

Price Flexibility, Informal Markets and Monetary Policy*

Giancarlo Oseguera[†] Javier Turen[‡] Alejandro Vicondoa[§]

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Abstract

What are the consequences of monetary policy on price adjustment when we account for the intrinsic formality of the market? Relying on micro prices used to compute the CPI series in Honduras, we study the implications of a US monetary policy shock on price adjustments. A US monetary policy tightening induces a decrease in aggregate prices and activity in Honduras. At the micro level, we show that the pricing response depends significantly on the type of establishment. While prices in formal markets start adjusting one year after the shock, prices in informal markets react promptly to US monetary policy shocks. Outlet characteristics are a determinant of the heterogeneous response across products.

Keywords: Price adjustments, informal markets, monetary policy shocks, CPI microdata.

JEL codes: E31, E32, E52, F41.

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[†]Central Bank of Honduras. Email: giancarlo.oseguera@bch.hn.

[‡]Instituto de Economía, Pontificia Universidad Católica de Chile. Email: jturen@uc.cl.

[§]Instituto de Economía, Pontificia Universidad Católica de Chile. Email: alejandro.vicondoa@uc.cl.

1 Introduction

Monetary policy (MP) generates distributional effects at the household level, with impacts varying by income (Cravino, Lan, and Levchenko, 2020). Similarly, the effectiveness of MP varies depending on the state of the economy (Vavra, 2014; Tenreyro and Thwaites, 2016). While most of this evidence comes from advanced economies, emerging markets exhibit significantly higher levels of informality, which introduces a distinct and underexplored layer that may shape both the distributional and transmission channels of MP. In this context, analyzing how MP affects prices in *formal versus informal* outlets is essential to better understand its heterogeneous and aggregate effects in less-developed economies.

Using a novel dataset from Honduras’ official Consumer Price Index (CPI), we revisit the distributional consequences of MP shocks by focusing on an unexplored dimension: the *retail outlet in which goods are sold*. We study the dynamic response of prices to MP shocks across formal retail channels (e.g., supermarkets or retail stores) and informal markets (e.g., farmers’ markets, street stalls, and corner stores).¹ While information about product-level prices sold at both formal and informal markets is scarce, we rely on detailed information about such prices collected by the Honduran Central Bank to compute the CPI. In fact, around 70% of the price quotes in the Food category of the CPI come from local informal markets. Extending the analysis for prices of goods offered in informal markets may be crucial to further characterize monetary policy transmission. Two important reasons support this statement. First, if prices in one type of outlet pervasively adjust more rapidly or with a greater magnitude, then the share of “informal goods” may affect the ultimate effectiveness of monetary policy. Second, if household shopping patterns differ across different outlets, then the shock will inherently bring distributional effects.

Instead of focusing on a local MP shock, we study the effects of a US MP shock in Honduras. We do this for two main reasons. First, Honduras follows a crawling band

¹Bachas, Gadenne, and Jensen (2024) proxy the informal sector through farmer’s market establishments and the formal sector using all the other types of stores in the economy.

exchange rate regime during our analyzed sample. Second, while there is now ample literature that identifies US MP shocks through a high-frequency approach ([Gertler and Karadi, 2015](#); [Nakamura and Steinsson, 2018a](#); [Jarociński and Karadi, 2020](#)), none of the previous works has identified a series of MP shocks for Honduras. Moreover, there is now large evidence that US MP shocks bring significant effects on emerging economies and Latin American countries.² We show that a US MP shock induces a significant fall in local CPI and economic activity, peaking around one year after the shock.

Relying on the Honduran CPI, we study the dynamic responses of micro prices at the product-store levels. We show that the probability of adjusting such prices upwards (downwards) significantly decreases (increases) after an interest rate tightening. The pace of the response is, however, significantly *different* depending on the outlet where products are sold. While the price of products sold in formal markets starts changing with a lag of approximately one year, prices in informal markets start adjusting only six months after the same shock. Regarding the magnitude of the price adjustments, we show that they significantly fall by approximately 0.2% one year after an increase of 5 basis points in the one-year US yield. The pricing response is, again, heterogeneous since the only meaningful reaction during the first year is found for goods offered across informal establishments.

To better understand the muted response in formal markets, we examine whether observed product characteristics help explain the heterogeneity. We begin by separating goods into domestically produced and imported. This distinction matters because U.S. monetary tightening tends to depreciate the exchange rate, raising the local price of imports, while simultaneously dampening aggregate demand. Consistent with these counteracting forces, we find that prices of imported goods show little response to monetary shocks, while prices of domestically produced goods fall. Since imported goods are more prevalent in formal outlets, this partly explains why the pricing reaction in such outlets is negligible.

Building on these results and using the latest Honduran household consumption survey,

²See, for example, [Canova \(2005\)](#); [Dedola, Rivolta, and Stracca \(2017\)](#); [Vicondoa \(2019\)](#); [Degasperis, Hong, and Ricco \(2023\)](#); [Camara \(2025\)](#).

we aim to further understand the potential distributional effects that the MP shock brings into the local economy. We document that high-income households buy disproportionately more from formal outlets, while poorer households rely more heavily on informal ones. Moreover, as expected, poorer households devote a larger share of their income to food. As we show that the degree of price flexibility is different across the two types of outlets, the MP shock brings distributional differences *between* income groups. This is consistent with [Auclert \(2019\)](#), who argues that the redistribution channel of MP is driven by agents' different marginal propensities to consume. Our results suggest that positive monetary shocks lead to stronger and more immediate deflation for poor households. In other words, we found evidence that the *speed* of transmission differs across outlet types, and therefore, by income group. Moreover, and beyond the distributional implications, our results provide additional empirical validation for the key role that heterogeneity plays in understanding the effects of MP transmission, which has boosted the literature developing HANK models (see, for example, [Kaplan, Moll, and Violante, 2018](#); [Kaplan, Nikolakoudis, and Violante, 2023](#)). In fact, and within this specific literature, our results speak directly to the model of [Lan, Li, and Li \(2025\)](#), where low-income households tend to have a larger marginal propensity to consume and buy goods whose prices are, on average, more flexible. In this context, the real effects of MP are considerably smaller. Through this evidence, we argue that focusing only on formal markets, particularly in less developed economies, could mistakenly lead to underestimating the distributional consequences of MP as well as to overestimating its true effectiveness.

Given the different dynamic effects across broad product characteristics, we ask whether such heterogeneous responses arise at the *within* product-outlet dimension. To characterize the differential effect driven by the same type of product offered at different stores, we rely on the subset of product categories available at both formal and informal outlets. Through this subsample, we focus on the cumulated differences between price adjustments for the two markets for the same product (i.e., a double-diff specification), after a MP shock. Consistent

with our previous findings, we show that the type of outlet significantly matters in explaining the price responses one year after the shock. In other words, the differential response of prices across markets cannot be explained solely by product characteristics.

The heterogeneous effects on micro prices and the relevance of the outlet type are consistent with both supply and demand-driven factors. Regarding supply, informal markets may display lower price-adjustment frictions than formal ones, which could ultimately lead to a faster adjustment in prices. Such frictions may be more prevalent in formal markets given the existence of buyer-seller contracts, menu costs, and the multiple steps required to adjust prices, see for example [Levy et al. \(1997\)](#). With respect to demand, prices in informal markets may be falling more than in formal ones since lower-income households consume more from this type of market ([Bachas, Gadenne, and Jensen, 2024](#)).³ While we can certainly interpret the MP shock as a demand disturbance, the different price flexibility depending on the outlet and the particular features of these less formal types of stores can also be mapped to supply features.

There is ample evidence that macroeconomic shocks have distributional consequences. [Cravino and Levchenko \(2017\)](#) show that large devaluations affect households differently because poorer households spend more on tradable goods, which react more strongly to such shocks. In the case of MP, [Coibion et al. \(2017\)](#) and [Mumtaz and Theophilopoulou \(2017\)](#) find that contractionary shocks increase income inequality in the U.S. and the U.K. Using microdata, [Cravino, Lan, and Levchenko \(2020\)](#) shows that MP shocks affect less high-income households since the prices of the goods they consume are more sticky and less volatile. Similarly, [Ampudia, Ehrmann, and Strasser \(2024\)](#) show that heterogeneous effects of MP arise from differences in consumption bundles, driven in part by shopping patterns: wealthier households substitute products more readily than poorer ones. We contribute to this literature in two ways. First, we document that in less developed economies, where

³Focusing on the specific effects of demand, [Cunha, De Giorgi, and Jayachandran \(2019\)](#) show that cash transfers lead to increases in food prices, particularly across less developed or integrated areas. Similarly, [Egger et al. \(2022\)](#) documents a significant but economically small local price inflation as a response to large cash transfers.

informal markets abound, low-income households not only rely more heavily on these outlets but also spend a larger share of their income there. Second, since price responses differ systematically between formal and informal outlets, we identify a “market-specific channel” through which MP shocks create additional distributional effects in such contexts. While product substitution, a feature we cannot observe, may dampen these differences, we conjecture that it would not overturn them either. Informal and formal markets differ markedly in the quality, variety, and availability of the products they offer to their customers. Moreover, recent evidence suggests that high-income households exert lower search effort, pay higher prices for identical goods, and systematically choose more expensive varieties, reinforcing the heterogeneity in price experiences across income groups (Nord, 2023).

Recent work has focused on the features of price stickiness to assess the implications of changes in the money supply (see, for example, Nakamura and Steinsson, 2008; Midrigan, 2011; Alvarez, Le Bihan, and Lippi, 2016). Among the main implications, the speed of response of micro prices is crucial to understanding the transmission of monetary policy. If prices are more flexible, this would affect the speed at which shocks are passed through the economy (Gopinath and Itskhoki, 2010). Higher price flexibility severely affects the effectiveness of MP as interest rate adjustments are more promptly absorbed by prices, limiting its ultimate effects on the real economy (see, for example, Vavra, 2014; Tenreyro and Thwaites, 2016). In this line, Gagnon, López-Salido, and Vincent (2013) argue that shocks contribute to aggregate prices’ flexibility by significantly altering the timing of individual price changes. We contribute to this literature by arguing that monetary policy shocks affect prices heterogeneously, depending on the type of market where products are sold. As informal markets are a very important type of outlet, especially for poor households, we interpret our findings as new evidence that MP could be less effective in emerging or poorer countries, where these types of markets abound.

Naturally, our paper builds on the evidence documenting distinct consumption and pricing patterns between formal and informal stores in developing economies. These sectors

differ in productivity, size, and product quality (La Porta and Shleifer, 2014). Using microdata of expenditure surveys from 32 low- and middle-income countries, Bachas, Gadenne, and Jensen (2024) show that as household income rises, consumption in formal stores (e.g., supermarkets) rises while consumption in informal stores (e.g., farmers’ markets) decreases. Moreover, Bachas, Gadenne, and Jensen (2024) argue that a key distinction between the pricing of the two types of markets is due to tax and regulatory factors.⁴ Similarly, Lagakos (2016) argues that informality provides an advantage for firms operating traditional technologies since, through tax evasion, they can lower their prices, relative to firms in the formal sector. However, there is also evidence that large formal retailers, such as foreign supermarkets, can charge lower prices for identical products compared to traditional stores, generating substantial household welfare gains (Atkin, Faber, and Gonzalez-Navarro, 2018). Building on this literature, we go beyond differences in average price levels and show that the frequency and magnitude of price adjustments also differ across the two types of markets following the same aggregate shock. Thus, heterogeneity arises not only in price levels but also in the dynamics of price adjustment.

The remaining of this paper is organized as follows. Section 2 describes the datasets used in the analysis. Section 3 presents the macroeconomic spillovers of US MP shocks in Honduras. Section 4 presents the effects of US MP shocks on prices conditioning on the market type. Section 5 analyzes the role of outlet characteristics in explaining the results. Finally, section 6 concludes.

2 Data

For the main analysis, our primary source of information is a confidential dataset of monthly product-level price quotes collected by the Central Bank of Honduras (CBH) to construct the CPI. This dataset, which spans January 2015 to December 2019, provides detailed

⁴As formal stores are more likely to comply with VAT and other regulations, higher prices are expected to prevail in formal stores as they partially pass through taxes or other compliance costs to their consumers.

information on prices at the product–store level.⁵ We complement this information with the 2024 National Household Income and Expenditure Survey (HIE), which we use to characterize consumption patterns across income groups and retail formats. While the time frames of these datasets do not align, we conjecture that consumption patterns and shopping behavior in Honduras —particularly the reliance on informal outlets among lower-income households—have remained relatively stable over time. We mostly use the HIE survey to further describe the heterogeneous shopping patterns across households. In the following sections, we present key stylized facts drawn from each dataset to motivate and support our main findings.

2.1 CPI Data

This dataset consists of panel data information on price quotes. Each quote corresponds to an individual item at a particular outlet.⁶ Given the consumption characteristics of the country, the CBH actively collects prices across both formal and informal outlets. Pricing quotes are gathered on a weekly basis for food-related items and monthly for other goods. For informal markets, the quotes come from major and well-known farmers’ markets and/or informal stores in each city. Since our analysis focuses on monthly macroeconomic aggregates, these prices are then averaged to produce a monthly quote. We ended up with monthly quotes of 229 items in 339 (formal and informal) outlets across the three main urban areas of Honduras: *Distrito Central (DC)*, *San Pedro Sula (SPS)*, and *La Ceiba (LC)*. These account for approximately 50% of consumer expenditures. Items are grouped according to the Classification of Individual Consumption by Purpose (CCIF) within 10 categories of goods.

⁵Unfortunately, and given the severity with which the COVID pandemic affected Honduras, many outlets (particularly informal ones) closed during these years. As a result, it is not possible to consistently track the prices of products previously sold at those outlets. Given this, we prefer to avoid relying on these years, as our conclusions could be masked by this situation.

⁶For example, a product in the database could be a one-pound bag of rice sold at a specific informal or formal store in *Tegucigalpa*. In this sense, through the data, we have information about the different price quotes for the same one-pound bag of rice sold in *Tegucigalpa*, relative to another store in another location, such as, for instance, *La Ceiba*.

Although we have detailed information on prices, we do not expect to fully replicate the Honduran CPI. There are two reasons behind this feature. First, as mentioned, the data covers only the three major urban areas in the country. Although these areas account for approximately 79% of the weight in the country’s CPI, we do not have information on the remaining areas that are considered for the CPI. Second, we do not have information on some items within certain categories, such as shelter and recreational expenses. The reason for not having these items is that they do not have a price quote on a monthly basis, which limits the frequency of our sample. Nevertheless, if we focus on the Food-related categories, we managed to correctly replicate the official inflation of posted food (see Figure A.2 in Appendix A.2).

2.1.1 Pricing Facts Across Types of Markets

We start by validating our data relative to some other (well-known) stylized facts in the literature, which also relies on CPI information. The median frequency of price adjustments is approximately 15%, which implies a price duration of roughly 6 months. Table A.1 in Appendix A.2.2 presents the frequency of price changes in Honduras across all CPI categories. We also add the weight for each of the categories used to account for the local CPI.⁷ If we split the frequency of prices that change upwards relative to negative revisions, we notice that increases are consistently more frequent than decreases. The facts on the overall frequency of adjustment and the share of positive relative to negative adjustments are consistent with US evidence, Nakamura and Steinsson (2008).⁸

With the intention of further validating our microdata relative to other well-known facts, Appendix A.2.4 shows the unconditional Hazard Rate for the case of Honduras. The hazard

⁷As mentioned, although the table includes all the categories, in our analysis, we remove some items from the “Shelter, water, and energy” category as well as from “Recreation” since they are not quoted on a monthly basis.

⁸The encountered frequency is comparable to the median range of 9-13% reported for the US by Nakamura and Steinsson (2008). The asymmetry in the sign of price changes is also consistent with other US evidence, where almost two-thirds of price changes in the US correspond to positive revisions. Moreover, the frequency of increases correlates with inflation in our sample period (see Figure A.3 in Appendix A.2.2).

rate computes the conditional probability that the price of each specific product-variety is adjusted, as a function of the price’s age, i.e., the number of months that the price has remained constant since its last adjustment. Consistent with the literature (Campbell and Eden, 2014), we show that the empirical Hazard Rate is downward sloping in Honduras.

2.1.2 Goods and Prices Across Markets

Most of the goods sold in informal markets belong to the “Food and Non-Alcoholic Beverages” category.⁹ As most products in this category are highly demanded essential goods, they are available in *both* types of markets. With respect to the production source, while domestically produced goods are more prevalent in either market, a non-negligible amount of imported goods are sold in informal markets too. In the sample, 74% of the price quotes of imported goods are from formal establishments, with the remaining 26% coming from informal stores. Moreover, only 27% of the pricing quotes within the “Food” Category in informal markets are explained by imported products.¹⁰

Focusing on the Food category, we analyze whether the frequencies of price adjustments are different in each outlet. This is shown in Table 1, where we also open the total frequency between prices collected in the three main urban areas. There are notable differences in the frequency of price changes depending on the product’s outlets, being significantly higher at informal establishments. Such frequencies imply a median price duration of 2.5 months in informal markets relative to 3.9 months in the formal sector.

Not only the frequency but also the price levels are *different* between the two markets. Through a simple comparison between the average price level for each product that is available in both markets, we found that 72% of products are cheaper at informal markets. As this simple comparison may obscure further unobserved heterogeneity at the product or

⁹The “Personal care” and “Clothing and Footwear” categories also include some goods sold in informal markets. However, the share of these goods is marginal relative to the other products sold in formal markets for these categories.

¹⁰For completeness, in Appendix A.2.5 we show the exact number of price quotes in each market and discuss a few specific examples of imported products offered in informal outlets.

Table 1: Frequency of Food and Beverage Price Changes by City and Type of Market

Type of Market	DC	SPS	LC	Total
Informal	30.9	29.3	42.6	32.7
Formal	19.3	20.7	32.2	22.8
Total	27.6	27.1	37.5	28.8

Notes: Median frequency of price changes in the food and non-alcoholic beverages category across formal and informal markets. Frequencies are expressed as percentages per month. Following the methodology of Nakamura and Steinsson (2008), the median frequency was obtained by first calculating the average frequency of price changes for each product and then taking the weighted median across each product, while the median implied duration was calculated as follows: $-1/\ln(1 - f)$, where f is the median frequency of price change.

time levels, we estimate the following specification:

$$p_{pst} = \beta_0 + \beta_1 \mathbf{1}_i + \alpha_p + \alpha_r + \alpha_t + \epsilon_{pst} \quad (1)$$

Where p_{pst} is the log price of product-variety p sell in store s in time t , $\mathbf{1}_i$ is a dummy variable equal to one when store s is labelled as an informal outlet, and the α 's account for product p , region r , and time t fixed effects. The product-level FE is key in our estimations to account for unobserved price differences while conditioning on the same type of products offered in the two outlets. The results of estimating (1) are presented in Table 2.

According to the results, prices at informal markets are 14% smaller on average, compared to formal markets. The results are robust if we control for calendar months rather than time fixed effects. When we split the effects between domestically $\mathbf{1}_d$ and imported goods $\mathbf{1}_{imp}$ (Column 3), we find that they are, on average, 15% and 12% cheaper, respectively, in informal markets. The difference between the two is, however, not statistically significant. In Appendix A.3, we re-estimate equation (1), but conditioning on specific product categories. While for most products, prices in informal markets are systematically lower, the price differences for products like “Shelled corn” or “Fresh cheese” are higher than 20%.

While we argue that a substantial portion of the lower prices observed in informal markets can be attributed to outlet characteristics and the income profiles of households more likely to shop there—a point we develop further below—other factors, such as differences in

Table 2: Price Differences Between Markets

	(1)	(2)	(3)
$\mathbf{1}_i$	-0.14*** (0.021)	-0.14*** (0.021)	
$\mathbf{1}_i \times \mathbf{1}_d$			-0.15*** (0.01)
$\mathbf{1}_i \times \mathbf{1}_{imp}$			-0.12** (0.04)
Product FE	✓	✓	✓
Region FE	✓	✓	✓
Time FE	✓	✗	✓
Calendar Month FE	✗	✓	✗
N° of Observations	377,421	377,421	377,421
R^2	0.02	0.02	0.18

Notes: The Table shows the results of estimating equation (1) by OLS. Each column shows the estimated coefficient attached to the dummy variable of informal markets. The third column shows the effects of interacting the informal market dummy with another dummy that accounts for whether the product p is domestically produced or imported. To deal with the potential non-stationarity of the log of prices p_{pst} , we control for Time FE α_t . Furthermore, we also confirm that the estimated residuals are stationary. Standard errors are clustered across groups (product-store), type of establishment, and time.

product quality or tax compliance, may also explain the differences. According to existing evidence, even after accounting for product quality differences, modern formal markets charged significantly higher prices than less modern informal markets [Schipmann and Qaim \(2011\)](#). Given our data, we do not have brands or other characteristics to account for fully identical products. Nonetheless, we interpret our results as consistent with the findings of [Kaplan and Schulhofer-Wohl \(2017\)](#) that, using scanned-level price data, argue that household-level inflation heterogeneity is largely driven by differences in prices paid for the same types of goods. Related to tax and regulatory factors, [Bachas, Gadenne, and Jensen \(2024\)](#) argue that unit prices in formal stores are 5-7% higher than in informal outlets, which is consistent with the intuition that formal retailers pass part of their taxes and other compliance costs to their customers, explaining their higher prices.

2.2 Household Income and Expenditure (HIE) Survey

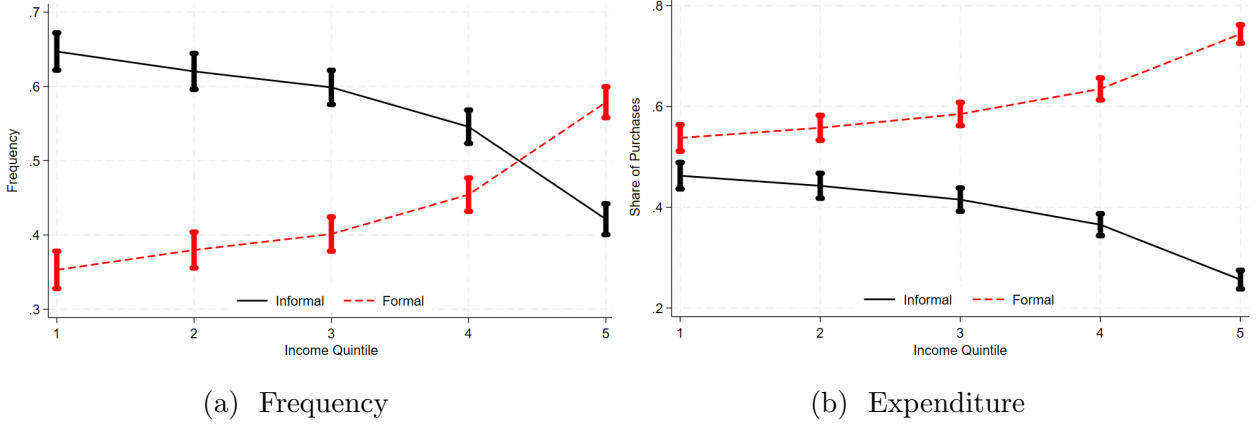
To characterize consumption patterns across different income levels, we use the 2024 National Household Income and Expenditure Survey (HIE). As discussed, although we acknowledge that the time frame is different with respect to the CPI data, we find this evidence valuable, as we conjecture that the frequency with which households visit each market and their consumption habits are, presumably, largely stable over time. Moreover, the previous consumption survey (which contains similar information) was done more than thirty years ago, and therefore contains more outdated information relative to the recent one.

The HIE, conducted also by the CBH, collects detailed information on household income, expenditure, and socioeconomic characteristics, serving as the primary source for analyzing living standards and consumption patterns in Honduras. It covers more than 8,000 households distributed across all regions, and households representing all socioeconomic statuses of the country. Data were collected over a one-year period through in-person household interviews. Following international standards, to collect income, households are asked about their earnings from labor, property, transfers, and remittances received during the last year. All income questions are self-reported. On the expenditure side, a distinctive feature of the survey is that it not only identifies the goods and services purchased, but also the location and type of outlet where the transactions occur, including supermarkets, retail stores, farmer markets, and/or corner stores.

2.2.1 Households' Consumption Across Different Markets

After classifying the surveyed households in five income quintiles, we estimate (1) the frequency with which households attend each type of market and (2) how much they spend on them, as a proportion of total expenditures. Within a month, the HIE Survey collects information about general purchases and the outlet where goods were bought, at the household

Figure 1: Purchases by Market's Type



Notes: The figure shows the distribution of household shopping behavior and expenditure patterns between formal and informal stores disaggregated by income quintile. Panel A reports the share of shopping trips by type of establishment, while panel B presents the corresponding shares of total household spending. Standard errors are computed using the Wald method, and 95% confidence intervals are reported.

level.¹¹ In addition, the survey collects information about the total expenditure in each market.

Figure 1a shows the average and confidence interval of the share of shopping visits by outlet type at different levels of income, while Figure 1b shows the corresponding share of expenditure. Some clear and systematic patterns emerge. On average, and as expected, households in the lowest income quintile visit informal markets 65% of the time, compared to 42% for households in the highest quintile. The fact that this gap is not only economically large but also statistically significant supports the existence of a large heterogeneity in shopping behavior across income levels. In terms of spending, purchases at formal markets account for a larger share of total expenditure across all quintiles, with a clear increasing trend as we move along the income quintiles. While poorer households shop more frequently at informal outlets, they spend relatively less at them on average. Building on the evidence in 2.1.2, we interpret this result as a reflection of the lower price levels observed in those markets. The gap in expenditure becomes more pronounced across the distribution, with

¹¹The survey question reads: Indicate the detailed name of what you bought, the place of purchase, its location, and the type of establishment where you acquired the product.

households in the top income quintile spending nearly 80% of their total purchases in formal establishments.

Overall, the evidence points to a pervasive and large difference in the shopping patterns across income groups. Moreover, if we look beyond the shopping mismatches between the two endpoints, we notice that informal markets arise as the most visited outlet for most households in the Honduran economy. The frequency of purchases on these markets is more than 50% even for households at the fourth quintile of income. This circles back, not only to the relevance of accounting for prices on these types of markets, but also, if price flexibility is indeed different, it sheds light on the possibility that a significant share of households face more flexible prices within the same economy.

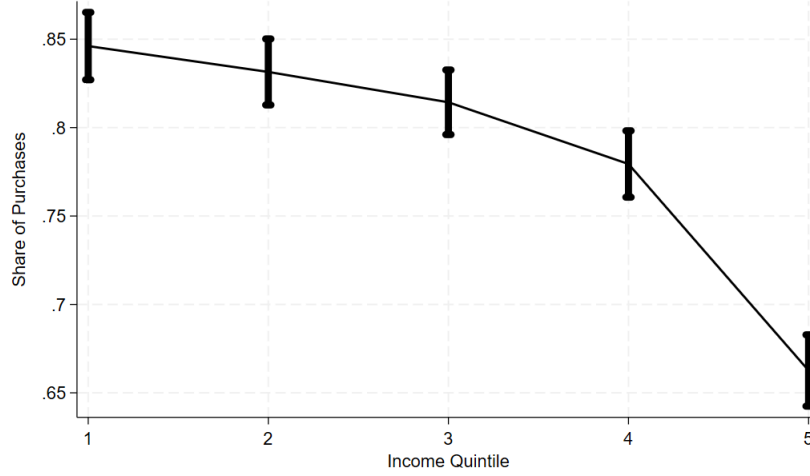
2.2.2 Heterogeneous Market-Driven Demand for Products

Relying on relevant CPI categories, we calculate the share of purchases in different products across quintiles. The specific details are presented in Appendix A.4. As expected, households of the lowest income quintiles spend approximately 32% of their income on food-related products, relative to the 18% spent by the richest households.¹² Another category that accounts for a larger share of purchases for poorer relative to richer households is related to housing expenditure (“Shelter, water and energy”). On the contrary, transport spending is significantly larger for richer households.

Besides the consistency with Engel’s Law, the data allows us to identify the share of “Food-related” expenditure in informal markets. This is shown in Figure 2. Among households in the lowest income quintile, 85% of food items are purchased in informal outlets, compared to 66% for those in the highest quintile. While this pattern is somewhat expected—given that food items are more readily available in informal markets—it is notable that higher-income households still purchase nearly 34% of their food from formal, and typically more expensive, establishments.

¹²These patterns are common across both developed and less developed economies, (see for example, Banks, Blundell, and Lewbel (1997); Hamilton (2001).)

Figure 2: Food Expenditure in Informal Markets



Notes: The figure shows the share of household expenditure on food and non-alcoholic beverages allocated to informal stores, by income quintile. Standard errors are computed using the Wald method, and 95% confidence intervals are reported.

3 Macroeconomic Effects of US Monetary Policy

Before studying the price reaction across outlet types, we assess the aggregate consequences of a US MP shock in Honduras. We rely on the series of US MP shocks computed by [Jarociński and Karadi \(2020\)](#), which are purged from information effects. With this series, we estimate the following Local Projection specification (see, for example, [Cloyne, Jordà, and Taylor, 2020](#); [Juvenal and Petrella, 2024](#)):

$$y_{t+h} - y_{t-1} = \alpha_h + \beta_h s_t^{mp} + \gamma_h (\mathbf{x}_{t-1} - \bar{\mathbf{x}}) + \theta_{x,h} (s_t^{mp} \times (\mathbf{x}_{t-1} - \bar{\mathbf{x}})) + u_{t+h} \quad (2)$$

where y_{t+h} denotes the aggregate variable of interest: economic activity, headline CPI, the nominal exchange rate with respect to the US Dollar, the local MP rate, and total net remittances (from the US to Honduras). All variables are expressed in logs at different horizons h and therefore, the dependent variables account for the accumulated log-differences between time $t + h$ and $t - 1$. The variable s_t^{mp} is the series of US MP shocks computed by [Jarociński and Karadi \(2020\)](#) standardized, x_{t-1} is a set of control variables with median $\bar{x}$

that includes the first lag of the Honduran MP rate, the depreciation rate of the nominal exchange rate, and the dependent variable in each case. This specification broadens the conventional LP specification by incorporating potential variability in the causal effect due to the interaction between the US MP shock and control variables. Thus, we allow for heterogeneous effects of US MP shocks depending on the level of control variables, to account especially for the MP stance in Honduras. The sample period spans from January 2015 to December 2019 to be consistent with the availability of the CPI data. Figure 3 displays the estimated effects in response to one standard deviation of the US MP shock.¹³

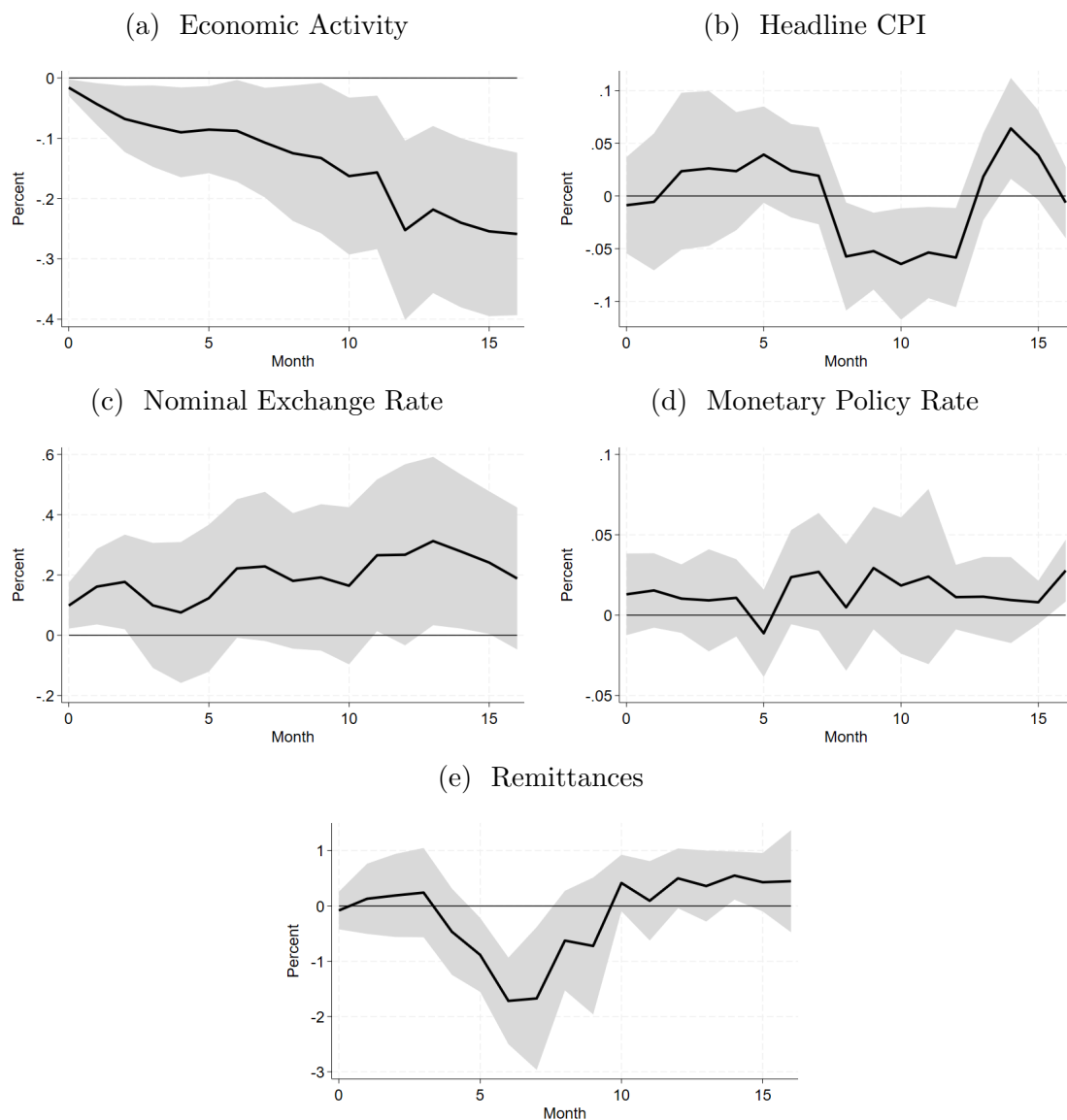
A monetary tightening in the United States induces a persistent decline in economic activity in Honduras, which reaches -0.3 percent around one year after the shock. The exchange rate depreciates 0.1 percent on impact, consistent with an exchange rate against the U.S. Dollar that is allowed to fluctuate by only 1 percent, keeping it within the desired bands. Thus, the decline in economic activity is not explained by the domestic MP rate, which does not significantly react to the shock. The stronger decline in economic activity after 8 months, together with the significant fall in headline CPI, can be partially explained by the fall in remittances, which occurs 5 months after the shock. A one standard deviation increase in the US short-term interest rate causes a decrease of approximately 1.8 percent in remittances six to seven months after the shock. Considering that remittances represent around 20 percent of GDP on average in this sample, the negative effect on remittances may be coupled with strong effects on Honduras' business cycle, contributing to explaining economic activity and price dynamics.¹⁴

To complement these results, we re-estimate the specifications but using the US MP shocks computed by Nakamura and Steinsson (2018b) instead. Appendix B.2 reports the results. We observe very similar responses using the alternative shock. Remittances and the CPI fall after five and eight months, respectively, resembling the dynamics of our baseline

¹³A one standard deviation US MP shock induces an increase of 5 basis points in the US 1Y yield (Jarociński and Karadi, 2020).

¹⁴Actually, Honduras is the economy that had the largest share of remittances to GDP (27%) across *all* Latin American countries in 2022. Almost all of the remittances come from the US.

Figure 3: Response of Macroeconomic Variables in Honduras to a US MP Shock



Notes. Estimated effects of a contractionary US MP shock on economic activity, Headline CPI, the nominal exchange rate relative to a US Dollar, the monetary policy rate, and remittances over the sample 2015M1-2019M12. The figures display the estimated β_h of equation (2) for each variable. Continuous lines denote the median IRFs to a US MP shock. Shaded areas denote 90% confidence intervals based on Newey-West standard errors. Horizon is in months.

results. The economic activity and the exchange rate also behave in a similar fashion.

4 Market-Driven Price Response of a MP Shock

We turn to study the response of price quotes across both formal and informal markets after a US MP shock. We focus on the effects of the shock on both the probability of price adjustments and the magnitude of such price revisions, conditioning on each market type.

4.1 Probability of Price Revisions

Following Karadi, Schoenle, and Wursten (2024), we define $I_{ps,t+h/t-1}^{\pm}$ as a dummy variable that indicates whether the price of product p in the store s has increased (decreased) between periods $t + h$ and $t - 1$. Through this variable, we estimate the following Linear Probability Model (LPM):

$$\begin{aligned} I_{ps,t+h/t-1}^{\pm} = & \alpha_{ps,h}^{\pm} + \beta_{1,h}^{\pm} (s_t^{mp} \times \mathbf{1}_i) + \beta_{2,h}^{\pm} (s_t^{mp} \times \mathbf{1}_f) + \beta_{3,h}^{\pm} Gap_{ps,t-1} + \beta_{4,h}^{\pm} Age_{ps,t-1} + \\ & \gamma_{0,h}^{\pm} (\mathbf{x}_{t-1} - \bar{\mathbf{x}}) + \theta_{x,h}^{\pm} (s_t^{mp} \times (\mathbf{x}_{t-1} - \bar{\mathbf{x}})) + \alpha_{m,h}^{\pm} + \epsilon_{ps,t+h}^{\pm} \end{aligned} \quad (3)$$

Where $\alpha_{ps,h}^{\pm}$ is a product-store fixed effect, s_t^{mp} is the Jarociński and Karadi (2020) measure of the US MP shock standardized, $\mathbf{1}_i$ and $\mathbf{1}_f$ are dummy variables that take the value of one if the price quote is collected from an informal or from a formal market, respectively. $Gap_{ps,t-1}$ is the one-month lagged “price gap” with respect to competitors, which is given by the distance between each individual store’s price relative to the average of all other stores’ prices for the same product. This variable has been proven to be relevant as a determinant of price adjustments (see, for example, Campbell and Eden, 2014).¹⁵ $Age_{ps,t-1}$ is the logarithm

¹⁵To calculate $Gap_{ps,t-1}$, we follow Karadi, Schoenle, and Wursten (2024) and define a proxy for the competitor-price gap for product p in-store s at month t as the distance of the log of reference price ($p_{ps,t}$) relative to the log of the average price of the same product across stores ($p_{p,t}$). More precisely, the price gap is defined as: $gap_{ps,t} = p_{ps,t} - p_{p,t} - \alpha_s$, where α_s is the average store-level gap that accounts for the fixed-effect heterogeneity across stores. The distribution of the price-gap measure is shown in Appendix A.2.3.

Table 3: Probability of Price Adjustments

	Price Increase				Price Decrease			
	$I_{t-1,t+3}$	$I_{t-1,t+6}$	$I_{t-1,t+12}$	$I_{t-1,t+15}$	$I_{t-1,t+3}$	$I_{t-1,t+6}$	$I_{t-1,t+12}$	$I_{t-1,t+15}$
$S_t^{MP} \times$ Informal	0.00 (0.34)	0.09 (0.19)	-1.31*** (0.23)	-0.80** (0.30)	0.11 (0.19)	0.39*** (0.07)	0.86*** (0.16)	0.67*** (0.17)
$S_t^{MP} \times$ Formal	0.03 (0.46)	0.88 (0.53)	-0.53* (0.26)	-0.71* (0.34)	0.13 (0.19)	0.08 (0.11)	0.56** (0.21)	0.81*** (0.12)
Gap_{t-1}	-0.79*** (0.02)	-0.98*** (0.01)	-1.16*** (0.02)	-1.24*** (0.01)	0.63*** (0.07)	0.76*** (0.08)	0.90*** (0.09)	0.97*** (0.12)
Age_{t-1}	0.03 (0.07)	0.26** (0.09)	0.71*** (0.15)	0.87*** (0.14)	-0.03 (0.08)	0.00 (0.09)	0.06 (0.09)	0.08 (0.09)
(Informal - Formal)	-0.04 (0.32)	-0.79* (0.40)	-0.78** (0.25)	-0.09 (0.11)	-0.01 (0.11)	0.31* (0.10)	0.30 (0.23)	-0.15 (0.13)
Product-Store FE	✓	✓	✓	✓	✓	✓	✓	✓
Calendar-Month FE	✓	✓	✓	✓	✓	✓	✓	✓
N	345,120	326,060	288,051	269,187	345,120	326,060	288,051	269,187
R	0.04	0.06	0.09	0.10	0.04	0.05	0.07	0.07

Notes. The table shows the estimation of (3) using the micro data for Honduras. The Gap corresponds to the log difference between the individual (product-store) price relative to the average price within that category. Age is defined as the logarithm of the number of months the price has remained constant. All the estimations include product-stores and month FE. Standard errors are clustered across groups (product-store), type of establishment, and time. * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

of the lagged age of a price, x_{t-1} is an additional set of macro controls, and $\alpha_{m,h}^{\pm}$ is a month fixed effect to account for any remaining seasonality. Consistent with the macro specification in the previous section, x_{t-1} includes the same set of variables: the first lags of the Honduran policy rate, the CPI growth, and the depreciation rate of the nominal exchange rate. In the estimation, we cluster standard errors across groups, types of establishments, and time. The results of estimating (3) by OLS for horizons $h = \{3, 6, 12, 15\}$ are presented in Table 3.

The differential effects on the probability of price adjustments clearly support the presence of heterogeneous price responses. On average, goods sold in informal markets respond more promptly to the MP shock than those in formal establishments. In fact, six months after a US MP tightening, the probability of a price decrease in informal markets is around 0.4% higher, with the marginal effect remaining statistically insignificant in formal establishments. While the probability of price decreases becomes significant in both markets after one year, the magnitude is still bigger in informal markets. It is only over longer horizons, at $h = 15$,

that the probability of price decreases is significant and similar across markets. A one standard deviation tightening of U.S. MP reduces the probability of a price increase in both informal and formal markets by approximately 0.8% and 0.7%, respectively, fifteen months after the shock. Similarly, this monetary tightening raises the likelihood of a price decrease in Honduras by about 0.7% in informal markets and 0.8% in formal markets over the same horizon. As a result, the shock leads to an overall 0.7% rise in the probability of a price decline at $h = 15$.¹⁶

Consistent with the literature, the gap with respect to the average price of competitors also matters for triggering price adjustments. In particular, a higher distance between the actual price and the competitors correlates negatively (positively) with the probability of an upward (downward) price revision. For the age of a price, we notice that the probability of a positive price revision significantly increases by approximately 0.8% with the number of months the price has remained unchanged. However, age is not a significant predictor of the decision to adjust prices downwards. These patterns are consistent with the presence of price-adjustment rigidities in the context of an economy with trend inflation (Karadi and Reiff, 2019).

4.2 Dynamic Adjustment of Prices by Market's formality

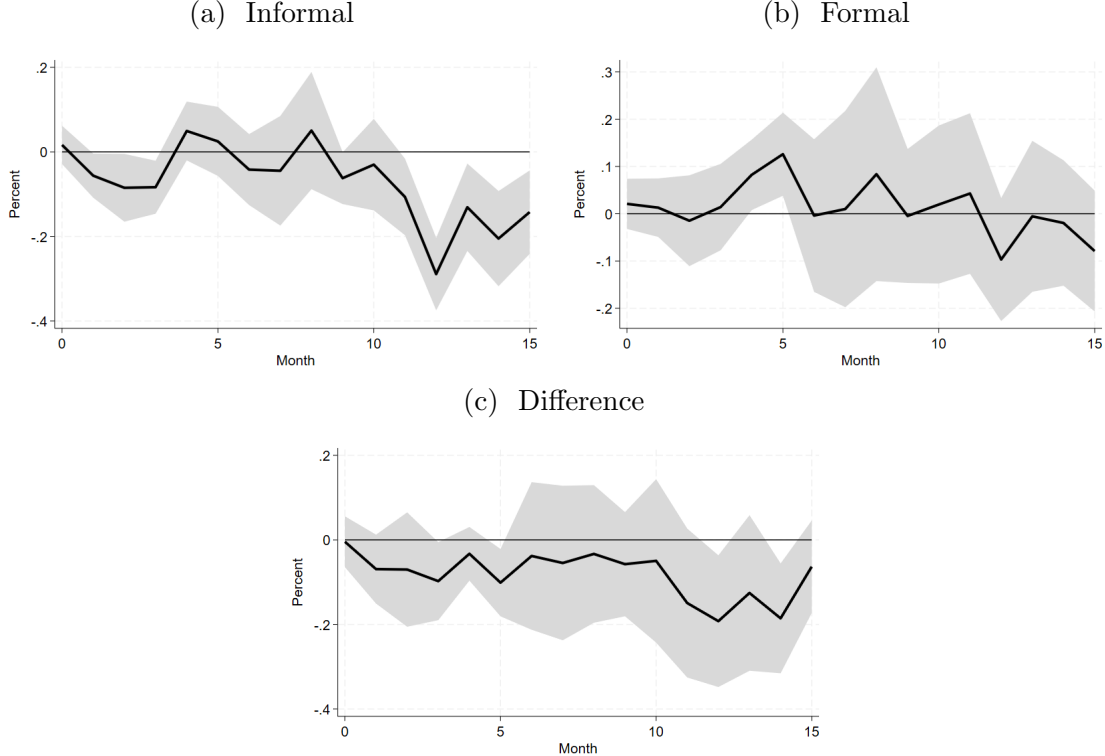
While the evidence suggests that a MP tightening in the US causes pricing revisions in Honduras, we now study its underlying adjustment dynamics. In particular, we aim to explore the magnitude and the specific timing by which prices in the two markets react to the shock. Following Cloyne, Jordà, and Taylor (2020), we estimate the following panel specification using Local Projections:

$$p_{ps,t+h} - p_{ps,t-1} = \alpha_{ps,h} + \beta_{1,h}(s_t^{mp} \times \mathbf{1}_i) + \beta_{2,h}(s_t^{mp} \times \mathbf{1}_f) + \beta_{3,h}Gap_{ps,t-1} + \beta_{4,h}Age_{ps,t-1} + \gamma_h(\mathbf{x}_{t-1} - \bar{\mathbf{x}}) + \theta_h(s_t^{mp} \times (\mathbf{x}_{t-1} - \bar{\mathbf{x}})) + \alpha_{m,h} + \epsilon_{ps,t+h} \quad (4)$$

¹⁶We compute this total effect by estimating (3) using only the shock instead of adding the two interactions by type of market.

Where $p_{ps,t}$ is the log of the price at product p in store s at time t , and the remaining controls and variables are the same as in equation (3). Again, we interact the Jarociński and Karadi (2020)’s US MP shock with the same two dummy variables that split between the product being sold at either informal or formal markets. Thus, the $\beta_{1,h}$ and $\beta_{2,h}$ coefficients will identify the size of the price response to the MP shock for each type of outlet. As before, we cluster the standard errors across groups, type of establishment, and time. The results are shown in Figure 4.

Figure 4: Responses of Prices in Informal/Formal Markets to a US MP Shock



Notes. Dynamic responses of product prices sold in formal and informal markets in Honduras to a US MP shock. The figure shows $\beta_{1,h}$ (top left figure) and $\beta_{2,h}$ (top right figure) estimated through equation (4). The bottom figure corresponds to the difference between the two estimated coefficients across each horizon. Continuous lines denote the median IRFs to a US MP shock. In the specification, we clustered the standard errors across groups (product-store), type of establishment, and time. Shaded grey areas denote 90% confidence intervals. Horizon is in months.

For informal markets, prices start decreasing quickly after the shock. In fact, there is a slight and significant downward revision in prices between two and three months. However, as expected, the biggest magnitude of price adjustments is concentrated at long horizons.

Prices are adjusted downwards by 0.2% on average one year after an increase of 5 basis points (one standard deviation) in the one-year US yield. The dynamic response of product prices is also consistent with the observed effect of the Macro series in Honduras of Figure 3, where remittances significantly and persistently drop in Honduras six months after the same shock. A similar feature is found in the local CPI, which drops between eight to twelve months after the shock. The magnitude of price adjustments in formal markets, while it is downward sloping towards the end of the horizon, is non-significant. The bottom panel of Figure 4 depicts the statistical difference between the coefficients associated with each market. To further understand the apparently muted reaction in formal markets, and the even positive response observed at some horizons, we distinguish goods with respect to other observable characteristics, starting with where they were produced.

4.2.1 Alternative Empirical Specifications

Building on the previous evidence, we discuss some additional robustness exercises and extensions to further validate our baseline results up to this point.

Local Projection Specification. Given our local projection specification, we show that the dynamic responses are quantitatively similar if we estimate an alternative specification of equations (2) and (4) instead. In such a specification, we remove the interactions between the shock and the macro controls, $(s_t^{mp} \times (\mathbf{x}_{t-1} - \bar{\mathbf{x}}))$, making the regression similar to the ones proposed by Jordà (2005) and Tenreyro and Thwaites (2016), among others. The results of the response of macro variables and prices are shown in Appendix B.1.

US MP Shock Series. As in Section 3, we re-estimate the effects on the probability of price adjustment and the magnitude of revisions using the US MP shocks computed by Nakamura and Steinsson (2018b) instead. Appendix B.2 shows these results for the regressions on the probability and the magnitude of price-adjustments. We confirm that all our baseline results hold when we rely on this alternative series for the shocks.

Temporary Sales. Unfortunately, our CPI data does not indicate whether a price

change was due to Sales or not. Hence, we cannot directly split between a *regular* price change and an adjustment due to a Sale. This is important, as sales are presumably more typical across formal establishments, like supermarkets. In Appendix B.3 we rely on the “V-shape filter” proposed by Nakamura and Steinsson (2008) to identify and remove sales from our data. Using the filtered series, we re-estimate the predicted magnitude of price adjustments at the product level. Our main results does not change, which further validates our main implications about different price adjustments dynamics across the two markets.

4.3 Domestic and Imported Goods

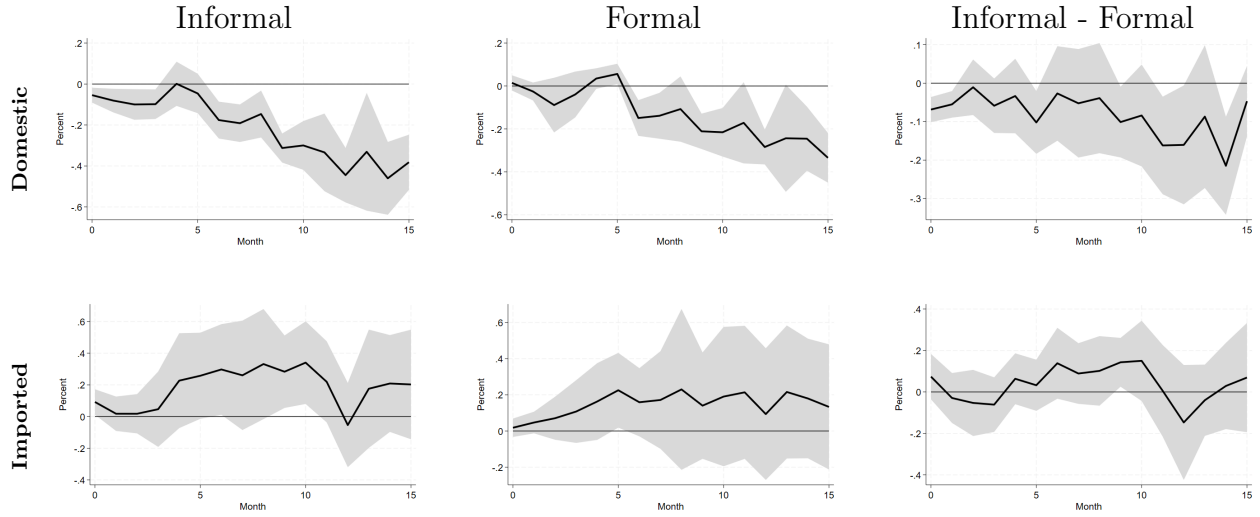
As discussed in Section 3, the nominal exchange rate in Honduras significantly depreciates on impact within the pre-established bands after the external shock, with the effect lasting for approximately 2 months. Hence, to assess whether this feature drives a different price reaction for these products, while conditioning on the type of market, we run the following specification:

$$\begin{aligned}
p_{ps,t+h} - p_{ps,t-1} = & \alpha_{ps,h} + \beta_{1,h} (s_t^{mp} \times \mathbf{1}_d \times \mathbf{1}_i) + \beta_{2,h} (s_t^{mp} \times \mathbf{1}_d \times \mathbf{1}_f) + \beta_{3,h} (s_t^{mp} \times \mathbf{1}_{imp} \times \mathbf{1}_i) \\
& + \beta_{4,h} (s_t^{mp} \times \mathbf{1}_{imp} \times \mathbf{1}_f) + \beta_{5,h} \text{Gap}_{ps,t-1} + \beta_{6,h} \text{Age}_{ps,t-1} + \gamma_h (\mathbf{x}_{t-1} - \bar{\mathbf{x}}) \\
& + \theta_h (s_t^{mp} \times (\mathbf{x}_{t-1} - \bar{\mathbf{x}})) + \alpha_{m,h} + \epsilon_{ps,t+h}
\end{aligned} \tag{5}$$

The dummy variables in (5) are the same as defined before, but we add $\mathbf{1}_d$ and $\mathbf{1}_{imp}$, which correspond to a dummy variable equal to one if the good is locally produced or imported, respectively. The estimated parameters for $(\beta_{1,h}, \beta_{2,h}, \beta_{3,h}, \beta_{4,h})$ are shown in Figure 5.

The dynamic effects are clearly different between good types. Prices of domestic products sold in both informal and formal markets now drop after a US monetary tightening. While the cumulated response of prices in informal markets is roughly 0.4% one year after the shock, the drop is close to 0.3% across formal markets. Interestingly, the dynamics of the responses are still different between markets. Prices of domestic goods in informal markets significantly

Figure 5: Responses of Prices Domestic/Imported Goods Sold at Informal/Formal Markets



Notes. Dynamic responses of micro prices of domestic and imported goods sold in formal and informal markets in Honduras to a US MP shock. The figures show the results for $\beta_{1,h}$ (top left figure), $\beta_{2,h}$ (top middle figure), $\beta_{3,h}$ (bottom left figure) and $\beta_{4,h}$ (bottom middle figure) estimated through equation (5). The last column shows the statistical difference between prices in informal relative to formal markets for domestic goods (top right figure) and imported goods (bottom right figure). Standard errors are clustered across groups (product-store), type of establishment, and time. Grey shaded areas denote 90% confidence intervals. Horizon is in months.

react promptly, while their formal market counterpart does not. The negative reaction in formal establishments only manifests after six months. Hence, the evidence supports that the degree of price flexibility is, in fact, largely different between the two markets across domestically produced goods.

On the contrary, the price reaction of imported goods is statistically negligible in either market. As discussed, the shock leads to an immediate depreciation of the exchange rate in the local economy, which should pass through to imported goods, putting positive pressure on these prices. However, at the same time, the prices of all goods should respond negatively to the contraction in aggregate demand that the external shock brings to the local economy. Hence, we interpret the lack of significance in the response as an implication of these two counteracting forces.

Given that most of the pricing quotes in informal markets come from the Food-related category, we interpret the immediate and significant reaction in Figure 5 as being driven by

this type of goods. To validate this intuition, in Appendix B.4, we re-run the specifications of the cumulative price change adding an additional interaction that accounts for whether the good belongs to the “Food and non-alcoholic beverages” category or not. We show that precisely this type of goods concentrate most of the quick and significant reaction after the external shock, particularly across informal outlets. More generally, by classifying goods across broad observable characteristics, we manage to refine and further interpret the different response rates. Therefore, in the next section, we study whether the evidence of an “outlet-dependent channel” holds even at the within-product level.

5 The Role of Product and Outlet Characteristics

As discussed in Section 2, low-income households are more prone to consume in informal outlets. Considering that this group displays a higher marginal propensity to consume and that its income is more sensitive to business cycle conditions, the differential effect on prices documented in Figure 5 could be explained by a stronger and more pronounced fall in the demand faced by informal outlets. Likewise, the asymmetric response of prices in informal stores may also be explained by outlet-specific characteristics such as different degrees of adjustment rigidities, more centralized pricing decisions in formal stores, or heterogeneous menu costs. We further assess whether the specific unobserved product-outlet characteristics contribute to explaining the differential price responses. In particular, we rely on the subset of products that are available and sold in both types of outlets to analyze if there is a different response at the outlet level while conditioning on the same product variety.

Following our baseline specification for the magnitude of adjustments, we augment equation (4) to consider the potential differential effect of monetary policy at the specific product-

markets levels:

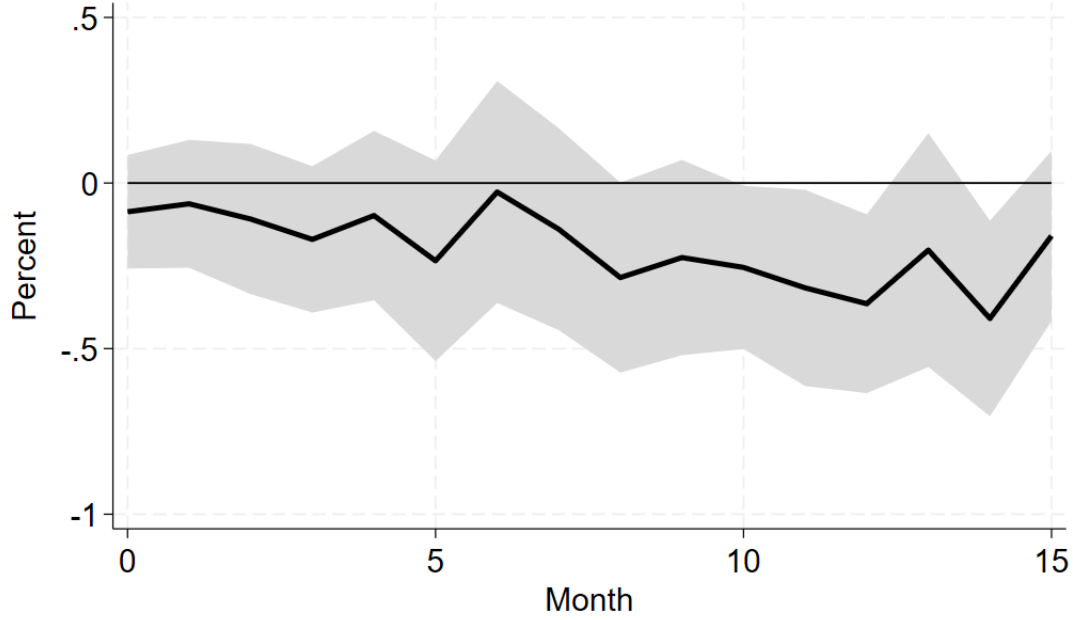
$$p_{ps,t+h} - p_{ps,t-1} = \alpha_{ps,h} + \beta_{1,h} (s_t^{mp} \times \mathbf{1}_i \times \alpha_{p,h}) + \beta_{2,h} (s_t^{mp} \times \mathbf{1}_f \times \alpha_{p,h}) + \beta_{3,h} Gap_{ps,t-1} + \beta_{4,h} Age_{ps,t-1} + \gamma_h (\mathbf{x}_{t-1} - \bar{\mathbf{x}}) + \theta_h (s_t^{mp} \times (\mathbf{x}_{t-1} - \bar{\mathbf{x}})) + \alpha_{m,h} + \epsilon_{ps,t+h} \quad (6)$$

The parameter $\alpha_{p,h}$ is a product p fixed effect at horizon h , while the remaining variables are the same as in equation (4). This specification allows the monetary policy shocks to bring differential pricing effects depending on the specific product category, consistent with the evidence found in the previous section. In equation (6), if $\beta_{1,h}$ is statistically different from $\beta_{2,h}$, we can argue that monetary policy has a differential effect on prices at the product level, depending on whether the product is sold at an informal or formal outlet. However, the actual estimation of (6) brings some efficiency challenges, mainly due to the large number of parameters to estimate at both store types. As we are mostly interested in pinning down the difference between $\beta_{1,h}$ and $\beta_{2,h}$, we express (6) in first differences conditioning on the same product p sold in *informal* market s relative to an *formal* market s' as:

$$\Delta p_{ps,t+h} - \Delta p_{ps',t+h} = \alpha_{ps-s',h} + (\beta_{1,h} - \beta_{2,h}) s_t^{mp} \times \alpha_{p,h} + \beta_{3,h} (Gap_{ps,t-1} - Gap_{ps',t-1}) + \beta_{4,h} (Age_{ps,t-1} - Age_{ps',t-1}) + \epsilon_{ps-s',t+h} \quad (7)$$

This same approach has been used to reduce the dimensionality of the equation in other setups, such as [Paravisini et al. \(2015\)](#) and [Villacorta, Villacorta, and Gutierrez \(2023\)](#). While we are interested in recovering $\tilde{\beta}_h \equiv (\beta_{1,h} - \beta_{2,h})$, this coefficient is identified up to scale given the product fixed effect $\alpha_{p,h}$. Nevertheless, if the differential response is explained due to product characteristics, then $\tilde{\beta}_h = 0$ and the product with the fixed effect $\alpha_{p,h}$ would be zero. On the contrary, if the type of outlet (i.e., formal or informal) matters, $\tilde{\beta}_h \neq 0$. This would imply that, conditioning on each specific product, the outlet had a relevant effect in explaining the different price dynamics. Figure 6 shows the estimated $\tilde{\beta}_h \times \alpha_{p,h}$ coefficients for different horizons $h = 0, \dots, 15$.

Figure 6: Effect of Monetary Policy on Price Adjustments Between Different Outlets



Notes: The figure shows the estimated $(\beta_{1,h} - \beta_{2,h}) \times \alpha_{p,h}$ from equation (7) using products that are sold in informal relative to formal. The specification includes fixed effects at the product, informal, and formal outlet levels. Standard errors are clustered at the product and time levels. Shaded areas denote 90% confidence intervals.

While the type of outlet in which a product is sold is not significant to explain price differential initially, it becomes a significant driver from 10 months onwards. This delayed effect is consistent with the findings of Figure 5 in which, after conditioning for domestic and imported goods, the differential response in price adjustment between formal and informal outlets becomes significant after 10 months. The difference is negative, meaning that prices in informal markets drop by a larger magnitude compared to formal outlets, from which we can argue that it is not only product characteristics that matter to explain the differential price responses, but also the outlet characteristics.

Such a response may be caused by different supply or demand characteristics. As discussed, on the supply side, this is consistent with different price adjustment rigidities between markets, the presence of contracts, or more centralized pricing decisions that prevent formal outlets from changing prices more easily. On the demand side, this could be driven

by different demand dynamics, elasticities, or variety preferences that make households more prone to buy products from one market relative to the other. Indeed, we know that overall demand contracts based on the responses of activity-related indicators, such as the drop in both economic activity and remittances in Honduras. However, through our data, we cannot claim which of these two channels is ultimately dominating. Under the assumption that households were indifferent between buying goods in either type of outlet (i.e., their demand was similar between markets), then $\alpha_{p,h}$ would absorb demand heterogeneity at the product level, and the store effect could be more directly mapped to supply factors. However, as we do not have information about how consumption baskets may have changed over the years of our CPI sample, we are not able to make such a clean statement.

6 Conclusions

In this paper, we document that MP can affect the rate at which micro prices adjust differently depending on the type of outlet where the products are sold. Using granular micro price data from Honduras, we classify price quotes depending on whether they were collected in an informal or formal market. While prices in formal markets start adjusting approximately one year after the shock, prices in informal markets start responding around six months after the shock. The MP brings distributional effects across the income distribution as prices become more flexible in outlets that are more frequently visited by poorer households to purchase goods.

The fact that prices are more flexible across informal markets suggests that MP can become less effective in less developed economies where these types of markets are much more prevalent. Our paper complements the evidence about the heterogeneous effects of MP on household consumption (Cloyne, Ferreira, and Surico, 2020), on prices faced by households of different incomes (Cravino, Lan, and Levchenko, 2020), geographical regions (Herreno and Pedemonte, 2022), production across sectors, (Pasten, Schoenle, and Weber,

2020), among other studies. Further evidence on the heterogeneous effects of monetary policy is relevant not only to fully characterize its transmission but also to anticipate and design prompt policy responses, particularly across less-developed economies.

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Price Setting, Informal Markets and Monetary Policy

Giancarlo Oseguera, Javier Turen and Alejandro Vicondoa

Online Appendix

A Data Appendix

A.1 Macroeconomic Data

In this Section, we describe the sources from which we collect the macroeconomic data to compute the results in Section 3.

A.1.1 Domestic Macroeconomic Series

Below, we provide the variables and the source from which we extract the time series of the Macro variables in Honduras.

- Economic Activity: The monthly IMAE index, which covers different production sectors of the economy - IMAE.¹⁷
- Consumer Price Index: Monthly releases of the official CPI in Honduras.
- Monetary Policy Interest Rate: Monthly data of the official monetary policy rate in Honduras, in percentage points.
- Nominal Exchange Rate with respect to the US Dollar. Official monthly exchange rate between the Honduran *Lempiras* and the US dollar.¹⁸
- Remittances: Monthly nominal level of remittances in Honduras. The remittances are deflated using the U.S. Consumer Price Index. The series of remittances turns out to be too volatile at the monthly frequency even after applying the X13 filter. We use a backward 3-month moving average to smooth the series.¹⁹

¹⁷The source of this and all other macro variables is extracted from the official statistics of the Central Bank of Honduras. For example, the source of the IMAE: <https://www.bch.hn/EN/economical-statistics/real-sector/monthly-economic-activity-index>

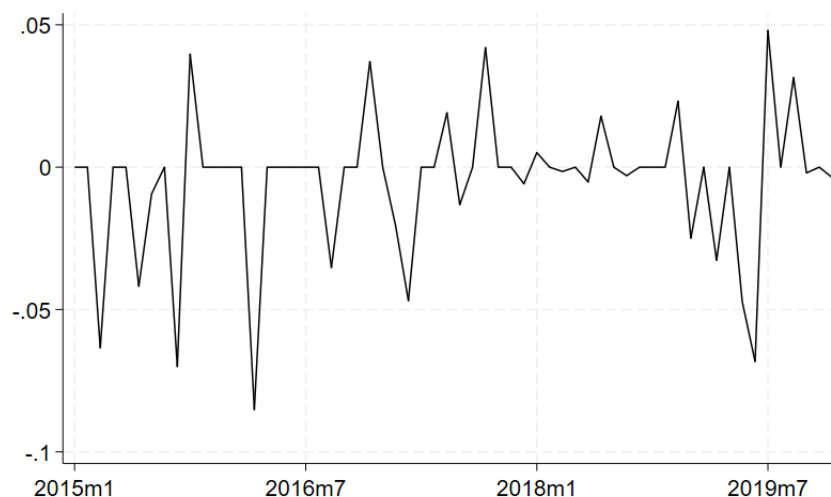
¹⁸Source of data: <https://www.bch.hn/estadisticas-y-publicaciones-economicas/tipo-de-cambio-nominal>

¹⁹Source of data: <https://www.bch.hn/EN/institutional-policies/exchange-policy/exchange-statistics/foreign-exchange-balance>

A.1.2 US Monetary Policy Shock

Figure A.1 displays the series of US MP shocks computed by [Jarociński and Karadi \(2020\)](#) for the sample of our analysis. This is a period with contractionary and expansionary US MP shocks.

Figure A.1: US MP Shock Series



Notes. US MP shock series identified by [Jarociński and Karadi \(2020\)](#).

A.2 Micro Price Data

In this Section, we provide further validation and additional stylized facts for our CPI product-level data in Honduras.

A.2.1 Replicating the CPI data

Using our price quotes data, we replicate the evolution of the “Food and Non-Alcoholic Beverages” category using our data for the three main urban areas in Honduras. We then compare our constructed CPI with the official posted figure. The evolution of the CPI is shown in Figure A.2.

Figure A.2: Replication of CPI Food Inflation Using Micro Prices



Notes. The figure displays the official year-on-year food inflation alongside its counterpart constructed from a Laspeyres price index base on micro-level prices and their corresponding weights.

We notice that our constructed measure closely resembles the evolution of the official CPI figure. In fact the correlation between the two measures is 0.87.

A.2.2 Price Changes

Table A.1 presents the frequency of price changes by major product groups in Honduras from 2015 to 2019. Following Nakamura and Steinsson (2008), we focus on regular price changes, excluding temporary sales. The median frequency of price adjustments is around 15%, indicating that prices typically remain unchanged for an average duration of about six months. Regarding price stickiness across categories, we notice that “Vehicle fuel” and “Food and non-alcoholic beverages” are the ones whose prices change the most in the sample, followed by medical care. On the other extreme, sectors like clothing and recreation keep their prices fixed for 29 months on average.

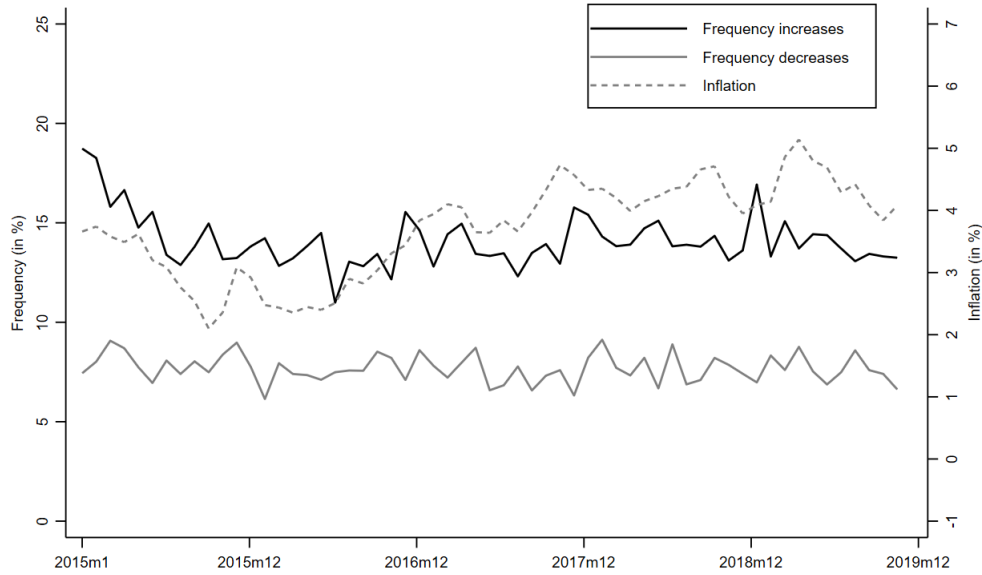
Figure A.3 illustrates the relationship between inflation and the frequency of price changes, revealing that the frequency of price increases closely follows inflation trends.

Table A.1: Frequency of Price Change by Major Group in 2015-2019

Sector	Weight	Median frequency	Median implied duration
Food and non-alcoholic beverages	31.8	28.8	2.9
Shelter, water, and energy	19.2	3.4	29.0
Alcoholic beverages and tobacco	0.4	6.8	14.2
Communications	1.7	1.8	56.5
Personal care	5.2	6.3	15.5
Household furnishings	6.7	5.1	19.2
Clothing and footwear	8.2	3.4	29.0
Recreation	4.0	3.4	29.0
Medical care	3.7	8.5	11.3
Vehicle fuel	3.2	100.0	-
Others	15.9	5.0	19.5
All sectors	100	15.3	6.0

Notes. All frequencies are expressed as percentages per month, and durations are reported in months. Following the methodology of [Nakamura and Steinsson \(2008\)](#), the median frequency was obtained by first calculating the average frequency of price changes for each product and then taking the weighted median across each product, while the median implied duration was calculated as follows: $-1/\ln(1 - f)$, where f is the median frequency of price change.

Figure A.3: Mean Frequency of Price Changes by Month and Inflation

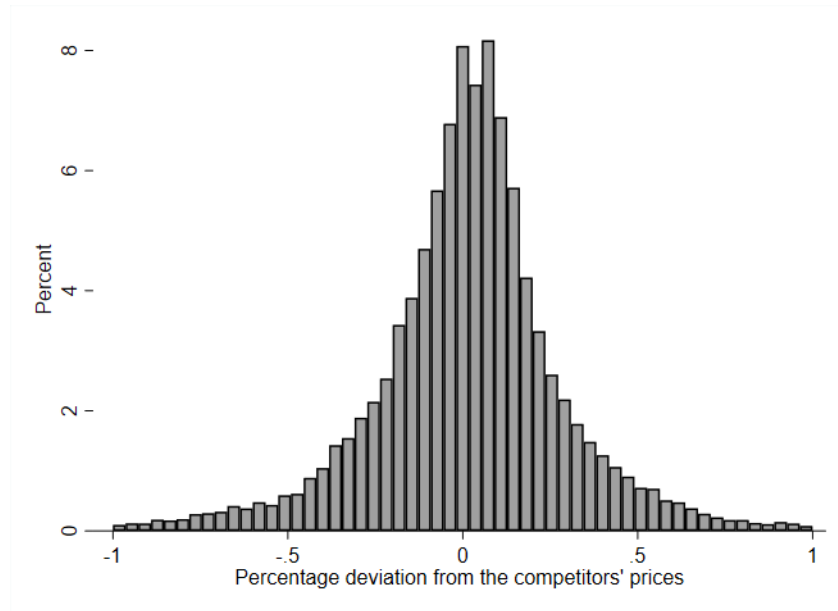


Notes. Mean frequency of regular price increases and decreases over time

A.2.3 Price-Gap Distribution

In this section, we show the distribution of the competitors price gap. We construct this using our micro price data for Honduras. As discussed, the measure accounts for the distance between $p_{ps,t}$ the individual store's price relative to $p_{p,t}$, the average of all other stores' prices, for the same product p at each month t . We build the measure following [Karadi, Schoenle, and Wursten \(2024\)](#), and define a proxy for the price gap as: $gap_{ps,t} = p_{ps,t} - p_{p,t} - \alpha_s$, where α_s is the average store-level gap. The store-level gap accounts for the fixed-effect heterogeneity across stores. The distribution of the price-gap measure is shown in [Figure A.4](#) and closely resembles what has been found in other countries, see [Campbell and Eden \(2014\)](#) for an example which uses US data.

Figure A.4: Competitor Price-Gap Density



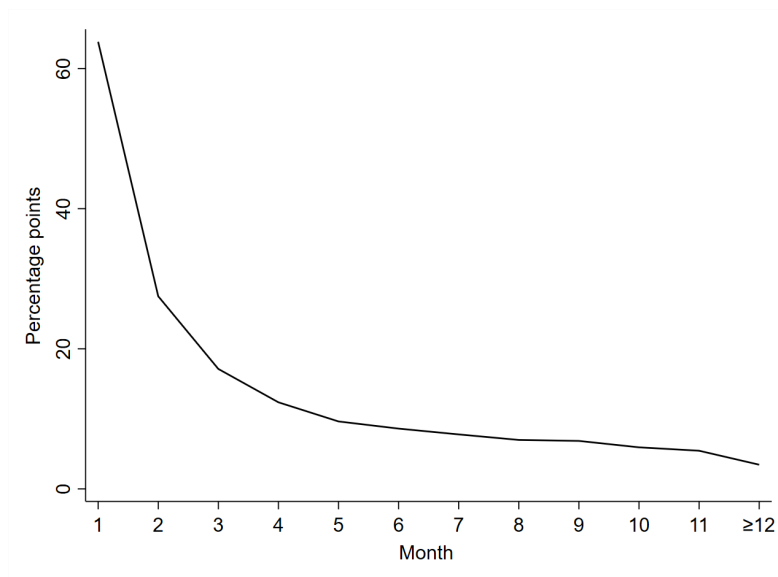
Notes: Distribution of price deviations relative to competitors' average prices. The x-axis measures the percentage deviation while the y-axis shows the percentage of observations in each range.

A.2.4 Hazard Rate

In this section, we compute the unconditional hazard-rate function, which shows the probability of a price revision as a function of the price's age, i.e., the number of months the price has

remained unchanged. The hazard rate has become relevant as a validation of different models of price-setting.²⁰ Figure A.5 displays the unconditional Hazard Rate using our data for Honduras. We show that the hazard rate is downward sloping as a function of the price age. This result is consistent in the empirical literature of price revisions, see [Nakamura and Steinsson \(2008\)](#) and [Campbell and Eden \(2014\)](#).

Figure A.5: Hazard Rate



Notes: The figure shows the probability of a price adjustment as a function of the price's age in months. As prices age, the probability of an adjustment decreases.

Motivated by this puzzling fact, a new array of models have been proposed aiming to rationalize this feature of prices. For example, while [Aruoba et al. \(2023\)](#) reconciles the downward sloping rate of the hazard through a price-setting model with adjustment frictions, [Baley and Blanco \(2019\)](#) matches it relying on information frictions. In our case, we perform this exercise as a further validation of our micro price data. While the Honduran price data has not been used much in pricing literature before, the stylized facts look similar to those from previous works.

²⁰For instance, under the well-known [Calvo \(1983\)](#)'s model of price revisions, the adjustment probability should remain constant throughout the age's profile. Similarly, models of state-dependent price adjustments predict that the hazard rate must be upward-sloping. Intuitively, this happens since no price-setter would want to pay the cost of a price revision (menu cost) after a new and theoretical optimal price has recently been set.

A.2.5 Prevalence of Domestic and Imported Goods

The left panel of Table A.2 shows the total number of product-store pricing quotes observed in our sample, divided between domestic and imported goods for each market. Likewise, the right panel of the table shows the same separation but just taking a specific month. Clearly, although pricing quotes are more prevalent across formal establishments, still a non-negligible quotes come from informal markets. Moreover, while formal markets concentrate a higher proportion of imported products, domestically produced products are more prevalent across informal markets.

Table A.2: Sample Composition

	All Sample			Jan. 2015		
	Informal	Formal	Total	Informal	Formal	Total
Domestic	112,578	76,903	189,481	1,863	1,293	3,156
Imported	48,672	139,268	187,940	813	2,326	3,139
Total	161,250	216,171	377,421	2,676	3,619	6,295

Notes: Number of observations of domestic and imported store-good in our sample. Each good-store is classified as domestic/imported and informal/formal depending on the market. The left panel reports the full sample, while the right panel reports only January 2015.

Similarly, Table A.3 shows the total number of product-store price quotes of domestic and imported goods within the “Food and Non-Alcoholic Beverages” category of the CPI. This is important since, as mentioned, all the products in this category are available in both formal and informal establishments.

Table A.3: Sample Composition for Food and Non-Alcoholic Beverages Category

	All Sample			Jan. 2015		
	Informal	Formal	Total	Informal	Formal	Total
Domestic	105,395	59,751	165,146	1,743	1,006	2,749
Imported	39,804	28,618	68,422	665	475	1,140
Total	145,199	88,369	233,568	2,408	1,481	3,889

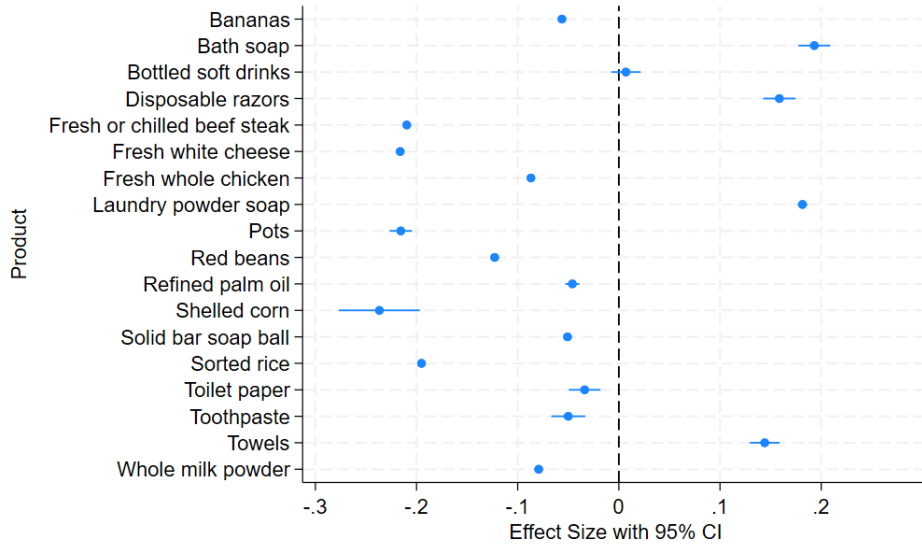
Notes: Number of observations of domestic and imported store-good in the Food and Non-Alcoholic Beverages category. Each good-store is classified as domestic/imported and informal/formal depending on the market. The left panel reports the full sample, while the right panel reports only January 2015.

Consistent with the evidence for all product categories in Table A.2, although informal markets concentrate much of the domestically produced goods, the number of imported goods is still significant. Regarding specific examples of imported goods sold in informal markets, within this category, we can mention: mayonnaise, instant noodle soup, powdered milk, and canned sardines, to name a few.

A.3 Product-Specific Differences Between Markets

As discussed in Section 2.1.2, we estimate equation (1) at the product-specific level to shed light on further price differences between products. We select a sample of approximately 20 different products, most of them from the “Food and Non-Alcoholic Beverages” category, and we estimate their pricing differences. We choose products within this category, since most products that are quoted in both markets are from this category. Figure A.6 shows the estimated coefficients.

Figure A.6: Price Difference in Informal Markets



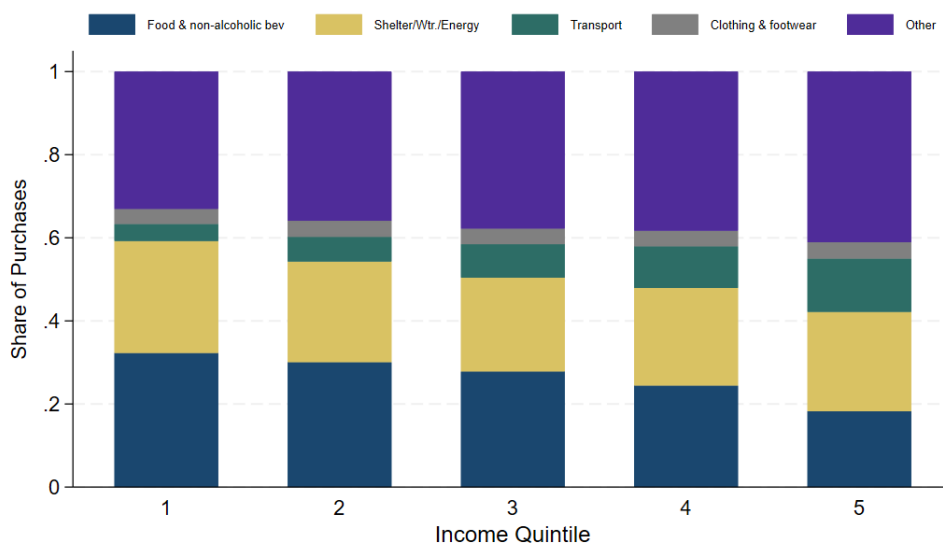
Notes: The figure presents the estimated price differences between formal and informal stores for each product, based on equation (1). Each point shows the effects of interacting the informal market dummy with another dummy that identifies a particular product. Standard errors are clustered across groups (product-store), type of establishment, and time.

Prices in informal markets are systematically lower compared to formal outlets. For some products, such as fresh cheese, pots, fresh beef, or rice, the differences are significant, reaching more than 20%. On the contrary, there are only a handful of products with higher prices in informal markets, most of them not from the Food category.

A.4 Share of Purchases Across Categories by Income Quintiles

We further characterize the main type of purchases that Honduran households made as a function of their income profiles. We perform this exercise using the 2024 HIE survey. We split purchases into five different CPI categories: Food and Non-Alcoholic Beverages, Shelter-Water-Energy expenses, transportation, Clothing and Footwear, and an additional classification for all the remaining categories. The results are shown in Figure A.7.

Figure A.7: Share of Purchases Across Income Categories



Notes: The figure shows the distribution of household expenditures by income quintile across five primary categories: food and non-alcoholic beverages; shelter, water, and energy; transport; clothing and footwear; and other goods and services.

In line with Engel's law, poorer households spend a larger share of their income on Food-related items, relative to wealthier households in the economy. This is observed by the

blue bar in the Figure. Likewise, lower-income households spend disproportionately more on housing bills, relative to the rest. Wealthier households tend to spend more on transportation and in other categories, such as personal care, furnishing, and recreation.

B Additional Empirical Specifications

Below, we report a series of robustness exercises to further validate our main conclusions regarding the macro and micro prices' reactions to a US MP shock.

B.1 Local Projection Specification

We challenge the degree to which the responses of macro outcomes are driven by our particular specification of local projection. As argued, while we rely on the extension of [Cloyne, Jordà, and Taylor \(2023\)](#) to account for the heterogeneous responses of variables to the shock, we could also estimate our main specification following the traditional specification, where we do not include the interaction between the shock and controls. This frames our specification within the traditional approach of local projection as the ones proposed by [Jordà \(2005\)](#) or [Tenreyro and Thwaites \(2016\)](#), for instance. In particular, we aim to estimate:

$$y_{t+h} - y_{t-1} = \alpha_h + \beta_h s_t^{mp} + \gamma_h (\mathbf{x}_{t-1} - \bar{\mathbf{x}}) + u_{t+h} \quad (8)$$

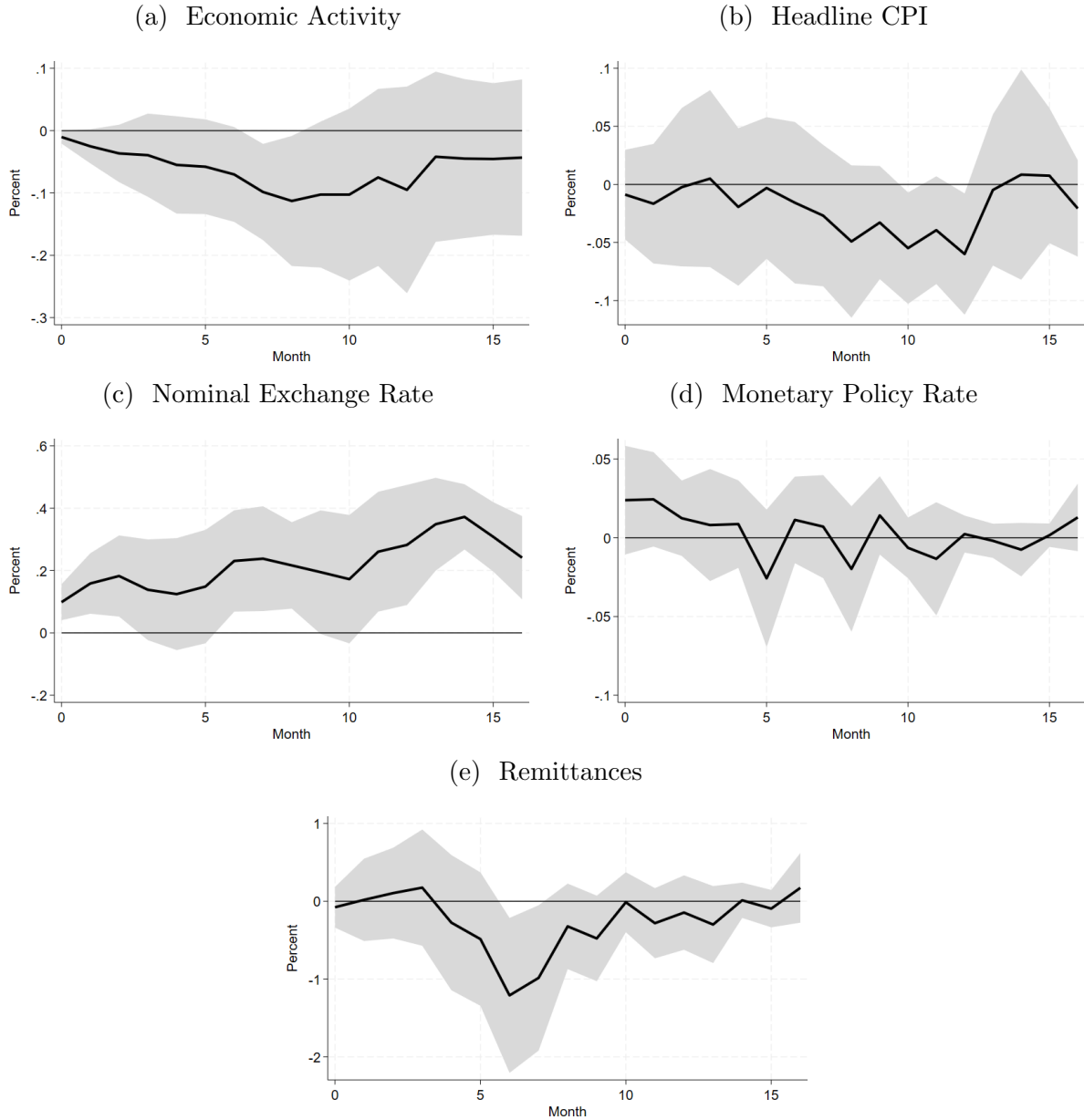
We study the response of the same macro variables in Honduras as in equation (2). Figure [B.1](#) replicates the Impulse Response Function in this case. We notice that most of the reported dynamics and significance of our results remain when we account for the more traditional LP specification.

Similarly, we also perform the estimation of micro price dynamics, excluding the interactions with the US MP shock:

$$\begin{aligned} p_{ps,t+h} - p_{ps,t-1} = & \alpha_{ps,h} + \beta_{1,h} (s_t^{mp} \times \mathbf{1}_i) + \beta_{2,h} (s_t^{mp} \times \mathbf{1}_f) + \beta_{3,h} Gap_{ps,t-1} \\ & + \beta_{4,h} Age_{ps,t-1} + \gamma_h (\mathbf{x}_{t-1} - \bar{\mathbf{x}}) + \alpha_{m,h} + \epsilon_{ps,t+h} \end{aligned} \quad (9)$$

Again, the variables are the same as in equation (4). Figure [B.2](#) shows that the swift and substantial reaction of informal market prices aligns closely with the baseline results

Figure B.1: Responses of Macroeconomic Variables to a US MP Shock (Alternative LP)

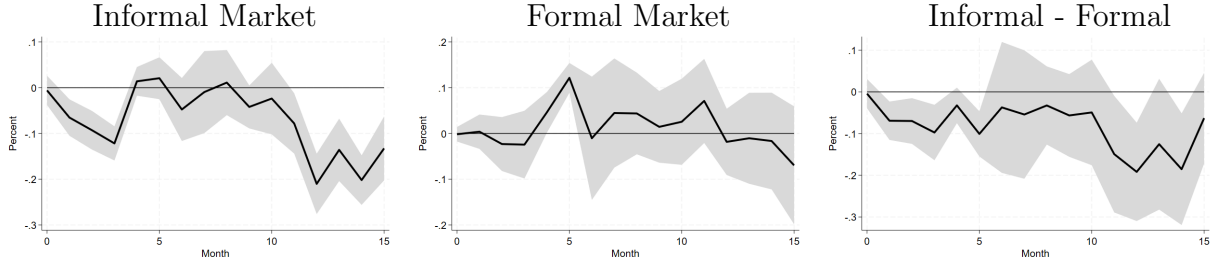


Notes: Estimated effects of a contractionary US MP shock on economic activity, Headline CPI, the nominal exchange rate relative to a US Dollar, the MP rate, and remittances in Honduras over the sample 2015M1-2019M12 based on estimating equation (8). Continuous lines denote the median IRFs to a US MP shock. Shaded areas denote 90% confidence intervals based on Newey-West standard errors. Horizon is in months.

illustrated in Figure 4 in the main text.²¹

²¹The results are also robust when considering the response of domestic and imported goods across both informal and formal markets.

Figure B.2: Responses of Prices in Informal/Markets to a US MP Shock (Conventional LP)



Notes: Dynamic responses of micro prices sold in formal and informal markets in Honduras to a US MP shock. The figure shows $\beta_{1,h}$ (left figure) and $\beta_{2,h}$ (middle figure) estimated through equation (9). The right figure corresponds to the difference between the two estimated coefficients across each horizon. Continuous lines denote the median IRFs to a US MP shock. In the specification, we clustered the standard errors across groups (product-store), type of establishment, and time. Shaded grey areas denote 90% confidence intervals. Horizon is in months.

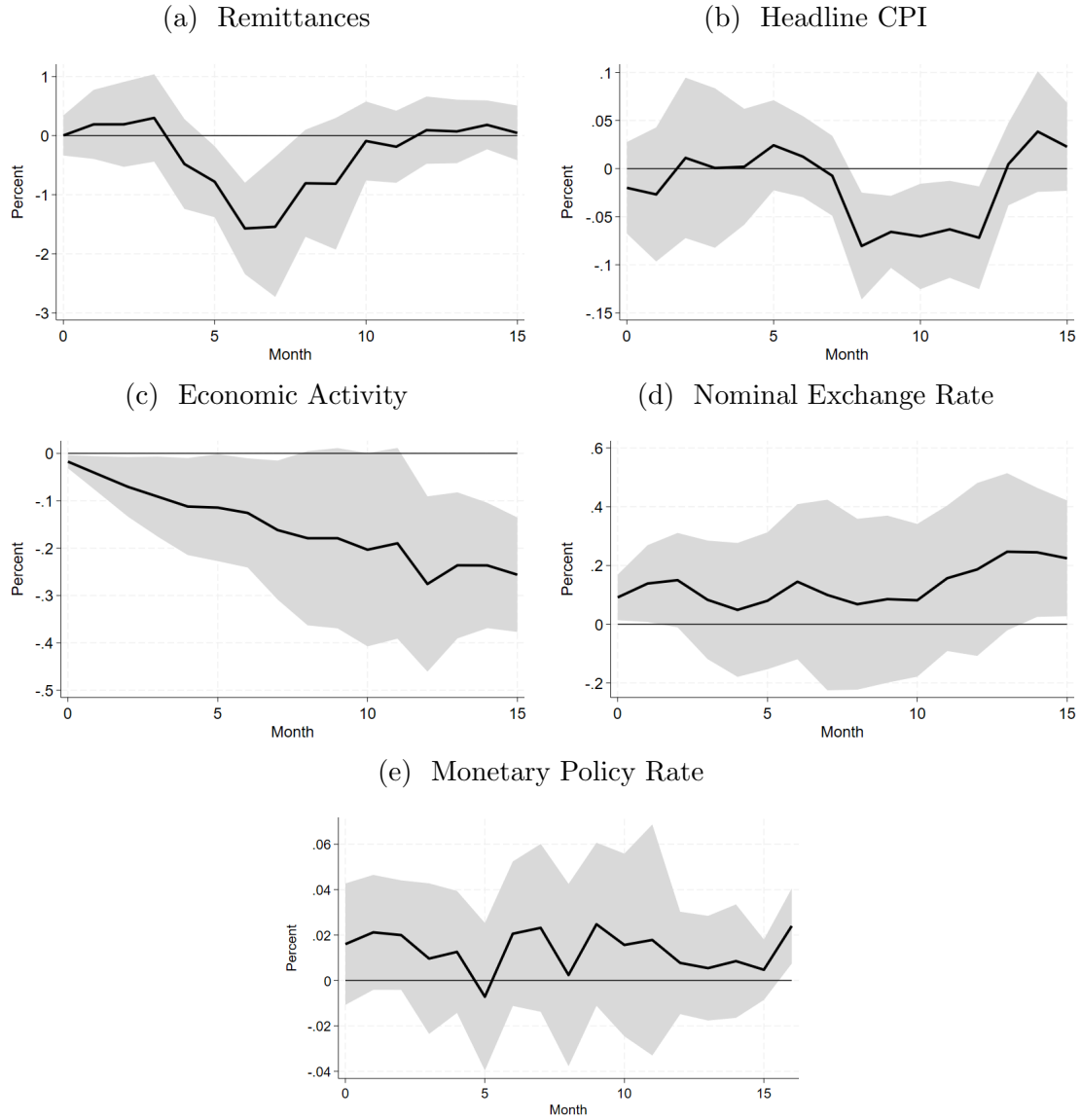
B.2 Alternative US MP Shock

Figure B.3 displays the macroeconomic responses of Honduras to a US MP shock using the MP shock series by Nakamura and Steinsson (2018b) instead of the ones of Jarociński and Karadi (2020). The responses of macroeconomic variables are estimated relying on equation (2). The responses are consistent with the baseline ones presented in Figure 3.

We also estimate the probability of price adjustment of equation (3) but now using the MP shocks computed by Nakamura and Steinsson (2018b). As shown in Table B.1, and in line with our baseline estimates, a positive MP shock in the US leads to a drop of approximately 1.1% in the probability of a price increase. In addition, the same shock brings an increase of 0.6% in the probability of a price decrease across informal markets, twelve months after the shock. As noticed by the probability of price decreases, the probability of price reductions starts reacting six months after the shocks hit, while the reaction in formal establishments acts with a delay. The relevance of the price gap and the age of a price in triggering price reaction also remains unaffected by the alternative shock.

Finally, we also re-estimate equation (4) using the Nakamura and Steinsson (2018b)'s MP shocks. The results are shown in Figure B.4. Again, in line with our baseline results, prices in informal markets react promptly to the shock. The average price decrease reaches 0.2%

Figure B.3: Responses of Macroeconomic Variables to an Alternative US MP Shock



Notes: Estimated effects of US MP shock on remittances, Core and Headline CPI, economic activity, and the nominal exchange rate over the sample 2015M1-2019M12 estimated using equation (2). Continuous lines denote the median IRFs to a US MP shock. Shaded areas denote 90% confidence intervals based on Newey-West standard errors. Horizon is in months.

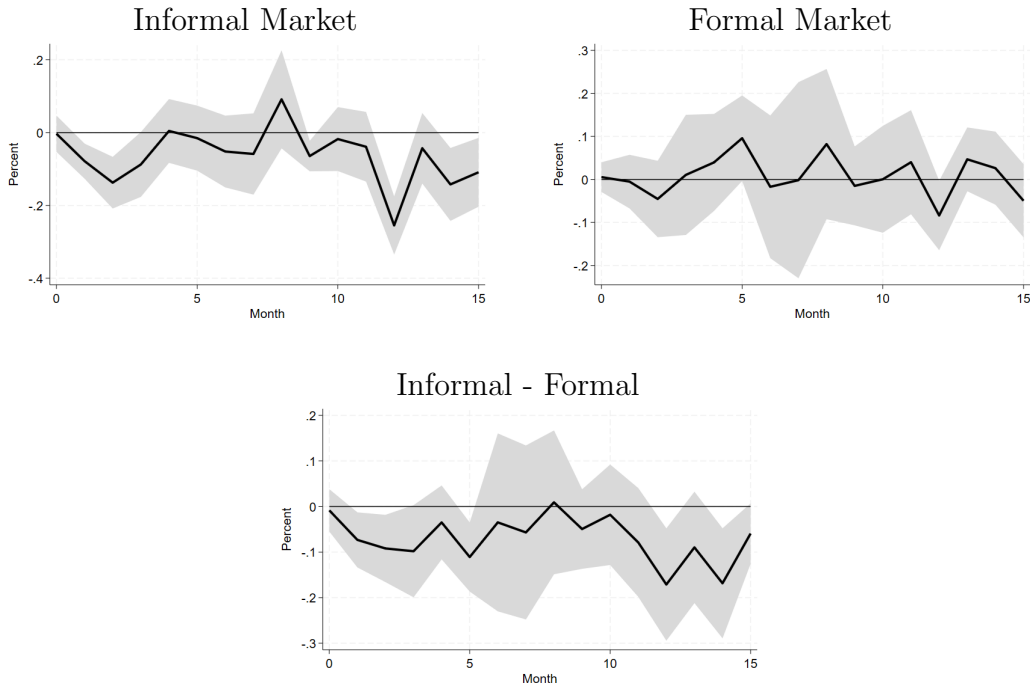
approximately one year later. On the contrary, prices in formal markets do not evidence a significant response.

Table B.1: Price Adjustment: Alternative US MP Shock

	Price Increase				Price Decrease			
	$I_{t-1,t+3}$	$I_{t-1,t+6}$	$I_{t-1,t+12}$	$I_{t-1,t+15}$	$I_{t-1,t+3}$	$I_{t-1,t+6}$	$I_{t-1,t+12}$	$I_{t-1,t+15}$
$S_t^{MP} \times Informal$	0.05 (0.36)	0.17 (0.23)	-1.10*** (0.25)	-0.54* (0.28)	0.04 (0.13)	0.29** (0.09)	0.63*** (0.10)	0.32** (0.11)
$S_t^{MP} \times Formal$	-0.01 (0.47)	0.87 (0.52)	-0.46 (0.31)	-0.45 (0.36)	0.12 (0.17)	0.09 (0.12)	0.49*** (0.14)	0.46*** (0.11)
$Informal - Formal$	0.06 (0.32)	-0.69 (0.43)	-0.63** (0.28)	-0.09 (0.22)	-0.08 (0.13)	0.20 (0.20)	0.13 (0.22)	-0.14 (0.12)
Gap_{pst-1}	-0.79*** (0.04)	-0.98*** (0.02)	-1.16*** (0.02)	-1.24*** (0.01)	0.63*** (0.07)	0.76*** (0.08)	0.90*** (0.10)	0.97*** (0.11)
Age_{pst-1}	0.02 (0.07)	0.26** (0.09)	0.71*** (0.13)	0.91*** (0.14)	-0.03 (0.07)	-0.01 (0.08)	0.06 (0.08)	0.08 (0.10)
Product-Store FE	✓	✓	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
N	345,120	326,060	288,051	269,187	345,120	326,060	288,051	269,187
R	0.04	0.06	0.09	0.10	0.04	0.05	0.07	0.07

Notes. The table shows the estimation of equation (3) using the micro data for Honduras. For this robustness exercise, we rely on the shocks computed by Nakamura and Steinsson (2018b). The Gap corresponds to the log difference between the individual (product-store) price relative to the average price within that category. Age is defined as the logarithm of the number of months the price has remained constant. All the estimations include product-stores and month FE. Standard errors are clustered across groups (product-store), type of establishment, and time. * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

Figure B.4: Impulse Responses to an Alternative US MP Shock

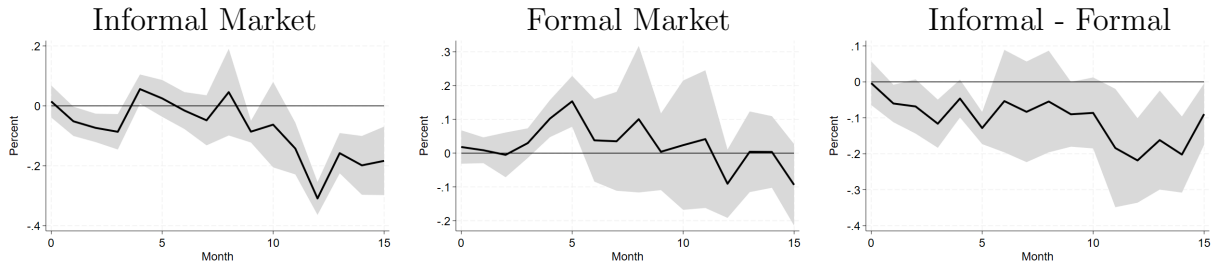


Notes: The figures show the dynamic responses of micro prices in Honduras to an external MP shock in the US. For this robustness exercise, we rely on the shocks computed by [Nakamura and Steinsson \(2018b\)](#). The figures show the results for $\beta_1^h, \beta_2^h, \beta_3^h$ and β_4^h for each group estimated through equation (5). In the specification, we clustered the standard errors across groups (product-store), type of establishment, and time. Shaded grey areas denote 90% confidence intervals.

B.3 Temporary Sales

In the Honduran CPI data, we cannot differentiate between a regular price change and prices that change because of sales. As sales could be particularly relevant across formal markets, in this section, we aim to remove prices that change because of a sale from our results. For doing so, we rely on the “V-Shape” filter originally proposed by Nakamura and Steinsson (2008). The idea is to identify sales as prices that drop by one or two periods at some moment in time, and then go back to the exact same level that they had before the adjustment. After applying the filter and removing sales, we re-estimate the response of price adjustments following specification 4. The results are shown in Figure B.5.

Figure B.5: Responses of Prices in Informal/Markets to a US MP Shock (Removing Sales)



Note. Dynamic responses of micro prices sold in formal and informal markets in Honduras to a US MP shock. The figure shows $\beta_{1,h}$ (left figure) and $\beta_{2,h}$ (middle figure) estimated through equation (4). The right figure corresponds to the difference between the two estimated coefficients across each horizon. Continuous lines denote the median IRFs to a US MP shock. In the specification, we clustered the standard errors across groups (product-store), type of establishment, and time. Shaded grey areas denote 90% confidence intervals. Horizon is in months.

As observed, our main results hold after we remove sales-type movements from the CPI data. Prices in informal markets drop by 0.2% approximately one year after the shock, while prices in formal markets do not evidence any significant reaction. The price-adjustment difference is again significant across markets, as shown by the right panel of the figure.

B.4 Price Reaction of Food and Beverages to the US MP Shock

Building on the evidence of Section 4.3, we explore more deeply which categories of goods are the ones that are responding more quickly to the international shock.

Given that Food is the category that accounts for the largest weight in the Honduran CPI, we split the sample between Food and Non-food goods. We do this through the dummy variable $\mathbf{1}_{fb}$, which is equal to one if the product belongs to the “Food and non-alcoholic beverages” category in the CPI and zero otherwise. Besides the external shock, we interact this variable with the domestic/imported dummy and with the informal and formal market indicator. Specifically, we estimate the following Local Projection specification:

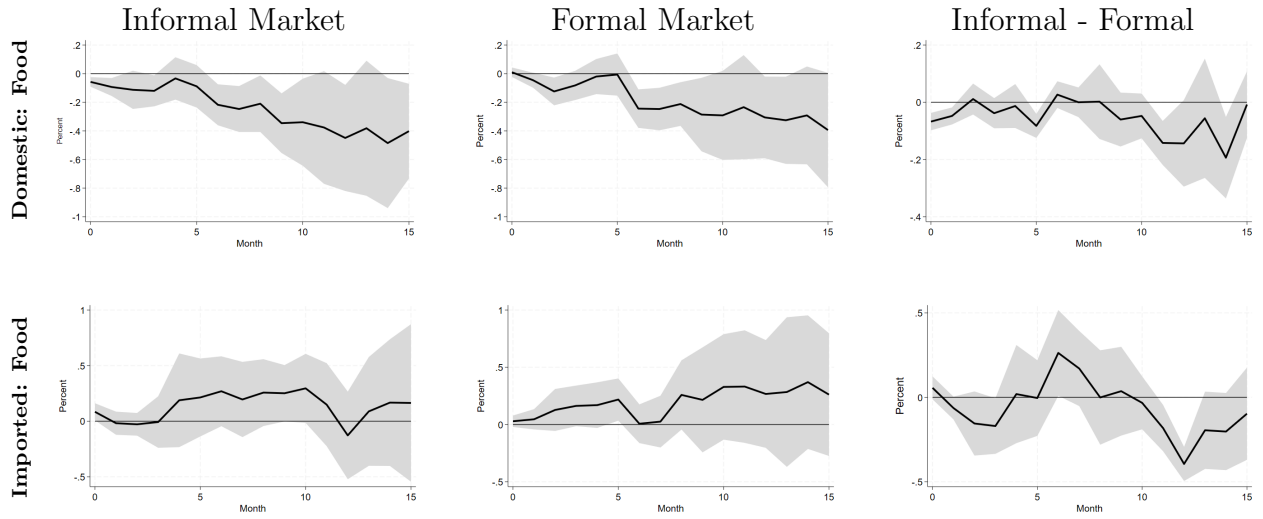
$$\begin{aligned}
 p_{ps,t+h} - p_{ps,t-1} = & \alpha_{ps,h} + \beta_{1,h} (s_t^{mp} \times \mathbf{1}_d \times \mathbf{1}_i \times \mathbf{1}_{fb}) + \beta_{2,h} (s_t^{mp} \times \mathbf{1}_d \times \mathbf{1}_f \times \mathbf{1}_{fb}) \\
 & + \beta_{3,h} (s_t^{mp} \times \mathbf{1}_{imp} \times \mathbf{1}_i \times \mathbf{1}_{fb}) + \beta_{4,h} (s_t^{mp} \times \mathbf{1}_{imp} \times \mathbf{1}_f \times \mathbf{1}_{fb}) + \beta_{5,h} \text{Gap}_{ps,t-1} \\
 & + \beta_{6,h} \text{Age}_{ps,t-1} + \gamma_h (\mathbf{x}_{t-1} - \bar{\mathbf{x}}) + \theta_h (s_t^{mp} \times (\mathbf{x}_{t-1} - \bar{\mathbf{x}})) + \alpha_{m,h} + \epsilon_{ps,t+h} \quad (10)
 \end{aligned}$$

The results of the four coefficients that account for the interactions across the different horizons, are presented in Figure B.6.

The prices of food-related items produced domestically and sold in informal markets are the ones that react promptly. Moreover, these type of goods not only reacts upon impact but also are the ones that evidence the stronger and more persistent response to the shock. On the contrary, food items sold in formal markets do not evidence the same immediate reaction, and even when the effect becomes significant, its magnitude is almost half of the informal market counterpart. Finally, and consistent with our previous results, prices of imported goods do not evidence any meaningful reaction.

This evidence reinforces our conjecture that we need to account for each product-specific characteristic to strip down the effect of the international MP shock. This is precisely what we do in Section 5 of the main text.

Figure B.6: Response of Prices to a US MP Shock



Notes: The figures show the dynamic responses of micro prices in Honduras to an external MP shock in the US. The figures show the results for $\beta_1^h, \beta_2^h, \beta_3^h$ and β_4^h for each group estimated through equation 10. In the specification, we clustered the standard errors across groups (product-store), type of establishment, and time. Shaded grey areas denote 90% confidence intervals.