}G_{it}}{P_{it}^{2}Q_{it}}\frac{\partial P_{it}}{\partial P_{t}^{G}} - \frac{P_{it}^{\widetilde{M}}\widetilde{M}_{it}}{P_{it}^{2}Q_{it}}\frac{\partial P_{it}}{\partial P_{t}^{G}} - \frac{\lambda_{it}}{P_{it}^{2}}\frac{\partial P_{it}}{\partial P_{t}^{G}}\right] \tag{12}$$

Note that $\partial P_{it}/\partial P_{t}^{G}$ is the cost pass-through of crop price of our interest, and we denote the cost pass-through elasticity by $\eta_{it}^{P,G} = (\partial P_{it}/\partial P_{t}^{G})(P_{t}^{G}/P_{it})$. Reorganizing (12), the markup elasticity with respect to crop price, $\eta_{it}^{\mu,G} = (\partial \mu_{it}/\partial P_{t}^{G})(P_{t}^{G}/\mu_{it})$, can be presented by the markup, expenditure shares, and the cost pass-through elasticity as shown in:

$$\frac{\partial \mu_{it}}{\partial P_t^G}\frac{P_t^G}{\mu_{it}} = \eta_{it}^{\mu,G} = -\mu_{it}\kappa_{it}\alpha_{it}^M + \eta_{it}^{P,G} \tag{13}$$

Equation (13) shows the relationship between $\eta_{it}^{\mu,G}$ and $\eta_{it}^{P,G}$, and we can present the cost pass-through elasticity as

$$\eta_{it}^{P,G} = \eta_{it}^{\mu,G} + \mu_{it}\kappa_{it}\alpha_{it}^M \tag{14}$$

Equation (14) implies that if we know the markup elasticity $\eta_{it}^{\mu,G}$ and the firm-specific expenditure share of imported crop within material expenditure κ_{it}, the pass-through of cost shocks from imported crops can be conjectured. It is notable that, in this study, we need to assume that $\partial\mu_{it}/\partial P_t^G$ is common across all firms in the same sector because we have unbalanced panel for firms, having some firms with insufficient observations to identify the firm-specific $\partial\mu_{it}/\partial P_t^G$. Note that, still, $\eta_{it}^{\mu,G}$ can vary by year and firm as we do know P_t^G/μ_{it} changes. Thus, in principle, we can identify a firm-level cost pass-through elasticity.

One might question about how the pass-through estimate addresses the cases in which firms are not directly using raw imported crops but using processed crops in their vertical chains. For instance, in our dataset, we observe that the meat processing sector demonstrates lower grain usage compared to the other sectors, but it heavily demands imported grains as a form of livestock feed. In this case, κ_{it} should not be high but the markup elasticity $\eta_{it}^{\mu,G}$ can account for this upstream cost pressure and resulting pricing decisions. As an illustrative example, let us consider a non-alcoholic beverage producing firm whose production does not rely on the imported crop of interest (i.e., $\kappa_{it} = 0$), yet its markup can positively respond to an increase in the crop price ($\eta_{it}^{\mu,G} > 0$), resulting in a positive cost pass-through elasticity ($\eta_{it}^{P,G} > 0$). In this situation, the firm's pricing is indirectly influenced by the import crop price, which is a consequence of competition against other companies. For instance, if firm i produces a product that is a close substitute for the products of other firms that heavily rely on the imported crop as an input, an increase in the import crop price can incentivize firm i to set a higher price (P_{it}), even though it does not utilize the import crop in its production. In consequence, the whole economy would likely observe the inflation pressure that reflects the *supply chain effect*.

It is useful to aggregate firm-specific pass-through elasticities at the sector level, to draw broader insight into the supply chain. Specifically, we take a weighted average of firm-level pass-through elasticities:

$$\eta_{st}^{P,G} = \sum_{i\in s}\eta_{it}^{P,G}w_{it}^r \quad \text{where} \quad w_{it}^r = \frac{P_{it}Q_{it}}{\sum_{j\in s}P_{jt}Q_{jt}} \tag{15}$$

Note that w_{it}^r represents the revenue-based weight of firm i within sector s as in De Loecker, Eeckhout, and Unger (2020). Straightforwardly, the industry-wise pass-through pattern can also be checked by expanding the sector to include all sectors collectively.

5.2 Estimation of pass-through elasticity

As shown in (14), the estimated markups enable the computation of the pass-through elasticity regarding imported crop prices, provided that we know (i) the markup elasticity with respect to imported crop prices $\eta_{it}^{\mu,G}$ and (ii) the expenditure share of imported crops within material expenses κ_{it}.

5.2.1 Markup elasticity with respect to imported crop prices

Our approach to measure the markup's response to import crop price is to carry out a fixed effect regression, as in the following equation:

$$\mu_{it} = \sum_{s=1}^{9}\sum_{v=1}^{3} \rho_{sv[i]} \ln P_t^G \, I_{s[i]t} I_{v[i]t} + \varphi^{oil} \ln P_t^{oil} + \varphi^{large} I_{it}^{large} + \zeta_t + \zeta_{s[i]} + \zeta_{v[i]} + e_{it} \quad (16)$$

with $G \in \{Total, Corn, Soybean, Wheat\}$, where 3 market stages that categorize firms into wholesaler, retailer, and mixed are indexed by v, and the 9 sectors are indexed by s. $I_{s[i]t}$ is an indicator variable for sector s in year t, $I_{v[i]}$ is an indicator for market stage v in year t, $\rho_{s[i]}$ is markup change with respect to import crop price specific to each sector, indicating $\partial\mu_{it}/(\partial P_t^G/P_t^G)$, $\ln P_t^{oil}$ is the logarithm of oil price, I_{it}^{large} is a dummy variable for a large firm, and ζ_t, $\zeta_{s[i]}$, $\zeta_{v[i]}$ denote fixed effects concerning year, sector, market stage, respectively. Lastly, e_{it} indicates the error term.

Note that our specification assumes that the markup response parameter $\rho_{sv[i]}$ is common across firms within the same market stage and sector. Our identification strategy to obtain the markup response to the imported crop prices is to control for confounders that can potentially affect the markups' responsiveness possibly due to the unobserved characteristics of sector, time, or firm types (size and market stage), using fixed effects and a large farm dummy. Also, it is noteworthy that we incorporate the log of the oil price into the regression equation to control for general cost pressure in the model, typically captured by energy expenses. Given the substantial correlation between energy prices and raw material prices, inclusion of the oil price variable is crucial for obtaining an unbiased parameter of interest $\rho_{s[i]}$ (Du, Cindy, and Hayes, 2011).[5]

Table 3 presents the estimation results of (16). In all sectors, retailers display a more pronounced sensitivity in markup responses, compared to wholesalers. This suggests that downstream prices unequivocally reflect upstream price shocks in the food industry. In addition, in the "Meat" and "Seafood" sectors, which arguably use not much raw crops, the markups appear to respond fairly sensitively to imported crop price. This highlights that our model adeptly captures indirect utilization of imported crop, such as livestock feed. The effects of oil price and the large firm dummy on firm markups are negative, which implies that large firms tend to pursue a strategy of quick returns with narrow margins.

Note that the "Dairy-Wholesale" and "Alcoholic beverage-Wholesale" groups are found to have especially low markup responsiveness for crop prices. A possible explanation for these

[5] Specifically, we sourced data on spot crude oil prices for West Texas Intermediate (WTI) from the Federal Reserve Bank of St. Louis (FRED). The series is adjusted for the exchange rate (KRW/USD) and deflated by the GDP deflator specific to South Korea, both sourced from FRED.

observations could be the presence of price regulation associated with these products. For example, since 2013, raw fluid milk in South Korea has become subject to price regulation, allowing milk producers to negotiate milk price only if annual production cost has changed over ±4% compared to the previous year. Following the policy implementation, raw milk prices have changed only three times (in 2016, 2018, and 2021), potentially limiting the impact of imported crop prices on firm markups in the Dairy sector. Similarly, the Alcoholic beverage industry is characterized by heavy taxation. Thus, our model estimates can be seen reasonably reflecting the market circumstances.

5.2.2 Expenditure share of imported crops within material expenses

In our case, the lack of available data for firm-specific κ_{it} challenges calculating the firm-level cost pass-through elasticity. We source pertinent information of grain use at each subsector, defined by 5-digit KSIC code, from *the Survey of Raw Material Usage by Food Manufacturing in South Korea.* Despite having detailed information on the imported crop usage within the food industry, there are two limitations concerning the crop usage data, which should be further addressed. First, the data represent the total input used by all food and beverage manufacturers nationwide. Second, the survey data is available only after 2011 and does not cover the preceding period. To address these limitations, $\kappa_{b[i]}$ is constructed as in the following equation[6]

$$\kappa_{b[i]} = \frac{1}{N_b} \sum_{i \in b} \frac{P_t^G \left(G_{b[i]t} \psi_t w_{it}^M \right)}{M_{it}} \tag{17}$$

, where $G_{b[i]t}$ is the quantity of each imported crop G used at the subsector b that i belongs to, ψ_t is the market share of our sample firms in relation to the whole industry[7], N_b is the number of firms in subsector b, and w_{it}^M denotes material cost weights assigned to firm i at time t defined at the subsector level. It should be noted that we aggregate all the imputed κ_{it}'s by a simple average. Denoting $\kappa_{b[i]}$ as the expenditure share of imported crop of subsector $b[i]$ that includes firm i,

[6] **Table S5** in Supplementary Appendix presents summary statistics of $\kappa_{b[i]}$ by subsector for each crop. We only report $\kappa_{b[i]}$ for the subsector where $\kappa_{b[i]} > 0$. It is observed that there is heterogeneity in $\kappa_{b[i]}$ across subsectors and crop items. Particularly, among the nine sectors, "Oils and fats," "Grain mill and Starch," and "Others" include some subsectors with higher dependence on imported crops. For instance, for all crop, $\kappa_{[i]}$ is 46.99% in *Milling of cereals* (KSIC codes: 10612), 41.76% in *Manufacture of vegetable oils and fats* (KSIC codes: 10402), and 19.79% in *Manufacture of other food additive products* (KSIC codes: 10749).

[7] To compute ψ_t, we use data on total industry sales from two surveys conducted by Statistics Korea: *The Census on Establishments* (CE) for the 2016-2021 period, and *The Mining and Manufacturing Survey* (MMS) for the 2000-2015 period (Statistics Korea, 2023a, 2023b). CE has advantages over MMS for capturing total market sales in our setting for two reasons. Firstly, CE includes a broader range of establishments. While CE targets firms operating or that have operated in South Korea with at least one employee, MMS focuses on those with at least 10 employees. Considering that 91% of food and beverage manufacturers in South Korea have less than 10 employees as of 2022, exclusion of small firms in MMS may lead to an underestimation of total industry sales. Secondly, CE provides data on firm sales, equivalent to the variable "revenue" in our dataset. In contrast, MMS reports the value of shipment, referring to the value of manufactured goods delivered to the buyer. However, this may not directly correspond to "revenue" due to the growing trend of diversification in the food industry. Thus, we rely on CE as a primary source, but for the years when revenue data are unavailable in CE, we alternatively use MMS. The annual market share of our sample is documented in **Table S8** of Supplementary Appendix.

$\kappa_{it} = \kappa_{b[i]} + \Delta_{it}$, where Δ_{it} is the deviation of κ_{it} from the $\kappa_{b[i]}$ which stands for the measurement error. As a result, similar to (14), the aggregated cost pass-through for sector s can be written as

$$\eta_{st}^{P,G} = \sum_{j\in s} w_{it}^{r}\eta_{it}^{P,G} = \sum_{j\in s} w_{it}^{r}\left(\eta_{it}^{\mu,G} + \mu_{it}\kappa_{b[i]}\alpha_{it}^{M}\right) + \sum_{j\in s} w_{it}^{r}\mu_{it}\Delta_{it}\alpha_{it}^{M}\text{, and} \tag{18}$$

$$\eta_{st}^{P,G}|_{\Delta_{it}=0} = \sum_{j\in s} w_{it}^{r}\left(\eta_{it}^{\mu,G} + \mu_{it}\kappa_{b[i]}\alpha_{it}^{M}\right)$$

In addition, by applying an observed maximum (minimum) expenditure share of import crop within each subsector, we can obtain a potential upper bound (lower bound) of pass-through elasticity. Namely, we postulate $\Delta_{it} \in \left[\min_{i\in b}(\kappa_{it}) - \kappa_{b[i]}, \max_{i\in b}(\kappa_{it}) - \kappa_{b[i]}\right]$ and the suggested range of pass-through elasticity is

$$\eta_{st}^{P,G}|_{\Delta_{it}=\min_{i\in b}(\kappa_{it})-\kappa_{b[i]}} < \eta_{st}^{P,G} < \eta_{st}^{P,G}|_{\Delta_{it}=\max_{i\in b}(\kappa_{it})-\kappa_{b[i]}} \tag{19}$$

5.3 Implication of the computed cost pass-through elasticity

Table 4 reports the snapshot of pass-through elasticities based on $\eta_{st}^{P,G}|_{\Delta_{it}=0}$.[8] Although the aggregate pass-through elasticity appears to remain steady over time at around 0.195 (Appendix Table S8), we observe significant variations in pass-through elasticities across sectors and market stages. For instance, "Grain mills and Starches" sector exhibits the highest pass-through elasticity to the "All" crop price, where for wholesalers 0.359, for retailers 0.510, and for firms engage in both stages (mixed) 0.406. This implies in this sector a 10% increase in the import wheat price would lead to a product price increase of 3.59% for wholesalers, and 5.10% for retailers, and 4.06% for firms in the mixed category. Conversely, the "Alcoholic beverages" sector shows the lowest pass-through elasticity for the average crop price, with estimated values of 0.085 for wholesalers and 0.086 for mixed-category firms. Comparing pass-throughs between crops, soybean price pass-through elasticities appear to be the lowest in most categories, except for firms who sell in retail market and fall into the "Oil and fat" sector (**Table 7**).

Figure 4 illustrates the evolution of sector-specific pass-through elasticities in response to the "All" crop price over time. The shaded area illustrates the range of pass-through elasticity that accounts for the potential impact of measurement error in κ_{it} as suggested in (19). It is observed that some sectors, including "Meat", "Fruit and vegetables", "Diary" and "Non-alcoholic beverage", indicate a narrow range of elasticity due to a small variation in $\kappa_{b[i]}$. The various range could be attributed to less reliance on imported crops across subsectors. Additionally, in **Figure 4**, the "Alcoholic beverage" sector exhibits an exceptionally low level of pass-through elasticities, which is not surprising given the stiff tax imposed on these products. A similar rationale can explain the relatively low pass-through elasticities found in the "Dairy" sector, where pricing is regulated more by government policy rather than crop prices directly.

Interestingly, a noteworthy finding from **Figure 4** is the upward trend in pass-through elasticities over the recent six years, except for 2021 due to the impact of the Covid pandemic. Starting from

[8] Note that pass-through elasticities are only calculated for observations within the upper and lower 1% of the markup distribution each year, and for categories with more than 5 observations.

2015, most non-beverage sectors, as well as the "Non-alcoholic beverage" sector, show an increase in pass-through elasticities. In the "Oils and fats" and "Grain mill and Starch" sectors, pass-through elasticities at least remain stable throughout the study period. This suggests that the impact of global food supply shocks on general food consumers has intensified, and this tendency may be further exacerbated as the global supply chain faces heightened uncertainty. This pattern is consistently confirmed in various specifications (see Appendix Figure S1-S4 and Appendix Table S8).

6 Model Validation

6.1 Comparison with dynamic GMM pass-through estimator

In this section, we compare our estimates with those obtained using a conventional approach of the literature that directly uses observed prices. Berck et al. (2009) have developed a dynamic estimator of pass-through elasticity for corn, wheat, and gasoline prices to the retail price of fresh chicken and ready-to-eat cereals, considering both farm and wholesale levels. Following this approach, we construct the reduced form specification as follows:

$$\ln y_{j,t} = \delta_{lag1} \ln y_{j,t-1} + \delta_{lag2} \ln y_{j,t-2} + \delta_G \ln P_t^G + \delta_{oil} \ln P_t^{oil} + \varphi_j + \varphi_t + u_{k,t} \tag{20}$$

with $G \in \{Total, Corn, Soybean, Wheat\}$, where $\ln y_{j,t}$ represents the log of the food price for item j in year t, $\ln y_{j,t-1}$ and $\ln y_{j,t-2}$ are lagged dependent variables to test for slow price adjustment, $\ln P_t^G$ is the log of the imported crop price (all-crops average, corn, soybean, and soybean), and $\ln P_t^{oil}$ is the log of the oil price. φ_j and φ_t represent item and year fixed effects, respectively. The parameter δ_G and $\delta_G/(1 - \delta_{lag1} - \delta_{lag2})$ captures the pass-through elasticity of imported crop price on food prices at the short-run and at the long-run, respectively.

Berck et al. (2009) used supermarket scanner data; however, since we lack scanner data for food products corresponding to our study period in South Korea, we instead utilize the producer price index for processed food and beverage items as a dependent variable, sourced from Bank of Korea (2023). The dataset covers price information for 84 representative food and beverage items sold by firms to various market stages, which aligns with the "revenue" data in our dataset. The price index is provided at the national level on annual basis, spanning from 2000 to 2021, calculated such that the price of 2015 is set at 100 for most products with 1,419 observations in total.

The null hypothesis of a unit root is rejected based on the Levin, Lin, and Chu (2002) test. We estimate equation (20) using the Generalized Method of Moments (GMM) with the Arellano and Bond (1991) estimator[9], given that our specification includes lagged dependent variables. We assume the lagged dependent variables as endogenous, and the log of imported crop price and oil price as exogenous due to the characteristic of the small open economy in South Korea. We employ

[9] To estimate the dynamic panel model, we employ the Stata command "*xtdpdgmm*," assuming that the lag(s) of the dependent variable are correlated with the unobserved panel-level effects, whether fixed or random. The estimator generated by this command is appropriate for datasets characterized by numerous panels and a limited number of periods, as observed in our dataset (Roodman, 2009).

one lag of the exogenous variables and the third and further lags of dependent variables as instrumental variables. The model selection pertaining to the number of lags is informed by the autocorrelation test results as well as the model and moment selection criteria using Akaike Information Criterion (MMSC-AIC) (Andrews and Lu, 2001). In addition, we include the item fixed effects to consider any time-invariant changes for each item and year fixed effects to control for time-specific confounders[10]. Our estimation involves the two-step approach to obtain asymptotically efficient estimators with the Windmeijer correction for small sample downward bias (Windmeijer, 2005)[11].

Table 5 exhibits the results of the dynamic panel regression model estimation and the computation of dynamic multipliers. Columns (1) through (4) present the regression outcomes for each type of crop – total, corn, soybean, and wheat – and the test statistics for autocorrelation and overidentification. All coefficients for the first-lag dependent variables and imported crop prices are statistically significant and positive. However, the estimates of second-lag dependent variables are negative and insignificant, consistent with the auto-correlation tests where only the order 1 is found significant. Despite their insignificance, we include the second lag of dependent variable in the model, as we obtain a significant AR (2) test result when only including the first lag dependent variable. Moreover, in all models, the null hypothesis of the Sargan-Hansen test of overidentification is not rejected.

The average short-run pass-through elasticities over the study period are 0.195 for all crops, 0.262 for corn, 0.161 for soybeans, and 0.248 for wheat. A comparison with the results from our model, as presented in Appendix Table S8, reveals similar outcomes: 0.195 for all crops, 0.166 for corn, 0.133 for soybeans, and 0.197 for wheat. The oil price effects are negative in all models, though statistically significant only for the corn price. The estimates from both approaches are comparable in magnitude, although our markup-based elasticities are largely smaller than the dynamic GMM estimates. This suggests that firm pricing behavior concerning wheat prices differs from their responses to prices of other crops, underscoring the potential insights gained by measuring pass-through elasticity through markup adjustments. Lastly, long-run elasticities calculated form the regression results are statistically significant and positive in all models, where the estimates are much larger than short-run estimates. This observation indicates that the influence of crop price changes on the dependent variable may accumulate over time, generating the greater lasting effects beyond the short-run.

6.2 Imputation of food price changes using the 2022 imported crop price shock

We extrapolate our model to predict the impact of recent crop price shocks on food prices South Korea, and compare the results with the actual outcomes in 2022. To compute the percentage changes in food prices, we use pass-through elasticities for the year 2021 at three different levels: industry-level ($\eta^{P,G}_{t=2021}$), sector-level ($\eta^{P,G}_{s,t=2021}$), and industry-and-sector level ($\eta^{P,G}_{v,t=2021}$) in 2021.

[10] While Berck et al. (2009) included a wide arrange of fixed effects to control for seasonal, event, and regional effects, we only include item and year fixed effects and oil prices as controls due to the annual frequency and aggregate structure of our dependent variable.

[11] We use "*collapse*" option to compress the numbers of lags of instruments, thereby avoiding inefficiencies arising from using excessive number of instruments. We use "*teffects*" option to account for year fixed effects.

They are multiplied with the percentage change in imported crop prices from 2021 to 2022 $((P^G_{2022} - P^G_{2021})/P^G_{2021})$.[12]

Table 6 presents the calculation result showing the changes in food prices due to changes in imported crop prices. South Korea has witnessed a sharp increase in imported crop prices from 2021 to 2022, by 45.3% for all crops, mainly due to the Russia-Ukraine war. We compare the results with the actual changes in the producer price index (PPI) for each sector in South Korea during the same period (Bank of Korea, 2023). The PPI of the entire industry has increased by 8.88%, which is comparable to our prediction of 8.97%. To be specific, the percentage increases of PPI for each sector are as follows: 8.68% in the "*Meat*" sector (our prediction: 9.11%), 6.88% in "*Seafood*" (our prediction: 10.07%), 6.77% in "*Fruit and Vegetable*" (our prediction: 8.67%), 4.78% in "*Dairy*" (our prediction: 5.98%), 6.05% in "*Alcoholic Beverage*" (our prediction: 3.77%), and 5.01% in "*Non-alcoholic Beverage*" (our prediction: 5.81%).[13] Interestingly, in most sectors, all these estimates do not largely differ with those derived from our model. This emphasizes that imported crop prices play a significant role in shaping food prices in South Korea, and demonstrates how our approach can be applied to evaluate changes in food prices in response to imported input price shocks.

7 Conclusion

Previous studies on the price of imported inputs have predominantly focused on vertical price transmission or upstream price development. However, much less attention has paid to the pass-through of a cost shock to an industry through markup adjustments. When firms face cost shocks resulting from increased imported crop prices, the extent of pass-through depends on whether the firms absorb or transfer these cost burdens to consumers through higher markups. In this respect, this paper introduces a novel framework to evaluate the cost pass-through of imported crop prices on domestic food prices in agricultural importing economies, and empirically measures the degree of such cost transmission.

Building on DLW, our framework measures cost pass-through elasticity based on firm-level markup elasticity. Our analysis covers firms in the nine sectors constituting the Korean food industry from 2000 to 2021. South Korea's position as a small open economy in the world grain market, characterized as a typical inelastic customer without market power, suggests that our approach has a potential for application in the similar small open economy contexts.

[12] As we did for the crop price series during the 2000-2021 period, import prices for each crop in 2022 – total, corn, soybean, and wheat – are also sourced from the FAO detailed trade matrix, and adjusted by the KRW/USD exchange rate and the GDP deflator specific to South Korea in 2022, obtained from FRED.

[13] Bank of Korea provides PPI data at the product-level, and we match them with the KSIC sectoral classification. However, for some products the data are aggregated into multiple categories or decomposed in detail. Yet, we cannot simply aggregate or average them as the data take an index form. Thus, we only present the calculation results of actual PPI changes only if they are matched to sectoral classification and directly compared with our sector-average elasticities. For example, while we have PPI data for *Milled Cereals* and *Starch and Starch Products*, it is not presented in the paragraph because they cannot be directly compared to the price increase in the "Grain mills and Starch" sector, predicted by our model.

The key findings of this paper have important implications for the South Korean food industry. First, our markup analysis reveals a polarization trend in firm markup distribution throughout the study period, with firms in the higher percentiles experiencing a more rapid increase in markups, which indicates a widening disparity in markups across firms. Second, we observe heterogenous impacts of the cost shock on the pass-through outcomes across sectors and market stages, with increasing cost pass-through elasticities during the last six years of our sample. This suggests a heightened impact of global food supply shocks on general food consumers, with the potential for further exacerbation if the global supply chain experiences additional supply shocks. Lastly, our model predicts a 8.97% increase in food prices in South Korea due to crop price shocks during the 2021-2022 period.

It is crucial to emphasize that this paper demonstrates the significant impact of imported crop prices on the food price increase in South Korea, and this impact has gradually intensified over time. Additionally, we highlight the generality and applicability of our approach in evaluating the transmission of cost shocks in a small open economy.

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Tables and Figures

Table 1. Summary statistics of firm financial variables and imported crop prices

Variable / Mean	All years	Period 2000-2004	2005-2010	2011-2015	2016-2021
No. of Firms	10,780*	2,427	1,135	3,005	4,213
No. of Observations	63,876*	8,591	7,858	15,513	31,914
Firm financial variables (Million KRW unless denoted)					
Sales	24,950	29,717	34,018	24,700	21,556
COGS	18,389	21,525	24,635	18,400	16,001
Material Cost	16,908	19,784	22,604	17,006	14,685
Capital Cost	3,293	4,011	4,565	3,289	2,789
Labor Cost	1,492	1,617	1,960	1,462	1,357
SG&A	4,888	5,897	7,012	4,771	4,151
Large Firms (%)	6.72	6.55	6.87	6.71	6.74
Firm type: Mixed (%)	90.37	83.94	85.73	90.54	93.15
Firm type: Wholesaler (%)	8.47	15.28	13.5	8.56	5.36
Firm type: Retailer (%)	1.16	0.78	0.76	0.9	1.49
Imported crop prices (1,000 KRW/ton)					
All	334	244	363	404	317
Corn	251	188	281	308	234
Soybean	545	393	564	669	521
Wheat	303	241	351	355	282
Tapioca	2,534	2,360	1,665	2,705	2,711
Sugar, centrifugal	432	310	472	535	406
Cocoa bean	3,401	2,706	3,467	3,438	3,555
Coffee bean	3,250	1,742	2,945	3,961	3,386
Sesame seed	1,829	1,200	1,755	2,242	1,816

Source: KISVALUE and FAO

Note: The total number of firms and observations are denoted in the "All years" column, with asterisks marked (*), and all others indicate the average of relevant variables during the designated period. The series of firm financial variables are deflated by (sub)sector-specific PPI. Crop item "All" represents the (quantity-weighted) average index for eight crops considered in the analysis. Import prices are converted from USD into KRW, using the exchange rate and GDP deflator specific to South Korea obtained from the Federal Reserve Bank of St. Louis.

Table 2. Distribution of firm-level markups by sector

Sector name (KSIC code)	percentile	2000-2004		2005-2010		2011-2015		2016-2021	
		Period							
Meat (101)	25th	0.92	(-5%)	0.93	(-5%)	0.92	(-5%)	0.91	(-6%)
	Median	0.97	(--)	0.98	(--)	0.97	(--)	0.96	(--)
	75th	1.06	(9%)	1.06	(9%)	1.05	(9%)	1.05	(9%)
Seafood (102)	25th	0.96	(-5%)	0.97	(-5%)	0.96	(-6%)	0.94	(-5%)
	Median	1.02	(--)	1.02	(--)	1.02	(--)	0.99	(--)
	75th	1.10	(8%)	1.10	(8%)	1.12	(10%)	1.10	(10%)
Fruit and vegetable (103)	25th	1.03	(-7%)	1.04	(-7%)	1.02	(-7%)	1.01	(-8%)
	Median	1.11	(--)	1.11	(--)	1.09	(--)	1.10	(--)
	75th	1.25	(12%)	1.24	(12%)	1.30	(19%)	1.28	(17%)
Oil and fat (104)	25th	0.97	(-3%)	0.96	(-3%)	0.97	(-4%)	0.95	(-5%)
	Median	1.00	(--)	1.00	(--)	1.01	(--)	1.00	(--)
	75th	1.06	(6%)	1.07	(7%)	1.08	(7%)	1.11	(12%)
Dairy (105)	25th	1.06	(-10%)	1.05	(-8%)	1.04	(-7%)	1.04	(-10%)
	Median	1.17	(--)	1.15	(--)	1.13	(--)	1.15	(--)
	75th	1.31	(11%)	1.24	(7%)	1.26	(11%)	1.44	(25%)
Grain mill and starch (106)	25th	1.01	(-7%)	1.01	(-8%)	1.02	(-7%)	1.01	(-8%)
	Median	1.09	(--)	1.10	(--)	1.09	(--)	1.10	(--)
	75th	1.18	(9%)	1.24	(13%)	1.25	(15%)	1.29	(17%)
Others (107)	25th	1.05	(-8%)	1.07	(-8%)	1.07	(-9%)	1.07	(-11%)
	Median	1.14	(--)	1.16	(--)	1.17	(--)	1.20	(--)
	75th	1.30	(14%)	1.34	(15%)	1.37	(17%)	1.45	(21%)
Alcoholic beverages (111)	25th	1.22	(-20%)	1.23	(-17%)	1.21	(-14%)	1.27	(-17%)
	Median	1.52	(--)	1.48	(--)	1.41	(--)	1.53	(--)
	75th	1.87	(23%)	1.80	(21%)	1.76	(24%)	1.89	(24%)
Non-alcoholic beverages (112)	25th	1.10	(-15%)	1.09	(-15%)	1.09	(-13%)	1.13	(-12%)
	Median	1.29	(--)	1.27	(--)	1.25	(--)	1.28	(--)
	75th	1.60	(23%)	1.60	(26%)	1.53	(22%)	1.56	(21%)

Note: At a given percentile and sector, the reported values are calculated by averaging the markups observed for each year within the specified period. Numbers in parenthesis indicate the percentage difference from the median.

Table 3. Fixed-effect regression of markup response to import crop prices

Dependent variable: $\boldsymbol{\mu_{it}}$			
	Market stage interaction index		
$\ln P_t^G$ (*interacted with*)	$\times I_{v[i]}$ (Mixed)	$\times I_{v[i]}$ (Wholesale)	$\times I_{v[i]}$ (Retail)
Sector interaction index $\times I_{s[i]}$(Meat)	0.192***	0.165***	0.315***
	(0.03)	(0.03)	(0.07)
$\times I_{s[i]}$(Seafood)	0.218***	0.196***	0.346***
	(0.03)	(0.03)	(0.07)
$\times I_{s[i]}$(Fruit and vegetable)	0.199***	0.172***	0.339***
	(0.03)	(0.04)	(0.07)
$\times I_{s[i]}$(Oil and fat)	0.220***	0.188***	0
	(0.04)	(0.04)	(.)
$\times I_{s[i]}$(Dairy)	0.157***	0.130**	0.289***
	(0.04)	(0.05)	(0.08)
$\times I_{s[i]}$(Grain mill and starch)	0.200***	0.170***	0.321***
	(0.03)	(0.04)	(0.07)
$\times I_{s[i]}$(Others)	0.208***	0.179***	0.341***
	(0.03)	(0.03)	(0.07)
$\times I_{s[i]}$(Alcoholic bev)	0.126	0.122	0.267**
	(0.08)	(0.08)	(0.10)
$\times I_{s[i]}$(Non-alcoholic bev)	0.167***	0.137**	0.293***
	(0.05)	(0.05)	(0.08)
$\ln P_t^{oil}$	-0.086***		
	(0.02)		
I_{it}^{large}	-0.012*		
	(0.01)		
Constant	-0.372		
	(0.23)		
Year FE (22)	Y		
Sector FE (9)	Y		
Market Stage FE (3)	Y		
N	63,876		

Note: Observations within the upper and lower 1% of the markup distribution are used in the estimation, with those outside this range dropped each year. Coefficient estimate for the "Oil and fat – Retail" sector is not obtained as there are no observations in this sector. Robust standard errors are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. Cost pass-through elasticity by sector and market stage

Sector (KSIC 3-digits)	Market stage	Entire period	Period 2000-2004	2005-2010	2011-2015	2016-2021
Meat (101)	Mixed	0.199	0.193	0.197	0.198	0.202
	Wholesale	0.172	0.173	0.171	0.172	0.171
	Retail	0.353				0.353
Seafood (102)	Mixed	0.222	0.222	0.217	0.218	0.225
	Wholesale	0.198	0.199	0.196	0.193	0.202
	Retail	0.368			0.358	0.372
Fruit and Vegetable (103)	Mixed	0.190	0.182	0.185	0.189	0.192
	Wholesale	0.150	0.150	0.139	0.147	0.155
	Retail	0.299			0.331	0.291
Oil and fat (104)	Mixed	0.393	0.396	0.397	0.396	0.389
	Wholesale	0.368	0.368	0.369	0.368	0.369
Dairy (105)	Mixed	0.139	0.130	0.136	0.139	0.144
	Wholesale	0.102	0.102	0.101	0.102	0.105
Grain mills and Starch (106)	Mixed	0.406	0.404	0.412	0.411	0.404
	Wholesale	0.359	0.373	0.360	0.360	0.351
	Retail	0.510				0.510
Others (107)	Mixed	0.204	0.198	0.200	0.205	0.207
	Wholesale	0.178	0.171	0.166	0.181	0.188
	Retail	0.350	0.328	0.364	0.363	0.348
Alcoholic Beverage (111)	Mixed	0.086	0.095	0.094	0.091	0.081
	Wholesale	0.085		0.085	0.086	0.087
Non-alcoholic Beverage (112)	Mixed	0.123	0.118	0.117	0.122	0.128
	Wholesale	0.123	0.127	0.125	0.122	0.118

Note: The sectoral average pass-through is calculated using the sales-weighted average as described in (15). Pass-through elasticities are calculated for observations within the upper and lower 1% of the markup distribution each year. We drop small categories with less than 5 observations.

Table 5. Pass-through elasticities estimated from dynamic panel regression

Dependent variable: $\ln y_{j,t}$		(1) G = All	(2) G = Corn	(3) G = Soy	(4) G = Wheat
$\ln y_{j,t-1}$		1.079^{***}	1.008^{***}	1.074^{***}	1.037^{***}
		(0.249)	(0.234)	(0.248)	(0.242)
$\ln y_{j,t-2}$		-0.205	-0.147	-0.201	-0.168
		(0.206)	(0.192)	(0.205)	(0.199)
$\ln P_t^G$ (short-term pass-through estimates)		0.195^{**}	0.262^{***}	0.161^{**}	0.248^{**}
		(0.066)	(0.076)	(0.054)	(0.080)
$\ln P_t^{oil}$		-0.053	-0.111^{**}	-0.041	-0.025
		(0.027)	(0.038)	(0.023)	(0.017)
Constant		-1.310^{***}	-1.394^{***}	-1.074^{***}	-2.238^{***}
		(0.390)	(0.382)	(0.313)	(0.668)
Dynamic Multiplier		1.547^{***}	1.886^{***}	1.270^{***}	1.896^{***}
(Long-run pass-through estimates)		(0.17)	(0.19)	(0.14)	(0.21)
Item FE (81)		Y	Y	Y	Y
Year FE (22)		Y	Y	Y	Y
N		1,419	1,419	1,419	1,419
AR (1)		-2.03^{**}	-2.00^{**}	-2.01^{**}	-2.00^{**}
AR (2)		-0.80	-0.99	-0.81	-0.89
Sargan-Hansen Test:	2-step w. matrix	8.91	9.67	8.83	8.67
	3-step w. matrix	9.19	9.45	9.29	10.11

Note: Robust standard errors are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Z-statistics and chi-square statistics are reported in the last four columns, showing the results of the Sargan-Hansen overidentifying restrictions.

Table 6. Imputing Food Price Changes using the 2022 Imported Crop Price Shock

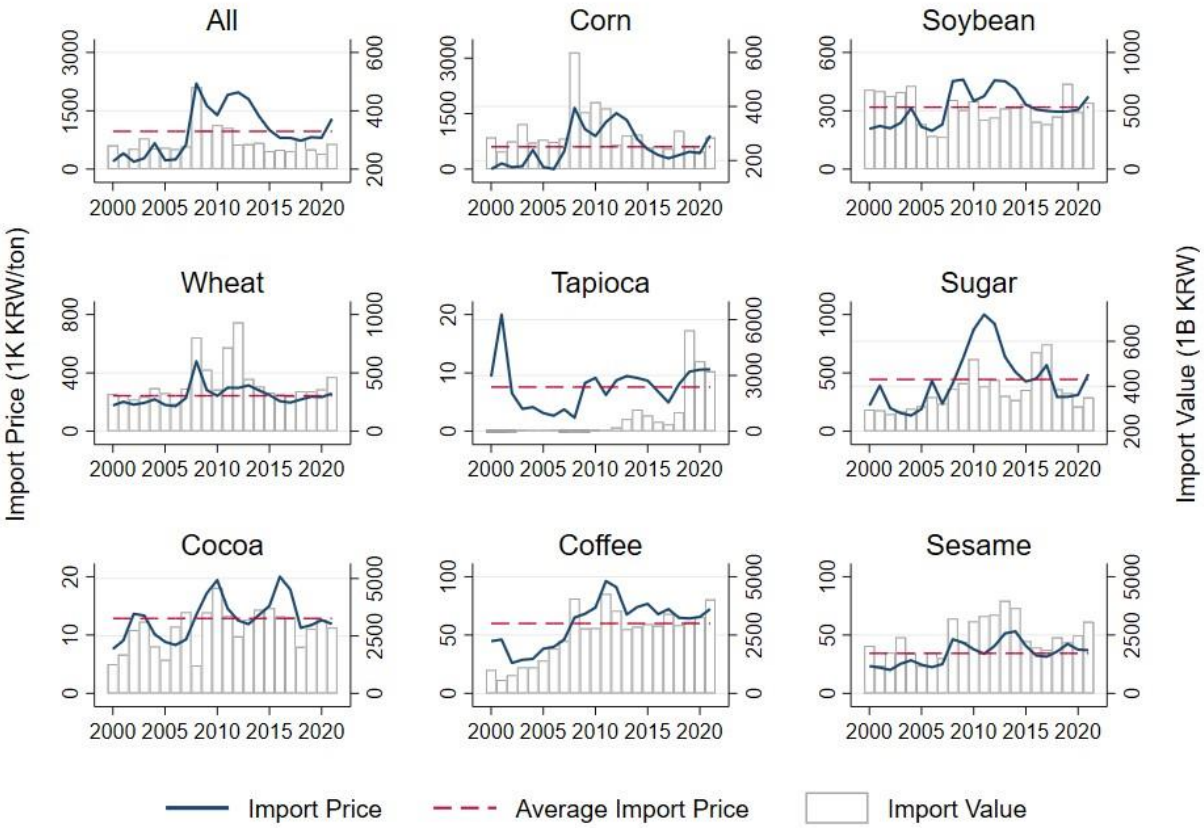
	Crop ("All" 8 commodities)				
		Model Prediction			
Sector (KSIC 3-digits)	*Observed* ΔPPI	Sector Average	Mixed	Wholesale	Retail
Total (Industry average)	***8.88%***	***8.97%***	---	---	---
Meat (101)	8.68%	9.11%	9.20%	7.73%	16.33%
Seafood (102)	6.88%	10.07%	10.07%	9.28%	16.61%
Fruit and Vegetable (103)	6.77%	8.67%	8.68%	7.12%	11.36%
Oil and fat (104)	--	17.32%	17.76%	*16.67%*	
Dairy (105)	4.78%	5.98%	6.52%	4.88%	
Grain mills and Starch (106)	--	17.24%	18.53%	16.01%	22.95%
Others (107)	--	9.12%	9.48%	8.58%	15.49%
Alcoholic Beverage (111)	6.05%	3.77%	3.75%		
Non-alcoholic Beverage (112)	5.01%	5.81%	5.82%	5.37%	

%Change of import crop price from 2021 to 2022 : 45.3%

- Import price in 2022 (1,000 KRW/ton) : 542
- Import price in 2021 (1,000 KRW/ton) : 373

Note: Pass-through elasticities are calculated for categories with more than 5 observations.

Figure 1. Imported crop market situation in South Korea



Note: Import prices are expressed in 1,000 KRW/ton and import values in a billion KRW. All series are adjusted by GDP deflator and KRW-dollar exchange rates.

Figure 2. Markup of the Korean food industry, 2000-2021

Fig 2-(a) Time Trend of Industry Markups

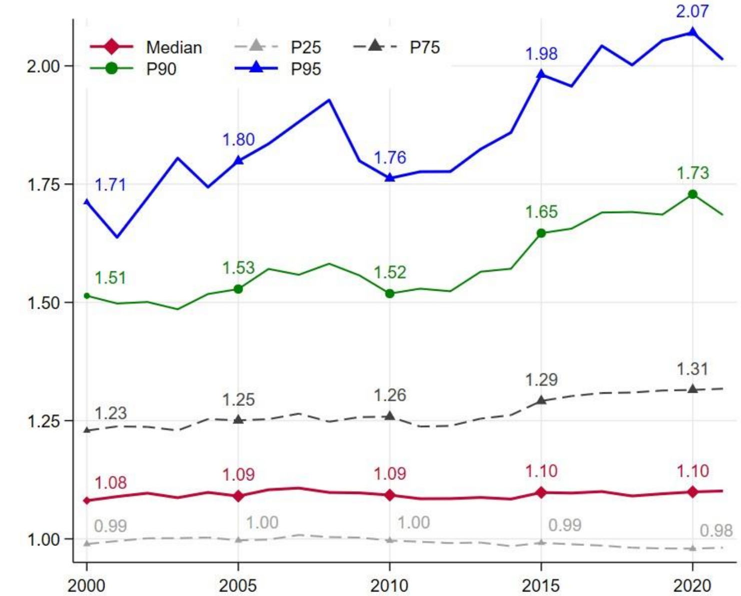
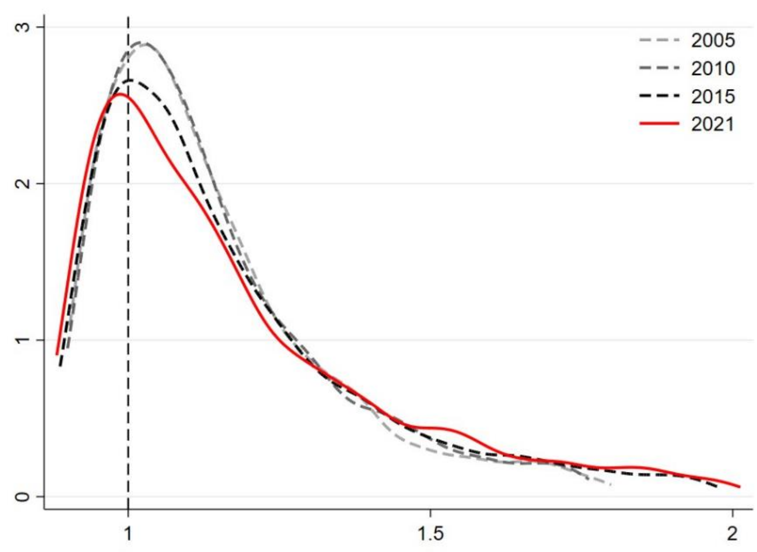


Fig 2-(b) Kernel density of firm-level markups



Note: **(A)** The trend represents statistics, such as quartiles, 90-th, and 95-th percentiles, of markups of each year. **(B)** The kernel density is generated without weighting the firms' revenues. Also, to remove extreme cases, we have trimmed the top 1% and bottom 1% of markup observations.

Figure 3: Sector-specific markup trends, 2000-2021

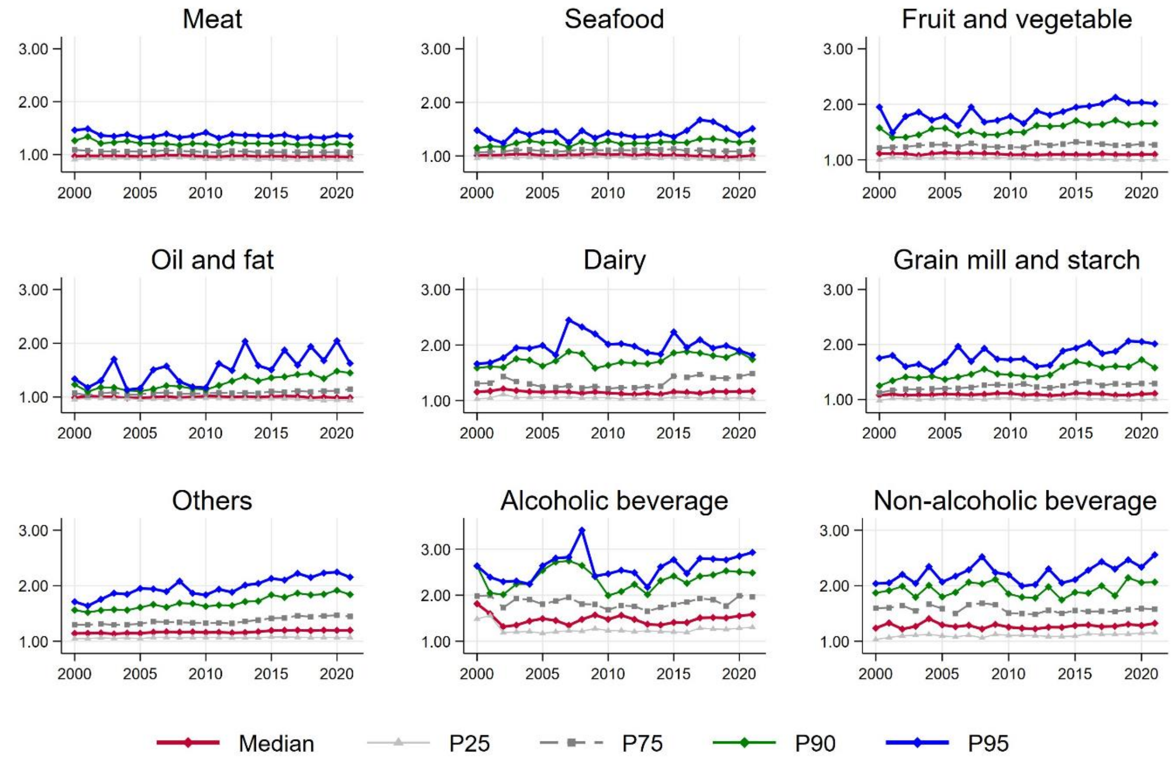
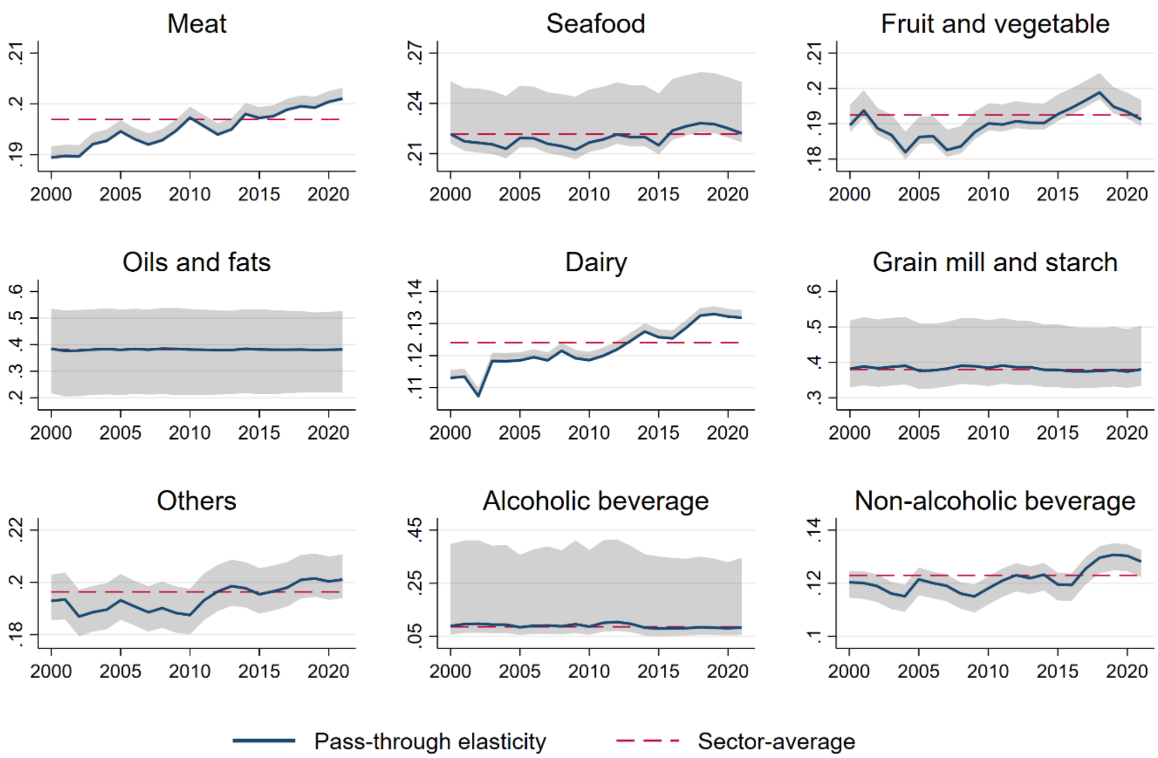


Figure 4. Sector-specific pass-through elasticity dynamics



Note: The shaded area illustrates the range of pass-through elasticity that captures the potential impact of measurement error in κ_{it}. In addition to relying on the subsector-specific average of crop expenditure share during 2011-2021, $\kappa_{b[i]}$ (the solid line), we use the observed minimum level and maximum level of expenditure shares of each subsector. They approximate reasonable lower bound and upper bound of pass-through elasticity.

ONLINE SUPPLEMENTARY APPENDIX

Measuring Agricultural Price Shocks in a Small Open Economy:
Imported Crop in South Korea

Minseong Kang and Seungki Lee

Supplementary Tables

Appendix Table S1. Firm-level summary statistics by firm size and firm type

Firm Size/ Firm Type	Variable	All years average	Period 2000-2004	2005-2010	2011-2015	2016-2021
Firm size: Large	Sales	292,284	350,617	376,949	289,816	256,938
	COGS	207,481	241,596	259,394	208,608	184,962
	Material Cost	189,551	220,259	235,704	191,856	168,802
	Capital Cost	41,414	50,787	54,568	41,816	35,461
	Labor Cost	18,069	19,848	22,899	17,581	16,626
	SG&A	62,727	77,541	87,012	61,255	53,462
Firm size: Others	Sales	5,684	7,212	8,713	5,630	4,553
	COGS	4,761	6,091	7,312	4,718	3,797
	Material Cost	4,466	5,724	6,879	4,428	3,552
	Capital Cost	546	730	876	517	429
	Labor Cost	297	338	415	303	254
	SG&A	720	872	1,109	708	589
Firm type: Mixed	Sales	23,390	26,120	18,156	15,441	18,341
	COGS	16,975	19,389	13,626	11,452	13,597
	Material Cost	15,536	17,810	12,588	10,497	12,489
	Capital Cost	3,098	3,313	2,225	1,922	2,305
	Labor Cost	1,350	1,528	1,080	991	1,120
	SG&A	4,535	5,019	3,380	2,931	3,485
Firm type: Wholesaler	Sales	65,503	84,957	94,938	131,571	97,421
	COGS	47,189	58,317	69,439	97,667	70,785
	Material Cost	43,717	53,324	64,181	89,818	65,193
	Capital Cost	9,183	12,633	14,729	18,389	14,130
	Labor Cost	3,148	4,788	5,611	7,965	5,596
	SG&A	13,631	19,992	19,855	26,181	20,372
Firm type: Retailer	Sales	9,319	20,110	14,957	7,955	10,379
	COGS	8,288	18,121	13,209	6,578	8,915
	Material Cost	7,910	17,579	12,739	6,148	8,473
	Capital Cost	892	2,473	1,436	855	1,099
	Labor Cost	339	491	489	449	450
	SG&A	855	1,296	1,168	1,115	1,116

Note: All values have a unit of million KRW.

Appendix Table S2. Robustness check without market stage interactions (comparable to Table 3)

Dependent variable: μ_{it}	(1) G = Total	(2) G = Corn	(3) G = Soybean	(4) G = Wheat
$\ln P_t^G \times I_{s[i]}(\textit{Meat})$	0.187***	0.200***	0.140***	0.233***
	(0.03)	(0.03)	(0.02)	(0.03)
$\ln P_t^G \times I_{s[i]}(\textit{Seafood})$	0.212***	0.214***	0.162***	0.246***
	(0.03)	(0.03)	(0.02)	(0.03)
$\ln P_t^G \times I_{s[i]}(\textit{Fruit and vegetable})$	0.197***	0.200***	0.158***	0.233***
	(0.03)	(0.03)	(0.03)	(0.04)
$\ln P_t^G \times I_{s[i]}(\textit{Oil and fat})$	0.218***	0.213***	0.179***	0.237***
	(0.04)	(0.04)	(0.03)	(0.04)
$\ln P_t^G \times I_{s[i]}(\textit{Dairy})$	0.149***	0.153***	0.114**	0.191***
	(0.04)	(0.04)	(0.04)	(0.05)
$\ln P_t^G \times I_{s[i]}(\textit{Grain mill and starch})$	0.196***	0.186***	0.155***	0.227***
	(0.03)	(0.03)	(0.03)	(0.04)
$\ln P_t^G \times I_{s[i]}(\textit{Others})$	0.205***	0.190***	0.170***	0.221***
	(0.03)	(0.03)	(0.02)	(0.03)
$\ln P_t^G \times I_{s[i]}(\textit{Alcoholic beverages})$	0.14	0.146*	0.090	0.194*
	(0.08)	(0.07)	(0.07)	(0.09)
$\ln P_t^G \times I_{s[i]}(\textit{Non-alcoholic beverages})$	0.164***	0.178***	0.134***	0.214***
	(0.05)	(0.04)	(0.04)	(0.05)
$\ln P_t^{oil}$	-0.084***	-0.107***	-0.071***	-0.053**
	(0.02)	(0.02)	(0.02)	(0.02)
I_{it}^{large}	-0.011*	-0.011*	-0.011*	-0.011*
	(0.01)	(0.01)	(0.01)	(0.01)
Constant	-0.360	-0.024	-0.073	-1.063***
	(0.23)	(0.20)	(0.20)	(0.31)
Year FE	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y
Market Stage FE	Y	Y	Y	Y
N	63,876	63,876	63,876	63,876

Note: Observations within the upper and lower 1% of the markup distribution are used in the estimation, with those outside this range dropped each year. Robust standard errors are in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01.

Appendix Table S3. Robustness check with firm fixed effects (comparable to Table 3)

Dependent variable: μ_{it}	(1) G = Total	(2) G = Corn	(3) G = Soy	(4) G = Wheat
$\ln P_t^G \times I_{s[i]}$(Meat) $\times I_{v[i]}$(Mixed)	0.096***	0.097***	0.080***	0.105***
	(0.02)	(0.02)	(0.02)	(0.03)
$\ln P_t^G \times I_{s[i]}$(Meat) $\times I_{v[i]}$(Wholesale)	0.108***	0.102***	0.088***	0.104***
	(0.03)	(0.02)	(0.02)	(0.03)
$\ln P_t^G \times I_{s[i]}$(Meat) $\times I_{v[i]}$(Retail)	0.157**	0.144**	0.124*	0.154***
	(0.06)	(0.05)	(0.05)	(0.04)
$\ln P_t^G \times I_{s[i]}$(Seafood) $\times I_{v[i]}$(Mixed)	0.124***	0.116***	0.099***	0.125***
	(0.03)	(0.02)	(0.02)	(0.03)
$\ln P_t^G \times I_{s[i]}$(Seafood) $\times I_{v[i]}$(Wholesale)	0.059	0.057	0.051	0.063
	(0.05)	(0.04)	(0.04)	(0.04)
$\ln P_t^G \times I_{s[i]}$(Seafood) $\times I_{v[i]}$(Retail)	0.046	0.058	0.024	0.059
	(0.09)	(0.07)	(0.09)	(0.08)
$\ln P_t^G \times I_{s[i]}$(Fruit and vegetable) $\times I_{v[i]}$(Mixed)	0.065*	0.072*	0.057*	0.082*
	(0.03)	(0.03)	(0.03)	(0.03)
$\ln P_t^G \times I_{s[i]}$(Fruit and vegetable) $\times I_{v[i]}$(Wholesale)	0.027	0.041	0.016	0.058
	(0.05)	(0.04)	(0.04)	(0.05)
$\ln P_t^G \times I_{s[i]}$(Fruit and vegetable) $\times I_{v[i]}$(Retail)	0.302**	0.259**	0.293***	0.241**
	(0.09)	(0.09)	(0.08)	(0.09)
$\ln P_t^G \times I_{s[i]}$(Oil and fat) $\times I_{v[i]}$(Mixed)	0.06	0.070*	0.046	0.082*
	(0.03)	(0.03)	(0.03)	(0.03)
$\ln P_t^G \times I_{s[i]}$(Oil and fat) $\times I_{v[i]}$(Wholesale)	0.044	0.05	0.028	0.055
	(0.03)	(0.03)	(0.03)	(0.03)
$\ln P_t^G \times I_{s[i]}$(Oil and fat) $\times I_{v[i]}$(Retail)	0	0	0	0
	(.)	(.)	(.)	(.)
$\ln P_t^G \times I_{s[i]}$(Dairy) $\times I_{v[i]}$(Mixed)	0.047	0.061	0.031	0.074*
	(0.04)	(0.03)	(0.03)	(0.04)
$\ln P_t^G \times I_{s[i]}$(Dairy) $\times I_{v[i]}$(Wholesale)	0.063	0.067	0.047	0.092
	(0.07)	(0.06)	(0.06)	(0.08)
$\ln P_t^G \times I_{s[i]}$(Dairy) $\times I_{v[i]}$(Retail)	0.503	0.311	0.687	0.412
	(0.87)	(0.66)	(0.61)	(0.74)
$\ln P_t^G \times I_{s[i]}$(Grain mill) $\times I_{v[i]}$(Mixed)	0.075**	0.069*	0.051*	0.088**
	(0.03)	(0.03)	(0.02)	(0.03)
$\ln P_t^G \times I_{s[i]}$(Grain mill) $\times I_{v[i]}$(Wholesale)	-0.015	-0.001	-0.033	0.016
	(0.05)	(0.05)	(0.05)	(0.06)
$\ln P_t^G \times I_{s[i]}$(Grain mill) $\times I_{v[i]}$(Retail)	0.670***	0.565**	0.549**	0.537**
	(0.20)	(0.18)	(0.18)	(0.20)
$\ln P_t^G \times I_{s[i]}$(Others) $\times I_{v[i]}$(Mixed)	0.062**	0.057*	0.049*	0.067*
	(0.02)	(0.02)	(0.02)	(0.03)
$\ln P_t^G \times I_{s[i]}$(Others) $\times I_{v[i]}$(Wholesale)	0.059*	0.061*	0.045	0.072*
	(0.03)	(0.03)	(0.02)	(0.03)
$\ln P_t^G \times I_{s[i]}$(Others) $\times I_{v[i]}$(Retail)	0.022	-0.019	0.051	0.003
	(0.08)	(0.08)	(0.08)	(0.09)

$\ln P_t^G \times I_{s[i]}$(Alcoholic beverage) $\times I_{v[i]}$(Mixed)	0.008	0.026	-0.018	0.058
	(0.06)	(0.06)	(0.05)	(0.06)
$\ln P_t^G \times I_{s[i]}$(Alcoholic beverage) $\times I_{v[i]}$(Wholesale)	-0.155	-0.10	-0.164	0.064
	(0.26)	(0.24)	(0.20)	(0.29)
$\ln P_t^G \times I_{s[i]}$(Alcoholic beverage) $\times I_{v[i]}$(Retail)	0.799	0.301	1.061	0.597
	(1.46)	(0.88)	(1.30)	(1.57)
$\ln P_t^G \times I_{s[i]}$(Non-alcoholic bev.) $\times I_{v[i]}$(Mixed)	0.059	0.075*	0.053	0.096*
	(0.04)	(0.04)	(0.03)	(0.04)
$\ln P_t^G \times I_{s[i]}$(Non-alcoholic bev.) $\times I_{v[i]}$(Wholesale)	-0.102	-0.094	-0.063	-0.085
	(0.08)	(0.07)	(0.08)	(0.08)
$\ln P_t^G \times I_{s[i]}$(Non-alcoholic bev.) $\times I_{v[i]}$(Retail)	-1.487	-1.151	-1.131	-3.124***
	(0.80)	(0.65)	(0.65)	(0.94)
$ln\, P_t^{OIL}$	-0.045***	-0.053***	-0.040**	-0.032**
	(0.01)	(0.02)	(0.01)	(0.01)
Constant	0.744***	0.873***	0.849***	0.494
	(0.20)	(0.17)	(0.17)	(0.27)
Year Dummy	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
N	62,264	62,264	62,264	62,264

Note: Observations within the upper and lower 1% of the markup distribution are used in the estimation, with those outside this range dropped each year. In the firm fixed-effect model, firms with only one observation are dropped. Thus, 1,612 firms are excluded from the estimation, leaving a total of 62,264 observations. Robust standard errors are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table S4. Market share of sample firms

		Total Sales (in billion KRW)		Market Share of Sample Firms (%)	
	(1)	(2)	(3)	(4)	(5)
Year	No. Firm	Sample	Population	Before adjustment	After adjustment
2000	1,092	37,584	60,484	0.621	0.621
2001	1,363	38,442	62,524	0.615	0.615
2002	1,569	43,155	66,437	0.650	0.650
2003	1,589	46,746	65,935	0.709	0.709
2004	1,489	46,302	67,658	0.684	0.684
2005	1,489	43,069	67,001	0.643	0.643
2006	1,557	44,201	67,329	0.656	0.656
2007	1,503	48,568	70,142	0.692	0.692
2008	1,563	56,440	70,012	0.806	0.806
2009	1,525	55,902	71,124	0.786	0.786
2010	1,710	62,202	73,400	0.847	0.847
2011	2,062	63,972	75,668	0.845	0.845
2012	2,554	73,928	78,021	0.948	0.948
2013	3,097	76,376	78,973	0.967	0.967
2014	3,631	81,792	80,363	1.018	1.000
2015	4,169	87,106	83,937	1.038	1.000
2016	4,640	93,351	108,389	0.861	0.861
2017	5,120	100,134	112,480	0.890	0.890
2018	5,363	116,557	119,849	0.973	0.973
2019	5,752	126,191	123,344	1.023	1.000
2020	5,672	122,938	121,691	1.010	1.000
2021	5,367	128,769	137,338	0.938	0.938
Total	63,876	89,122	97,289	0.896	0.889

Note: Column (1) represents the number of firms in our sample. Columns (2) and (3) present total sales from our sample and the entire market, respectively.

Appendix Table S5. Summary statistics of κ_{it} (unweighted)

	Sector (KSIC 3-digits)					
	Meat (101)		Seafood (102)		Fruit and Veg. (103)	
Crop	Mean	Max	Mean	Max	Mean	Max
All	0.000	0.003	0.007	0.045	0.002	0.009
Corn	0.000	0.000	0.000	0.000	0.000	0.000
Soy	0.000	0.001	0.000	0.001	0.000	0.001
Wheat	0.000	0.000	0.000	0.000	0.000	0.000
Tapioca	0.000	0.000	0.000	0.004	0.000	0.000
Raw Sugar	0.000	0.000	0.000	0.000	0.000	0.000
Cocoa beans	-	-	-	-	-	-
Coffee beans	-	-	0.000	0.000	-	-
Sesame seed	0.000	0.003	0.007	0.045	0.002	0.009
	Oil and fat (104)		Dairy (105)		Grain mill and starch (106)	
Crop	Mean	Max	Mean	Max	Mean	Max
All	0.208	0.388	0.001	0.004	0.275	0.445
Corn	0.012	0.023	-	-	0.110	0.201
Soy	0.192	0.376	0.000	0.001	0.000	0.001
Wheat	0.000	0.000	-	-	0.153	0.202
Tapioca	0.000	0.000	-	-	0.004	0.050
Raw Sugar	-	-	0.000	0.000	0.006	0.017
Cocoa beans	-	-	0.000	0.000	-	-
Coffee beans	-	-	0.000	0.003	0.000	0.000
Sesame seed	0.004	0.030	0.000	0.000	0.001	0.008
	Others (107)		Alcoholic Bev. (111)		Non-alcoholic Bev. (112)	
Crop	Mean	Max	Mean	Max	Mean	Max
All	0.033	0.046	0.040	0.416	0.013	0.019
Corn	0.000	0.002	0.000	0.000	0.000	0.000
Soy	0.004	0.007	-	-	0.008	0.019
Wheat	0.000	0.001	0.000	0.002	-	-
Tapioca	0.005	0.012	0.040	0.414	0.000	0.000
Raw Sugar	0.017	0.038	0.000	0.000	0.000	0.000
Cocoa beans	0.000	0.001	-	-	0.000	0.000
Coffee beans	0.005	0.008	-	-	0.005	0.012
Sesame seed	0.001	0.002	-	-	0.000	0.001

Note: Summary Statistics are reported only for subsectors with κ_{it}. The minimum value of κ_{it} is 0 for all subsectors. Zero-values are recorded as “-”.

Appendix Table S6. Raw ingredient usage by Korean food processing firms in 2021

Item	Total	Imported Inputs		Item	Total	Imported Inputs	
Tapioca	98,177	98,177	(100.0%)	Green Onion	33,893	3,359	(9.9%)
Centrifugal Sugar	1,860,733	1,860,733	(100.0%)	Strawberry	23,095	1,640	(7.1%)
Coffee Bean	85,904	85,904	(100.0%)	Onion	78,004	4,675	(6.0%)
Cocoa Bean	4,072	4,072	(100.0%)	Grapes	6,393	266	(4.2%)
Corn	2,387,679	2,384,757	(99.9%)	Sweet Potato	17,197	418	(2.4%)
Wheat	2,168,996	2,166,868	(99.9%)	Mushroom	1,256	29	(2.3%)
Pollack	44,542	44,344	(99.6%)	Radish	338,658	7,157	(2.1%)
Soybean	1,129,719	1,067029	(94.5%)	Egg	137,126	1,922	(1.4%)
Peanut	12,817	11,688	(91.2%)	Duck Meat	18,633	48	(0.3%)
Sesame	23,469	23,780	(90.4%)	Cabbage	430,478	96	(0.0%)
Red Bean	19,319	15,668	(81.1%)	Ginseng	12,182	0	(0.0%)
Peach	5,459	4,370	(80.1%)	Red Ginseng	1,424	0	(0.0%)
Beef	100,098	76,369	(76.3%)	Cucumber	4,251	0	(0.0%)
Buckwheat	2,949	1,945	(66.0%)	Watermelon	265	0	(0.0%)
Dried Chili	42,868	24,809	(57.9%)	Cantaloupe	105	0	(0.0%)
Squid	93,675	52,853	(56.4%)	Tomato	4,331	0	(0.0%)
Barley	1,339	670	(50.0%)	Apple	49,437	0	(0.0%)
Pepper	20,452	9,839	(48.1%)	Pear	12,512	0	(0.0%)
Rice	605,311	217,190	(35.9%)	Mandarin Orange	137,601	0	(0.0%)
Carrot	12,276	3,813	(31.1%)	Persimmon	17,197	0	(0.0%)
Potato	68,060	18,874	(27.7%)	Asian Plum	993	0	(0.0%)
Pork	429,634	115,982	(27.0%)	Raw Milk	2,408,888	23	(0.0%)
Garlic	54,408	12,575	(23.1%)	Seaweed	220,290	0	(0.0%)
Chicken	336,898	74,380	(22.1%)	Dried Nori	43,487	0	(0.0%)
Ginger	7,999	1,566	(19.6%)				

Note: “Total” is the aggregate quantity of imported and domestic usage of each raw material. Usage units are denoted in tons, and the share of imported is in parentheses.

Appendix Table S7. Cost pass-through elasticity by sector

Sector (KSIC 3-digits)	Crop	All years average	Period 2000-2004	2005-2010	2011-2015	2016-2021
Meat (101)	Total	0.197	0.191	0.194	0.196	0.199
	Corn	0.209	0.203	0.206	0.208	0.212
	Soy	0.147	0.143	0.145	0.147	0.149
	Wheat	0.243	0.236	0.240	0.242	0.246
Seafood (102)	Total	0.222	0.217	0.216	0.219	0.226
	Corn	0.215	0.212	0.210	0.212	0.219
	Soy	0.168	0.162	0.162	0.166	0.171
	Wheat	0.246	0.244	0.241	0.242	0.250
Fruit and Vegetable (103)	Total	0.193	0.187	0.186	0.191	0.195
	Corn	0.191	0.185	0.184	0.189	0.193
	Soy	0.155	0.151	0.151	0.154	0.157
	Wheat	0.221	0.214	0.212	0.219	0.223
Oil and fat (104)	Total	0.381	0.381	0.383	0.382	0.381
	Corn	0.219	0.214	0.216	0.218	0.221
	Soy	0.327	0.326	0.329	0.327	0.327
	Wheat	0.233	0.228	0.230	0.232	0.236
Dairy (105)	Total	0.124	0.115	0.119	0.124	0.131
	Corn	0.127	0.119	0.123	0.127	0.134
	Soy	0.093	0.085	0.089	0.093	0.099
	Wheat	0.159	0.149	0.154	0.159	0.167
Grain mills and Starch (106)	Total	0.380	0.385	0.384	0.383	0.376
	Corn	0.251	0.248	0.250	0.252	0.252
	Soy	0.136	0.126	0.131	0.135	0.139
	Wheat	0.322	0.319	0.321	0.323	0.322
Others (107)	Total	0.196	0.191	0.189	0.196	0.200
	Corn	0.161	0.154	0.153	0.160	0.165
	Soy	0.143	0.138	0.137	0.143	0.146
	Wheat	0.187	0.179	0.178	0.186	0.192
Alcoholic Beverage (111)	Total	0.086	0.092	0.090	0.090	0.082
	Corn	0.058	0.063	0.061	0.061	0.056
	Soy	0.036	0.039	0.037	0.038	0.035
	Wheat	0.077	0.083	0.081	0.081	0.074
Non-alcoholic Beverage (112)	Total	0.123	0.119	0.118	0.122	0.127
	Corn	0.123	0.118	0.117	0.121	0.128
	Soy	0.098	0.095	0.094	0.097	0.102
	Wheat	0.147	0.142	0.141	0.146	0.153

Note: Pass-through at the sector-level is calculated by the sales-weighted average as in (15).

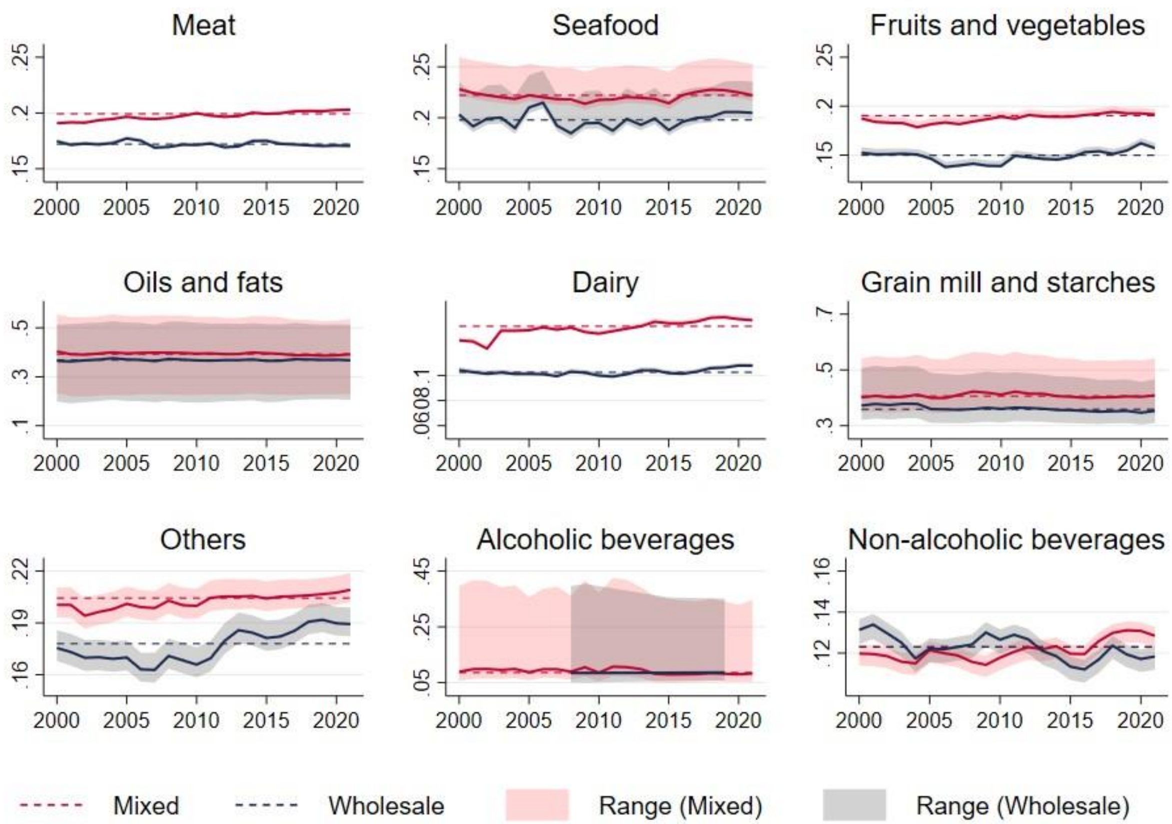
Appendix Table S8. Annual cost pass-through elasticity, aggregated for the entire industry

Year	Total	Corn	Soy	Wheat
2000	0.207	0.166	0.124	0.201
2001	0.203	0.165	0.123	0.199
2002	0.197	0.160	0.120	0.193
2003	0.196	0.161	0.121	0.195
2004	0.200	0.166	0.125	0.199
2005	0.193	0.163	0.126	0.195
2006	0.193	0.163	0.126	0.195
2007	0.192	0.161	0.126	0.193
2008	0.191	0.162	0.128	0.193
2009	0.191	0.161	0.127	0.192
2010	0.189	0.157	0.124	0.187
2011	0.196	0.165	0.131	0.196
2012	0.195	0.164	0.131	0.195
2013	0.199	0.169	0.135	0.201
2014	0.194	0.165	0.131	0.196
2015	0.192	0.163	0.130	0.194
2016	0.192	0.164	0.133	0.194
2017	0.194	0.166	0.135	0.196
2018	0.197	0.169	0.139	0.199
2019	0.197	0.170	0.139	0.200
2020	0.197	0.169	0.138	0.200
2021	0.198	0.170	0.139	0.201
Total	**0.195**	**0.166**	**0.133**	**0.197**

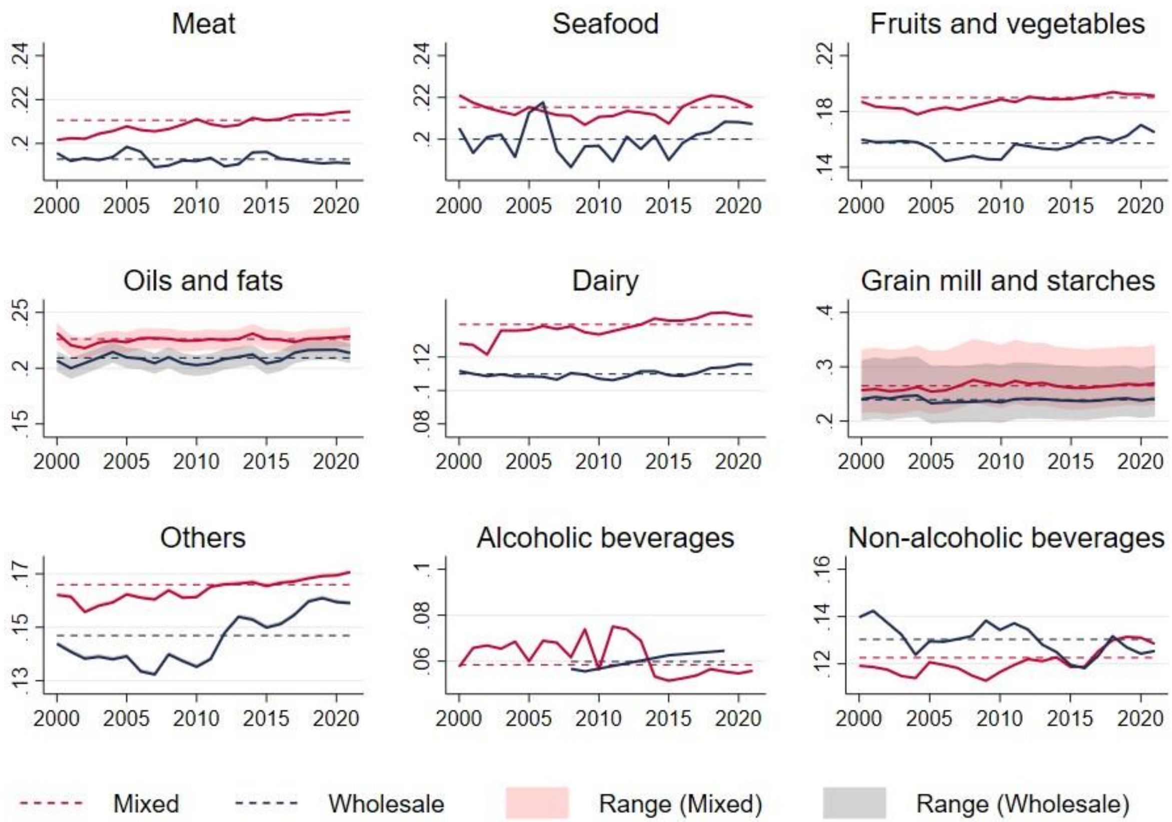
Note: The aggregate pass-through is calculated by the sales-weighted average as in (15).

Supplementary Figures

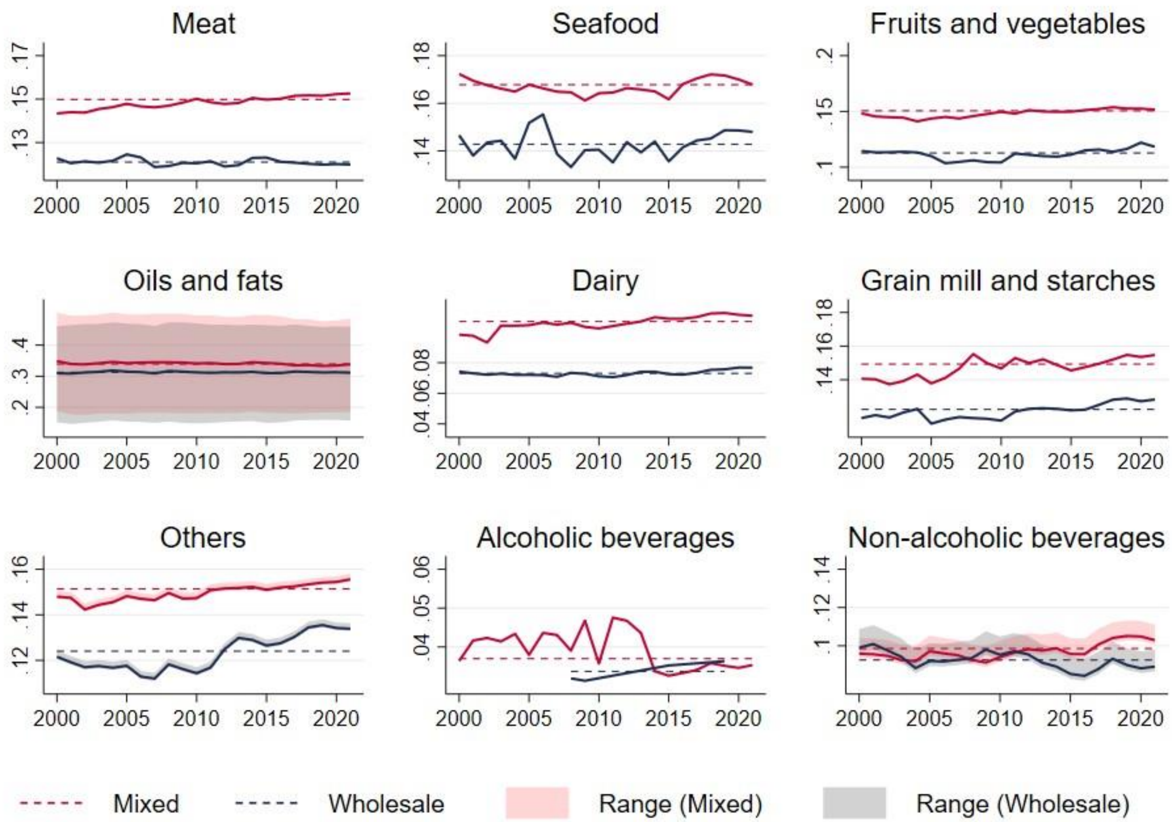
Appendix Figure S1. Pass-through elasticities with two types of firms – mixed and wholesaler – for all 8 imported crops



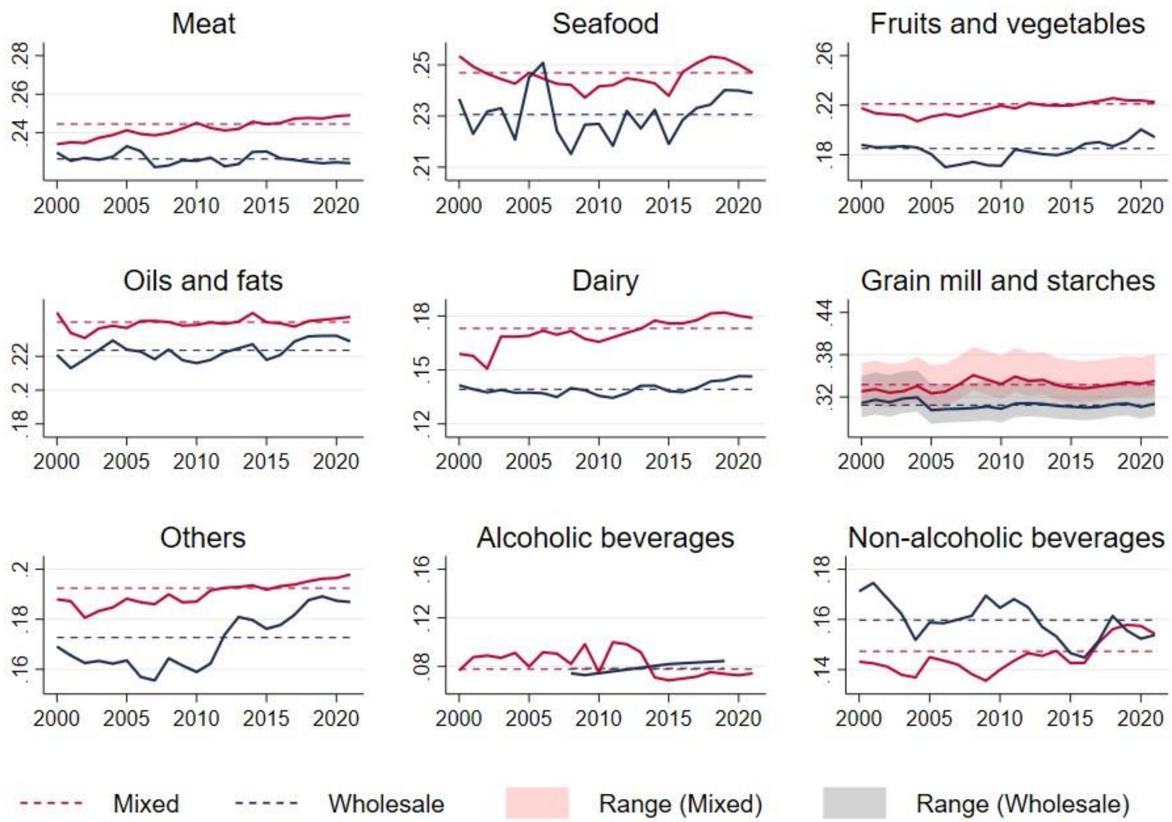
Appendix Figure S2. Pass-through elasticities with two types of firms – mixed and wholesaler – for corn



Appendix Figure S3. Pass-through elasticities with two types of firms – mixed and wholesaler – for soybeans



Appendix Figure S4. Pass-through elasticities with two types of firms – mixed and wholesaler – for wheat



Appendix Figure S5. Comparison of pass-through elasticity between sector fixed effect model and firm fixed effect model