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Abstract

This paper provides new evidence on the impact of exchange rate depreciation on pricing behavior. Using micro data on consumer price quotes in Iran from 2006 to 2022, we study price adjustments across a wide range of macroeconomic conditions—from low to high inflation and from stable to volatile exchange rates. While most existing studies emphasize the role of inflation, our analysis highlights the distinct contribution of exchange rate depreciation. We find that (1) in the short run, both the frequency and absolute size of price changes respond more to inflation than to exchange rate depreciation, but FX effects is stronger over longer horizons; (2) FX depreciation has a pronounced nonlinear effect on frequency of price changes, showing a significant impact only at high depreciation levels, while inflation displays a more linear pattern; (3) we find no evidence of nonlinear effects for either inflation or FX depreciation on the absolute size of price changes; and (4) expected inflation influences pricing behavior independently of actual inflation.

Keywords: inflation, exchange rate, pricing behavior, price rigidity, expected inflation, frequency of price changes
JEL Classifications: E31, E32, L11

ملخص

تقدم هذه الورقة أدلة جديدة حول تأثير انخفاض سعر الصرف على سلوك التسعير. باستخدام البيانات الجزئية حول أسعار المستهلك في إيران من عام 2006 إلى عام 2022، قمنا بدراسة تعديلات الأسعار عبر مجموعة واسعة من الظروف الاقتصادية الكلية —من التضخم المنخفض إلى المرتفع ومن أسعار الصرف المستقرة إلى المتقلبة. وفي حين تؤكد معظم الدراسات القائمة على دور التضخم، فإن تحليلنا يسلط الضوء على المساهمة المتميزة لانخفاض سعر الصرف. نجد أن (1) في الأمد القريب، يستجيب كل من تواتر وحجم التغيرات المطلقة في الأسعار للتضخم أكثر من انخفاض سعر الصرف، ولكن تأثيرات النقد الأجنبي أقوى على مدى آفاق أطول؛ (2) انخفاض سعر الصرف الأجنبي له تأثير غير خطي واضح على تواتر التغيرات في الأسعار، ويظهر تأثيرًا كبيرًا فقط عند مستويات انخفاض عالية، في حين يُظهر التضخم نمطًا أكثر خطية؛ (3) لم نجد أي دليل على وجود تأثيرات غير خطية للتضخم أو انخفاض قيمة العملات الأجنبية على الحجم المطلق لتغيرات الأسعار؛ و(4) يؤثر التضخم المتوقع على سلوك التسعير بشكل مستقل عن التضخم الفعلي.

1 Introduction

The timing and magnitude of price adjustments—referred to as pricing behavior—are central to understanding the neutrality of money and have implications for the real effects of macroeconomic shocks, including monetary policy. Pricing behavior is typically measured by the frequency and absolute size of price changes, and the response of these indicators to aggregate shocks provides key evidence for evaluating monetary non-neutrality in practice.[1] In line with this view, most empirical studies have focused on the effect of inflation as an aggregate shock on pricing behavior.[2]

Pricing models offer different predictions about how aggregate shocks affect pricing behavior. In most empirical studies, aggregate shocks are proxied by CPI inflation.[3] Choosing a proxy for aggregate shocks is not particularly challenging in stable macroeconomic environments, where different indicators tend to convey similar information to price setters about the overall state of the economy. However, after large aggregate shocks, macroeconomic indicators may diverge and offer complementary information about the state of the economy. In such cases, price setters may consider multiple variables, as no single measure fully captures the relevant environment.

Exchange rate (FX) movements—particularly depreciation[4]—alter input costs and can act as a nominal anchor in the absence of credible monetary frameworks, thereby influencing inflation expectations. As a result, FX is a key determinant of macroeconomic stability, especially in emerging economies. These dual roles—raising firms' costs and shaping inflation expectations—suggest that FX depreciation can have a direct impact on pricing decisions and may provide information beyond what is captured by CPI inflation. Price setters—especially in developing countries with weakly anchored expectations—may view FX fluctuations not just as a cost shock but also as a signal of future inflation, making FX an important macroeconomic variable to study alongside CPI inflation.

Given the importance of FX movements for macroeconomic stability and the limited empirical evidence on how FX shocks affect pricing behavior, this paper studies the impact of FX depreciation on pricing behavior using Iranian consumer prices from 2006 to 2022. During this period, the Iranian economy experienced a wide range of macroeco-

[1]The inverse of the frequency of price changes—implied duration—is commonly used as a measure of price rigidity. In addition, Nakamura et al. (2018) argue that the absolute size of price changes can consider as a proxy for price dispersion.

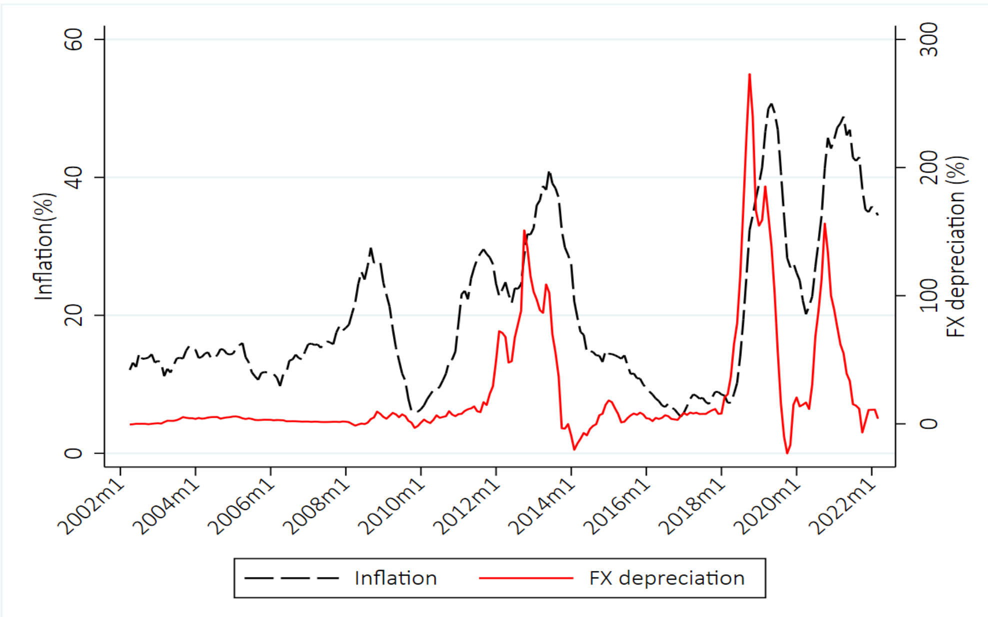
[2]See Klenow and Malin (2010) and Nakamura and Steinsson (2013) for reviews.

[3]Some studies use alternative proxies: Golosov and Lucas Jr (2007) consider nominal wage growth, while Alvarez and Neumeyer (2020) focus on cost shocks, defined as a combination of wages and input prices.

[4]FX (foreign exchange) depreciation refers to a decline in the value of the domestic currency, the Iranian rial, relative to foreign currencies such as the U.S. dollar.

nomic conditions—from low to high inflation, and from stable FX to sharp depreciation episodes—making it a valuable setting for analyzing the effects of FX shocks on pricing decisions (Figure 1). We examine whether and how FX depreciation influences the frequency and absolute size of price changes, extending the literature that focuses primarily on inflation as the dominant macroeconomic driver of pricing behavior.

Figure 1: Inflation and FX depreciation



Notes: Inflation is calculated as the 12-month growth rate of the urban CPI (excluding housing rent). FX depreciation is measured by the 12-month growth in the USD cash price in the non-regulated market, where an increase reflects depreciation of the Iranian rial.

To address this question, we use consumer price quotes from urban areas in Iran between 2006 and 2022. The data, collected by the Statistical Center of Iran (SCI), are used to construct the CPI. Our dataset contains more than 34 million observations spanning all 31 provinces, with a sampling process and weighting scheme specifically designed to measure inflation at the province level. Unlike many studies that focus on specific geographic areas,[1] our dataset extends beyond major cities. By including 231 cities, we can analyze pricing behavior across provinces with differing inflation rates.

To examine the relationship between FX depreciation and pricing behavior, we estimate fixed-effects regressions at the item level.[2] It allows us to capture price-setting be-

[1]For example, studies using U.S. price quotes—such as Klenow and Kryvtsov (2008), Nakamura and Steinsson (2008), and Nakamura et al. (2018)—are limited to the metropolitan areas of Los Angeles, New York, and Chicago. Similarly, studies using Argentine data focus on Buenos Aires, either at the metropolitan level (e.g., Alvarez et al. (2019)) or city level (e.g., Alvarez and Neumeyer (2020)).

[2]This approach builds on earlier studies such as Gagnon (2009) and Nakamura and Steinsson (2008),

havior with higher granularity than most existing studies. The dependent variables are the frequency and absolute size of price changes. On the right-hand side, we include CPI inflation, FX depreciation, and expected inflation. Because FX depreciation may be associated with both cost shocks and shifts in inflation expectations, controlling for expected inflation allows us to assess the extent to which each channel contributes to observed pricing behavior. Our specifications include fixed effects and additional controls—such as lagged and squared terms of inflation and FX depreciation—to account for nonlinearities and persistence. This empirical framework provides descriptive evidence on how pricing behavior responds to FX depreciation.

Our results show that rising inflation increases both the frequency and absolute size of price changes, consistent with the findings of previous studies.[1] The central finding of this paper is new evidence on how pricing behavior changes with FX depreciation. We find that FX depreciation increases both the frequency and absolute size of price changes, but this effect disappears once we control for inflation. This pattern holds in the short run; however, in the long run, FX depreciation has a statistically and economically significant effect on both the frequency and absolute size of price changes.

While we do not find strong evidence for a linear effect of FX depreciation on pricing behavior, we do find robust nonlinear effects. Both the interaction between FX depreciation and inflation, and the squared term of FX depreciation, significantly increase the frequency of price changes—even after controlling for inflation and expected inflation. These results suggest that the effect of FX depreciation becomes more evident when depreciation episodes are large.

This paper contributes to the literature on pricing behavior by providing evidence on how FX depreciation affects price adjustments. Most existing studies focus on inflation as the primary macroeconomic driver of pricing behavior. By contrast, we show that FX depreciation influences both the frequency and absolute size of price changes, particularly during large depreciation episodes. Our framework also allows us to separately examine cost and expectation channels by controlling for expected inflation. A key advantage of our dataset is that it enables the use of province-level inflation, allowing us to exploit variation in inflation across provinces while controlling for national shocks.

Our work also connects to the *FX pass-through* literature, which traditionally examines how FX movements influence consumer and import prices using aggregate or product-level data. Early macro studies established a generally low pass-through[2] while recent

which use country-level and item-level indices, respectively.

[1]For example, Nakamura and Steinsson (2008), Gagnon (2009), Wulfsberg (2016), and Alvarez et al. (2019).

[2]For example, see Campa and Goldberg (2005) and Devereux and Yetman (2010)

studies by using micro-level data prices, open new ideas in this literature, like relationship between frequency of price changes and pass-through and the effect of currency invoicing FX pass through.[1] We contribute to this strand by focusing on consumer prices in a high-inflation emerging market, emphasizing nonlinear responses to large depreciation episodes, and using high-resolution data to detect dynamic pricing effects.

Our work also connects to the *FX pass-through* literature, which traditionally examines how FX movements influence consumer and import prices using aggregate or product-level data. Early macro studies found that pass-through is generally low,[2] while more recent work using micro-level price data has introduced new ideas to this literature, such as the relationship between the frequency of price changes and pass-through, and the role of currency invoicing.[3] We contribute to this strand by focusing on consumer prices in a high-inflation emerging market, emphasizing nonlinear responses to large depreciation episodes, and using high-resolution data to detect dynamic pricing patterns.

2 Institutional context

This section outlines two institutional features of the Iran's economy—price control and dual exchange rates—that may be questioning for our results. These policies are common in countries experiencing high inflation and large FX depreciation shocks.[4]

Price control

In response to nominal shocks, Iranian authorities have used price controls to shield consumers from rising costs, particularly for essential goods. While often framed as a welfare policy, such controls are rarely effective at suppressing aggregate inflation.[5] We categorize products into three groups: (i) those under effective price control, such as utilities, bread and gasoline, where the state can subsidize supply and control the price; (ii) partially controlled goods like meat and dairy, where regulated prices exist by queue and quote alongside unregulated market prices; and (iii) uncontrolled goods, which are freely priced.

[1] For example, see Gopinath and Itskhoki (2010), Gopinath et al. (2010), Cavallo et al. (2024), and Auer et al. (2021).

[2] For example, see Campa and Goldberg (2005) and Devereux and Yetman (2010).

[3] For example, see Gopinath and Itskhoki (2010), Gopinath et al. (2010), Cavallo et al. (2024), and Auer et al. (2021).

[4] See Alvarez and Neumeyer (2020) and Aparicio and Cavallo (2021) on Argentina's experience with both policies.

[5] Aparicio and Cavallo (2021) show evidence for price control ineffectiveness.

Price controls can influence our results in two main ways. First, for products under strict regulation, the frequency of price changes may be artificially low, not because of market forces but due to administrative constraints. This is especially relevant for goods like utilities, bread and gasoline, where the government either sets prices directly or compensates suppliers. However, this concern is limited in scope. Only a small share of the consumer basket is subject to fully effective price control, and most goods in our sample operate under market conditions. Moreover, this institutional feature is not unique to Iran—many emerging and even advanced economies adopt temporary price controls during high inflation episodes. Thus, the existence of price control does not limit generalizing our findings.

Second, there is a potential concern that the consumer price quotes data may be biased toward controlled prices.[1] SCI reports that its price data fairly represents both regulated and unregulated outlets, with sampling designed to reflect their shares in the consumer basket. As a result, our dataset includes both controlled and market-based prices. Our dataset supports this claim: we observe substantially more frequent price changes in markets where government control is weak or absent. This pattern—detailed further in Figure 6—suggests that our pricing measures capture genuine market behavior, even in the presence of partial controls.

Dual exchange rate

During inflationary episodes, policymakers in Iran have adopted a dual (or multi-tiered) FX regime. The Iranian economy has typically operated with three distinct exchange rates: (i) a regulated rate, applied to government-owned foreign currency used to finance essential imports such as food and medicine; (ii) a semi-regulated rate, imposed on government-owned companies and private exporters; and (iii) a market rate, which applies more broadly to any FX transactions not subject to government control.

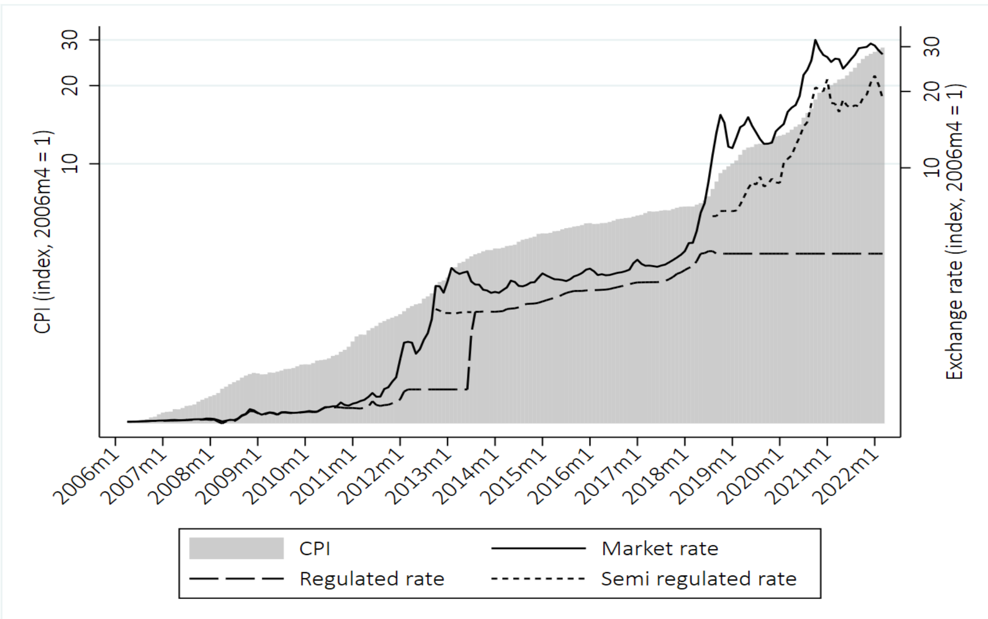
Among these, the market rate plays the role of the de facto nominal anchor for most economic decisions. A wide range of goods—particularly those not subject to effective price control—are priced with direct reference to the market FX rate. Moreover, inflation expectations among agents are also formed based on this rate. The Central Bank of Iran (CBI) collects expectations from professionals and businesses through regular surveys, and in doing so, focuses on the market rate as the relevant benchmark—not the regulated

[1]For example, Cavallo (2013) use online prices from several Latin American countries and show that between 2007 and 2011, Argentina's official CPI was three times lower than the CPI derived from market prices, while other countries reported CPI more aligned with actual pricing data. This difference comes from official statistics relying heavily on controlled prices.

or semi-regulated rates.

Given this context, we adopt market FX depreciation as the main macroeconomic shock in our analysis. As shown in Figure 2, the persistent gap between the regulated and market FX rates highlights the limited effectiveness of administrative pricing and underscores the relevance of the market rate in Iran's inflationary environment.

Figure 2: CPI and FX indices in Iran (2006–2022)



Notes: All series are indexed to 1 in April 2006. The CPI reflects urban consumer prices (excluding rent). The regulated FX refers to the official rate set by CBI. The non-regulated FX corresponds to the cash market rate. The semi-regulated FX rate is derived from two sources: the Currency Exchange Center rate (Oct. 2012–Jul. 2013) and the Integrated Foreign Exchange Trading (NIMA) system (Aug. 2018–Mar. 2022). The non-regulated rate is used to establish the initial value for the semi-regulated series in April 2006, as no data is available for that period.

3 Data and indices

We use monthly price quotes collected by the SCI from urban areas between April 2006 and March 2022. These quotes reflect shelf-level consumer prices across a wide range of goods and services. These products account for 66% of consumer expenditures, with the remaining portion attributed to housing rent. After removing unreliable observations, those with extreme month-to-month price changes, and entries with zero weights, the cleaned dataset consists of over 34 million observations. The data cover all 31 provinces, 231 cities, and include more than 306,000 retail outlets and 453 products classified using the COICOP classification. Additional details on sample construction and classification are provided in Appendix B..

Indices of pricing behavior: frequency and size

To characterize pricing behavior, we focus on two standard measures: the *frequency* and the *absolute size* of price changes. Let p_{oit} denote the price of product i at outlet o in month t. The price change indicator is defined as:

$$I_{oit} = \begin{cases} 1 & \text{if } p_{oit} \neq p_{oit-1} \\ 0 & \text{if } p_{oit} = p_{oit-1} \end{cases} \tag{1}$$

The frequency of price changes for product i in month t is the share of prices that change:

$$fr_{it} = \frac{\sum_o I_{oit}}{\sum_o 1_{oit}} \tag{2}$$

The absolute size of price changes is defined as the average magnitude of monthly price growth, conditional on a change:

$$\Delta p_{oit} = 100 \times \left| \frac{p_{oit}}{p_{oit-1}} - 1 \right| \tag{3}$$

$$\Delta p_{it} = \frac{\sum_{I_{oit}=1} \Delta p_{oit}}{\sum_o I_{oit}} \tag{4}$$

At the aggregate level, we compute the weighted median and mean of these product-level indices, following Bils and Klenow (2004) and Klenow and Kryvtsov (2008).

Table 1 indicates that the mean (median) frequency of price changes across products is 23.6% (15%). The table also shows that the mean (median) absolute size of price changes is 14.7% (11.2%). These values are close to those reported in previous studies.[1] Figure 3 illustrates the co-movement between inflation and pricing behavior over time. As inflation rises from 8% to 60%, the frequency of price changes fluctuates between 10% and 45%, while the absolute size increases from 10% to 20%.

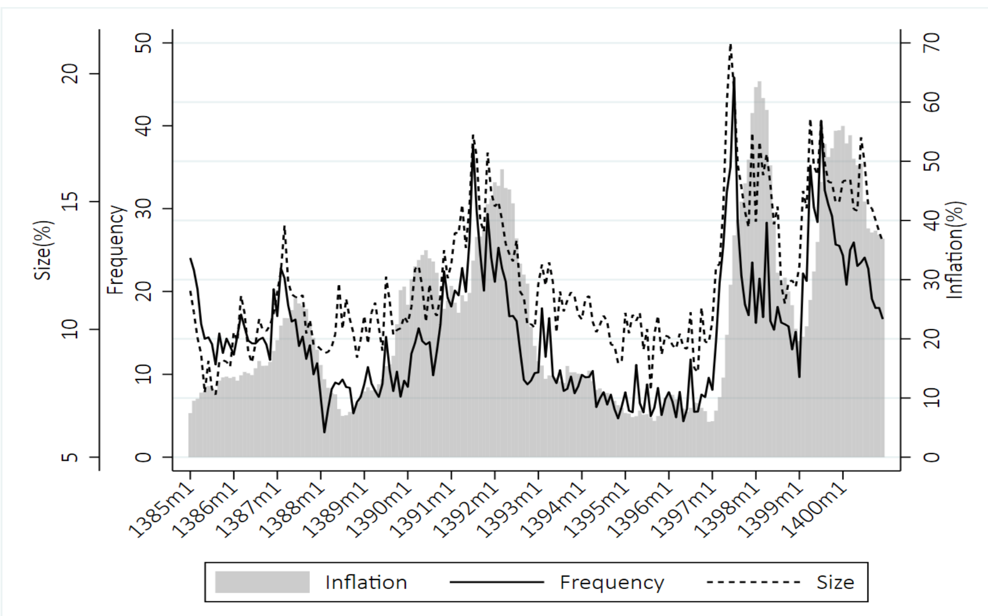
[1]For example, Nakamura and Steinsson (2008) report a mean (median) frequency of 26.5% (19.4%) and a median absolute size of 10.7% for the U.S. during 1998–2005. Wulfsberg (2016) find a mean (median) frequency of 21.9% (14.3%) in Norway over 1975–2004. While he does not directly report the absolute size of price changes, he provides the size of price increases and decreases. The reported mean (median) size of price increases is 12.3% (9.3%), and the mean (median) size of price decreases is 10.5% (9.7%). We can approximately infer that the mean (median) absolute size of price changes in Norway is about 12% (9%).

Table 1: Frequency and absolute size of price changes during 2006-2022.

		Frequency	Size
Simple Price Changes	Mean	23.6	14.7
	Med	15	11.9
Without Sales and Subs. Price Changes	Mean	21.2	14.8
	Med	13.7	12
Simple Price Increase	Mean	17.5	15.3
	Med	12.5	12.2
Simple Price Decrease	Mean	6	7.2
	Med	0.6	5.6

Notes: All statistics are weighted. *Mean* and *Med* represent the weighted average and median of the statistics, respectively. *Simple Price Changes* displays the statistics without filters. *Without Sales and Subs. Price Changes* shows statistics that filter out any sales (V-shape price changes in the 1-month window) and any observation reported as substitution. *Simple Price Increases* and *Simple Price Decreases* provide statistics without any filtering out that focus on price increases and price decreases.

Figure 3: Inflation, frequency of price changes and absolute size of price changes



Notes: Frequency and absolute size of price changes are calculated as the weighed median over the products. Inflation is calculated as the 12-month urban CPI (excluding rent) growth rate.

Sales-related observations account for a small share of price changes in our dataset and have little impact on the aggregate indices. Table 1 shows that excluding sales and substitution-related changes reduces the mean frequency of price changes only modestly—from 23.6% to 21.2%, and the median from 15% to 13.7%. We identify potential sales using short-term V-shaped price movements, following Nakamura and Steinsson (2008). The full procedure and robustness results excluding these observations are reported in Appendix D..

Expected inflation

We construct two proxies for expected inflation. The first follows the approach of Alvarez et al. (2019), where expected inflation is calculated using realized CPI growth over an implied duration determined by the inverse of the frequency of price changes. Specifically,

$$\pi_t^e = \left(\left(\frac{CPI_{t+k_t}}{CPI_t} \right)^{\frac{1}{k_t}} - 1 \right) \times 100, \quad \begin{cases} k_t = \frac{1}{fr_t}, & \text{if } \frac{1}{fr_t} \leq 12 \\ k_t = 1, & \text{if } \frac{1}{fr_t} > 12 \end{cases} \tag{5}$$

where fr_t denotes the weighted median frequency of price changes across products in month t.

This formula modifies the original method in Alvarez et al. (2019), which uses $k_t = 1/fr_t$ without restriction. In our context, we cap k_t at 12 months to avoid unrealistically long implied durations during periods of low frequency. Without this cap, the formula may average inflation too far into the future, producing a distorted pattern in which high inflation in later periods artificially increases the expected inflation estimate for earlier months. For example, in 2017, the implied duration exceeds 20 months, so the expected inflation estimate for that year would reflect inflation realized in 2019, well before agents had actually revised their expectations upward.Survey-based proxies from the Monetary and Banking Research Institute (MBRI), a research institute affiliated with the Central Bank of Iran, indicates that expected inflation remained moderate throughout 2017 and only began to rise in the months leading up to the 2018 FX shock.

In addition, we use a survey-based proxy constructed from forecasts reported by MBRI. Since 2016, MBRI has conducted surveys of professional forecasters, collecting expectations for key macroeconomic variables including inflation and the FX. While this measure is only available for 19 periods, it closely tracks the Alvarez et al. (2019) index and confirms its results. We report regressions using this survey-based proxy as robustness evidence in Appendix C..

In addition to expected inflation, our analysis includes two other macroeconomic variables: CPI inflation and FX depreciation. Inflation is measured as the monthly growth rate of the urban CPI (excluding rent), as reported by SCI. FX depreciation is measured as the monthly growth rate of the USD cash price in the non-regulated market, using data published by the CBI. An increase in this variable indicates a depreciation of the Iranian rial. Table 2 reports summary statistics for these variables, including both monthly and

Table 2: Summary statistics for macroeconomic variables used in regressions

	Mean	SD	Median	Min	Max
Monthly inflation (π_t)	1.77	1.57	1.51	-0.82	8.44
Monthly FX depreciation (Δe_t)	1.93	6.27	0.57	-19.49	35.36
Monthly expected inflation (π_t^e)	1.97	1.32	1.75	0.29	6.15
12-month inflation ($\pi_{12,t}$)	23.42	15.00	17.54	5.97	63.51
12-month FX depreciation ($\Delta e_{12,t}$)	30.37	51.40	7.82	-22.98	272.89
12-month expected inflation ($\pi_{12,t}^e$)	27.85	21.62	23.22	3.58	104.76

Notes: *Inflation* is calculated using the urban CPI (excluding rent), and *FX depreciation* is calculated as the growth in the USD cash price in the non-regulated market. All variables are expressed as percentage changes. Monthly variables represent one-month growth; 12-month variables reflect 12-month growth. Expected inflation is constructed following the method of Alvarez et al. (2019), using the urban CPI (excluding rent).

12-month versions used in the regression analysis.

4 Empirical strategy

The objective of this research is to provide empirical evidence on how pricing behavior varies with FX depreciation. These results can be interpreted in light of theoretical pricing models, particularly those related to the neutrality of money, and may help inform future model development.

We follow the approach used in Nakamura and Steinsson (2008) and Gagnon (2009), estimating OLS regressions to examine how pricing behavior varies with macroeconomic conditions. This method allows us to control for other variables that may correlate with FX depreciation and influence pricing decisions, such as CPI inflation and expected inflation. While our goal is not to establish causality, OLS regressions help isolate the relationship between FX depreciation and pricing behavior, net of other macroeconomic influences.

Our dataset allows us to estimate fixed-effect regressions at different levels, including product, province-by-product, and outlet-by-product. In this paper, we focus on product-level regressions as the main specification. Results from regressions at the province-by-product and outlet-by-product levels are presented in Appendix C..

We focus on the following product-level fixed-effects regression:

$$y_{it} = \beta_0 + \beta_1 \pi_t + \beta_2 \Delta e_t + \beta_3 \pi_t^e + \beta_4 (\pi_t \times \Delta e_t) + \beta_5 \pi_t^2 + \beta_6 \Delta e_t^2 + FE_i + \epsilon_{it} \tag{6}$$

Where i indexes products and t indexes months. The dependent variable y_{it} represents either the frequency or the absolute size of price changes at the product level (see Equations 2 and 4). All explanatory variables—monthly inflation (π_t), FX depreciation (Δe_t), and expected inflation (π_t^e)—are defined in Section 3. FE_i denotes product-level fixed effects.

We include expected inflation, π_t^e, to help distinguish between cost and expectation channels. Controlling for π_t^e allows us to examine whether FX depreciation provides additional information for pricing behavior beyond its role in shaping expectations.

To capture nonlinearities in the relationship between pricing behavior and macroeconomic conditions, our main specification includes both the interaction term $\pi_t \times \Delta e_t$ and squared terms for inflation and FX depreciation. The interaction term allows us to examine whether the relationship between inflation and FX depreciation is conditional on the level of either variable—for example, whether high inflation increases the relevance of FX depreciation for pricing behavior, or vice versa. The squared terms test whether the influence of inflation and FX depreciation is linear or depends on their levels; that is, whether the sensitivity of pricing behavior strengthens or weakens when either variable is high. These components help us assess whether pricing behavior responds more sharply during high-inflation or large-depreciation episodes.

We also include lagged values of inflation and FX depreciation in extended specifications to capture delayed pricing responses. Since firms may adjust prices based not only on current conditions but also on past shocks, incorporating lags allows us to explore whether observed price changes reflect previous macroeconomic developments. This is particularly relevant in the presence of gradual pass-through or when pricing decisions rely on information accumulated over time.

All regressions are weighted by product expenditure shares, using CPI weights from the 2016 HIES. These are the same weights used in the construction of urban CPI. We do not include time fixed effects, such as month or year dummies, because all explanatory variables—except product fixed effects—vary only over time. Including time fixed effects would absorb the variation in inflation and FX depreciation that we aim to capture. However, our main findings remain stable when we include month or year fixed effects as a robustness check.

5 Results

We estimate the regression in Equation 6 to examine how pricing behavior varies with FX depreciation. Table 3 reports results for the frequency of price changes, while Table 4 presents results for the absolute size of price changes. Both outcomes are measured at the product level. All coefficients and standard errors, except for the constant, are standardized and reflect the change in the dependent variable associated with a one-standard-deviation increase in the corresponding explanatory variable.[1] Columns (1)–(6) and (8) use monthly inflation, FX depreciation, and expected inflation, while Column (7) uses 12-month rates to assess long-run relationships. Column (8) includes 24 monthly lags of inflation and FX depreciation, following the approach of Gopinath et al. (2010), to capture delayed pricing responses to macroeconomic shocks.

Table 3: Frequency of price changes: Product-level fixed effects estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
π_t	4.715***		4.747***	4.275***	3.788***	3.395***	3.766***	1.886***
	(0.272)		(0.289)	(0.220)	(0.215)	(0.377)	(1.032)	(0.589)
π_t^2						0.584	-0.656	0.911
						(0.438)	(1.260)	(0.661)
Δe_t		2.081***	-0.057	-0.352***	-1.476***	-1.238***	3.562***	-0.317
		(0.131)	(0.099)	(0.122)	(0.230)	(0.253)	(0.680)	(0.253)
Δe_t^2						1.249***	0.688*	0.662***
						(0.168)	(0.410)	(0.167)
$\pi_t \cdot \Delta e_t$					1.609***	0.108	-2.560***	0.095
					(0.300)	(0.396)	(0.777)	(0.473)
π_t^e				1.321***	1.413***	1.278***	1.120***	0.835***
				(0.253)	(0.259)	(0.256)	(0.288)	(0.281)
Constant	18.300***	22.900***	18.300***	16.900***	17.300***	17.500***	15.500***	15.100***
	(0.309)	(0.046)	(0.316)	(0.551)	(0.530)	(0.522)	(0.732)	(0.948)
Observations	77,944	77,944	77,944	77,944	77,944	77,944	77,944	55,904
R-squared	0.131	0.031	0.131	0.138	0.141	0.144	0.153	0.212

Notes: The dependent variable is the product-level frequency of price changes, measured on a 0–100 scale. All coefficients and standard errors, except for the constant, are standardized and reflect the effect of a one-standard deviation increase in the corresponding independent variable. All regressions include fixed effects for 453 products. π_t, Δe_t, and π_t^e denote monthly inflation, FX depreciation, and expected inflation, respectively. Expected inflation is constructed following the method of Alvarez et al. (2019), using the urban CPI (excluding rent). Column (7) uses 12-month inflation, FX depreciation, and expected inflation to capture long-run patterns. Column (8) includes 24 monthly lags of inflation and FX depreciation to capture delayed pricing responses, though lag coefficients are not reported. Standard errors are clustered at the product level and shown in parentheses. Observations are weighted by product expenditure shares. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Column (1) of Table 3 presents a baseline specification that includes only inflation as the explanatory variable. The coefficient is large, positive, and highly significant: a one-standard deviation increase in monthly inflation (1.57%, see Table 2) is associated with a 4.7 percentage point (ppt) increase in the frequency of price changes. This finding confirms the standard result in the literature that inflation is strongly correlated with more frequent price adjustments.[2]

[1] For reference, the mean and standard deviation of explanatory variables are reported in Table 2.

[2] See, for example, Nakamura and Steinsson (2008), Klenow and Kryvtsov (2008), Gagnon (2009), Wulfsberg (2016), and Alvarez et al. (2019).

Column (2) shows that FX depreciation is strongly and positively associated with the frequency of price changes. A one-standard deviation increase in monthly FX depreciation $(6.27\%$, see Table 2) is linked to 2.1 ppt increase in the frequency. However, once inflation is included in Column (3), the coefficient on FX depreciation becomes statistically insignificant and near zero. This pattern suggests that the simple correlation between FX and frequency is largely absorbed by the inflation term. In Column (4), we add expected inflation, which enters with a significant positive coefficient, while FX depreciation is not positively significant.

Columns (5) and (6) introduce nonlinearity in pricing behavior. In Column (5), the interaction term $\pi_t \cdot \Delta e_t$ is large (1.61), positive, and statistically significant, suggesting that the effect of FX depreciation on the frequency of price changes is amplified in high-inflation environments. In Column (6), we add squared terms for both inflation and FX depreciation. The squared FX term (Δe_t^2) enters significantly and positively (1.25), indicating that larger depreciations are associated with disproportionately higher frequency of price changes. In contrast, the squared inflation term (π_t^2) is small and statistically insignificant (0.58). These results imply that the frequency response to FX depreciation is not linear, and that large depreciation episodes are more likely to trigger price adjustments—particularly when inflation is already elevated.

Columns (7) and (8) explore the long run effects of explanatory variables. In Column (7), we replace monthly inflation and FX depreciation with their 12-month growth counterparts. The scale of expected inflation index, that is constructed by Alvarez et al. (2019) method, is transferred to 12-month scale. While inflation and expected inflation are under control, the coefficient on 12-month FX depreciation is large (3.56) and statistically significant, indicating that FX depreciation has a strong long run association with the frequency of price changes. In Column (8), we return to monthly data but include 24 lags of both inflation and FX depreciation. While the coefficient of FX depreciation is again small and insignificant, the squared FX depreciation term remains strongly positive (0.66). These results suggest that the effects of FX depreciation on the frequency of price changes become more pronounced either over time and during large depreciation episodes.

Columns (7) and (8) explore the long-run effects of macroeconomic variables on the frequency of price changes. In Column (7), we replace monthly inflation and FX depreciation with their 12-month growth counterparts. The expected inflation index—constructed following the method of Alvarez et al. (2019)—is also rescaled to a 12-month horizon. While inflation and expected inflation are included as controls, the coefficient on 12-month FX depreciation is large (3.56) and statistically significant, indicating a strong long-run association with the frequency of price changes. In Column (8), we return to monthly data but include 24 lags of both inflation and FX depreciation. The contemporaneous coefficient on FX depreciation remains small and insignificant, but the squared FX term continues to be large and statistically significant (0.66). These results suggest that the effect of FX depreciation on pricing frequency becomes more pronounced over time and during large depreciation episodes.

Table 4: Absolute size of price changes: Product-level fixed effects estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
π_t	1.855***		2.004***	1.808***	1.729***	1.666***	2.535***	1.753***
	(0.112)		(0.130)	(0.128)	(0.162)	(0.173)	(0.767)	(0.330)
π_t^2						0.092	-0.847	-0.800**
						(0.225)	(0.705)	(0.336)
Δe_t		0.645***	-0.265***	-0.380***	-0.565***	-0.531***	1.176**	-0.522**
		(0.062)	(0.071)	(0.071)	(0.143)	(0.162)	(0.459)	(0.210)
Δe_t^2						0.187	0.467*	0.109
						(0.120)	(0.244)	(0.111)
$\pi_t \cdot \Delta e_t$					0.267	0.041	-1.391***	0.656**
					(0.209)	(0.270)	(0.385)	(0.306)
π_t^e				0.532***	0.547***	0.529***	0.386***	0.475**
				(0.090)	(0.090)	(0.097)	(0.133)	(0.230)
Constant	12.670***	14.560***	12.590***	12.040***	12.100***	12.130***	10.740***	11.280***
	(0.128)	(0.022)	(0.136)	(0.179)	(0.202)	(0.199)	(0.609)	(0.265)
Observations	74,690	74,690	74,690	74,690	74,690	74,690	74,690	54,661
R-squared	0.037	0.006	0.038	0.040	0.041	0.041	0.046	0.077

Notes: The dependent variable is the product-level absolute size of price changes. All coefficients and standard errors, except for the constant, are standardized and reflect the effect of a one-standard-deviation increase in the corresponding independent variable. All regressions include fixed effects for 453 products. π_t, Δe_t, and π_t^e denote monthly inflation, FX depreciation, and expected inflation, respectively. Expected inflation is constructed following the method of Alvarez et al. (2019), using the urban CPI (excluding rent). Column (7) uses 12-month inflation, FX depreciation, and expected inflation to capture long-run patterns. Column (8) includes 24 monthly lags of inflation and FX depreciation to capture delayed pricing responses, though lag coefficients are not reported. Standard errors are clustered at the product level and shown in parentheses. Observations are weighted by product expenditure shares. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Column (1) of Table 4 shows the effect of inflation on the absolute size of price changes. The coefficient on monthly inflation is positive (1.86) and statistically significant, indicating that one-standard-deviation increase in inflation is associated with a 1.86 ppt increase in the absolute size of price changes. Unlike the consistent evidence for inflation's effect on the frequency of price changes, prior findings for its relationship with the absolute size are more mixed. Nakamura and Steinsson (2008) report a weak and unstable positive correlation across periods in the U.S., while Gagnon (2009) finds a positive relationship in Mexico. In contrast, Wulfsberg (2016) documents a negative correlation for Norway. Against this background, our result adds evidence that inflation is positively associated with the absolute size of price adjustments, at least in the Iranian context.

In Column (2), FX depreciation is positively and significantly associated with the absolute size of price changes, with a one-standard-deviation increase in FX depreciation linked to a 0.65 ppt increase. However, once inflation is included in Column (3), the coefficient on FX depreciation turns negative and statistically significant, and remains so in Column (4) after adding expected inflation. This pattern mirrors the frequency results, suggesting that the raw correlation between FX and pricing behavior reflects common inflationary pressures. Expected inflation remains positively associated with the absolute size of price changes.

Columns (5) and (6) introduce nonlinear specifications. Unlike in the frequency regressions, the interaction term between inflation and FX depreciation is small and statistically insignificant. The squared term for FX depreciation in Column (6) is also insignificant. These results suggest that the absolute size of price changes is less sensitive to large shocks or nonlinearities than the frequency of price changes.

Columns (7) and (8) examine long-run and lagged effects. In Column (7), 12-month FX depreciation is positively associated with the absolute size of price changes (1.18) and statistically significant. In Column (8), where 24 monthly lags are included, the FX depreciation coefficient and its squared are not positively significant.

Our results yield four main findings about the determinant of pricing behavior:

1. Both the frequency and absolute size of price changes increase with inflation. This confirms earlier findings on the positive relationship between inflation and the frequency of price changes, and provides additional evidence supporting a positive link between inflation and the absolute size of price changes—a relationship that has been more mixed in the literature.

2. FX depreciation is positively associated with both the frequency and absolute size of price changes when considered alone, but this relationship will be insignificant once inflation is controlled for. Overall, our evidence suggests that FX depreciation does not exert a strong independent influence on pricing behavior in the short run and cannot compete with inflation in explanatory power.

3. Expected inflation consistently exhibits a strong positive correlation with pricing behavior across specifications. Its effect remains robust after controlling for current inflation, FX depreciation, and their lags. This pattern holds even when we use an alternative measure of expectations based on the MBRI survey, as shown in Appendix C..

4. The interaction between inflation and FX depreciation is significantly positive for the frequency of price changes, but not for the absolute size. This suggests that the effect of macroeconomic instability on pricing behavior operates primarily through the timing (frequency) of adjustments. While the interaction term itself is symmetric and does not reveal which variable's effect is state-dependent, the squared terms help clarify this point: the squared term for FX depreciation is significantly positive, while that for inflation is not. This pattern indicates that the effect of FX depreciation is nonlinear and becomes stronger in large depreciation episodes, whereas the effect of inflation is linear and does not vary across macroeconomic conditions.[1] Consistent with this interpretation, the interaction term becomes insignificant when the squared FX term is included in the regression, reflecting overlapping explanatory power. The insignificant coefficient on the interaction term in Table 3 suggests that the effect of FX depreciation does not depend on inflation levels, but rather on the size of depreciation itself.

5. The long-run regression in Column (7), which uses 12-month growth rates for inflation, FX depreciation, and expected inflation, shows that FX depreciation remains significance and exhibits a much larger association with the frequency and absolute size of price changes. This suggests that the effect of FX depreciation becomes more pronounced over longer horizons. These findings highlight the importance of allowing for dynamic responses in pricing behavior to macroeconomic shocks.

6 Conclusion

This paper provides new evidence on how pricing behavior responds to FX depreciation and inflation under varying macroeconomic conditions. Using a large dataset of consumer price quotes from Iran between 2006 and 2022, we show that both the frequency and absolute size of price changes increase with inflation. While FX depreciation also influences pricing behavior, its short-run effect is weaker than that of inflation and becomes statistically insignificant when inflation is controlled for. However, nonlinear specifications and long-run regressions reveal that FX depreciation plays a prominent role during large depreciation episodes and over extended time horizons.

A novel feature of this study is its ability to distinguish between two mechanisms through which FX depreciation affects pricing behavior: by raising firms' input costs (cost shocks) or by influencing inflation expectations. Our evidence shows that even after con-

[1] This linear relationship can be observed in Figure 5.

trolling for expected inflation, FX depreciation continues to affect the frequency of price changes—providing support for the cost shock mechanism.

These findings speak to a broader theoretical point: after large macroeconomic shocks, price setters appear to incorporate information from multiple variables—including FX depreciation and expected inflation—into their decisions. This suggests that pricing models built around a single nominal anchor may fail to capture the full scope of macroeconomic conditions in volatile environments.

These results also carry important policy implications. Large FX depreciations are associated with increased frequency of price changes, which reduces nominal rigidity. For central banks aiming to maintain price stability, close monitoring of FX depreciation is essential—not only because of its pass-through to inflation, but also due to its direct and indirect effects on pricing behavior at the micro level.

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Appendix A. Institutional and macroeconomic context: Iran, 2006–2022

Iran economy experienced different macroeconomic conditions between 2006 and 2022, providing a valuable laboratory for investigating the role of inflation and FX in shaping pricing behavior (Figure 4). From 2006 to 2010, Iran faced high inflation alongside a stable FX. During this period, M1 and M2 growth were high, but the FX remained stable due to foreign currency income from petroleum export. Due to sanctions, exports declined in 2011, leading to high inflation together with FX growth between 2011 and 2013.

In 2014, following a change in government, expectations of sanction relief increased, and with forecasts of improved export conditions, expected FX stabilized and expected inflation declined. Consequently, between 2014 and 2017, the economy entered a stable phase marked by single-digit inflation and a stable FX. However, this stability was short-lived. After 2018, with the imposition of new sanctions, macroeconomic variables became unstable once again[1]. During these periods, the country faced various conditions, ranging from stable FX to sharp FX jumps, and inflation fluctuations between 5% and 60%. These diverse conditions offer a useful environment to analyze the effects of inflation, expected inflation, and FX growth on pricing behavior.

Iran economy is a valuable case study for examining the effects of aggregate shocks on pricing behavior. Golosov and Lucas Jr (2007) introduce idiosyncratic shocks into the standard menu cost model, improving its ability to explain key facts, such as the substantial share of price decreases among total price changes. Expanding on Golosov and Lucas's model, Alvarez et al. (2019) analyze how the influence of idiosyncratic shocks on pricing decisions changes with the scale of common shocks. They found that during hyperinflationary periods, the impact of idiosyncratic shocks diminishes, leading to a smaller share of price decreases in the total frequency of price changes. Under these conditions, the menu cost model proposed by Golosov and Lucas Jr (2007) aligns more closely with the earlier model of Sheshinski and Weiss (1977).

Figure 5 shows the frequency and absolute size of price increases and decreases[2]. This figure indicates that the price decreases constitute a small share of total price changes, and their frequency and absolute size respond minimally to rising inflation. Conversely, price increases are very sensitive to inflation, with both the frequency and absolute size of price increases showing a linear relationship with inflation. Considering the findings of

[1]The political background and policies shaping these macroeconomic environments are discussed in Appendix A.

[2]The method of calculating the frequency and absolute size of price increases and decreases follows the approach used by Nakamura and Steinsson (2008) and Alvarez et al. (2019), as detailed in section 3.

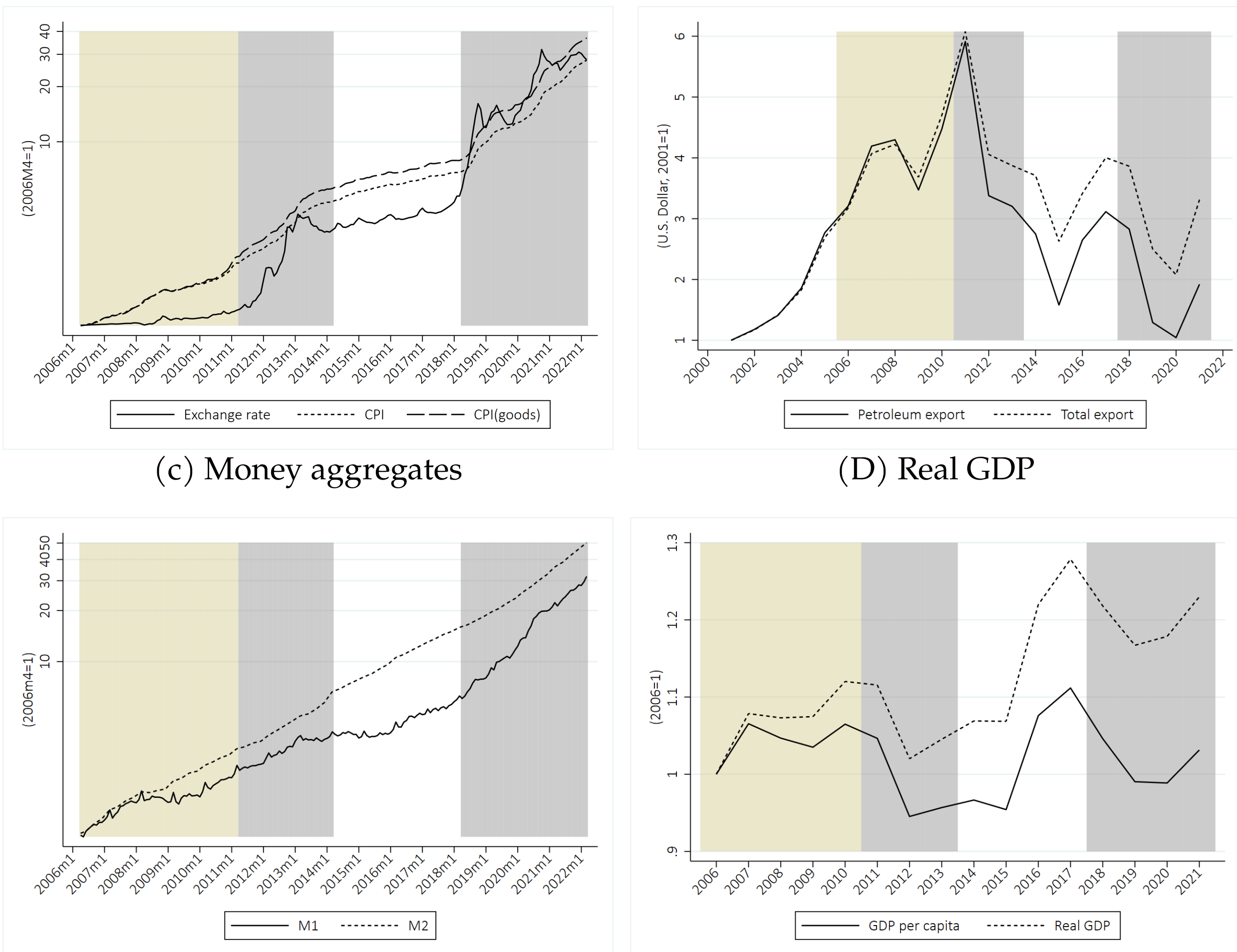
Figure 4: Iran economy in 2006-2022

(A) FX and price index

(B) Total Export and Petroleum export

(c) Money aggregates

(D) Real GDP



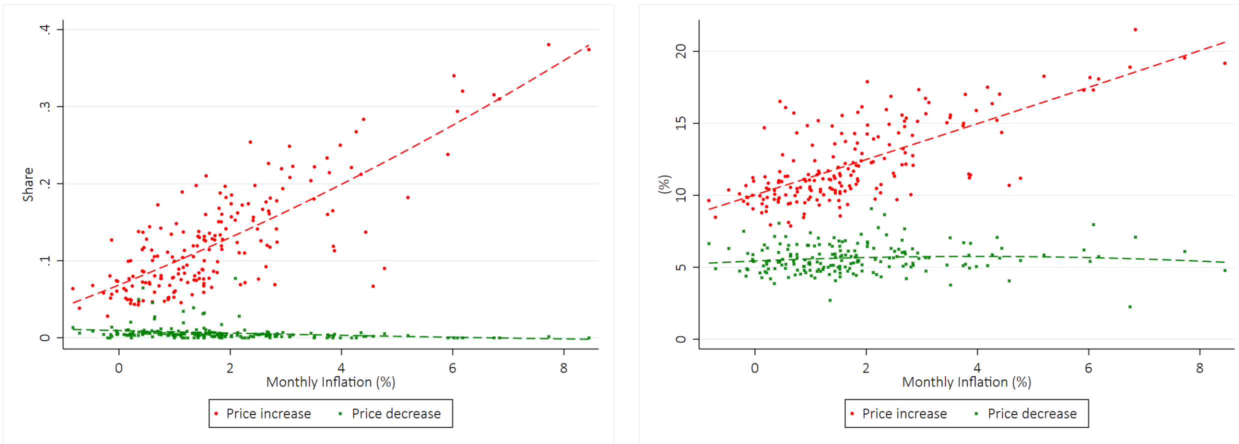
Notes: In Panel A, the FX shows the USD cash price in the unofficial (non-regulated) market, and CPI does not include housing rent. In Panel B, petroleum export is reported by Central Bank of Iran and it is defined as "the value of crude oil, oil products, natural gas, and natural gas condensate and liquids (Tariff Codes: 2709, 2710 and 2711) exported by National Iranian Oil Company (NIOC), National Iranian Gas Company (NIGC), National Iranian Oil Refining and Distribution Company (NIORDC), petrochemical companies, and other companies (customs and non-customs)". In Panel D, real GDP is reported by SCI based on the base year 2011. Real GDP per capita is calculated using real GDP and the yearly population. The khaki background shows inflationary periods without jumps in the FX (2006m4 – 2011m3) and the gray background shows inflationary periods with jumps in the FX(2011m4-2014m3 and 2018m4-2022m3). All variables are normalized to their values at the first observation.

Alvarez et al. (2019), Figure 5 suggests that inflation as a common shock plays a dominant role in pricing decisions in Iran. Thus, the Iran economy provides a suitable environment for studying the impact of aggregate shocks on pricing behavior.

Research on pricing behavior in Iran faces the challenge of price controls. In response to an unstable macroeconomic environment, policymakers implement price controls on

Figure 5: Frequency and absolute size of price changes vs monthly inflation

Frequency of price changes | Absolute size of price changes



Notes: Frequency and absolute size of price changes are calculated as the weighed median over the products. Inflation is calculated as the monthly urban CPI (excluding housing rent) growth rate. Fitted lines are allowed to be quadratic.

specific products, influencing both regulated and unregulated markets.

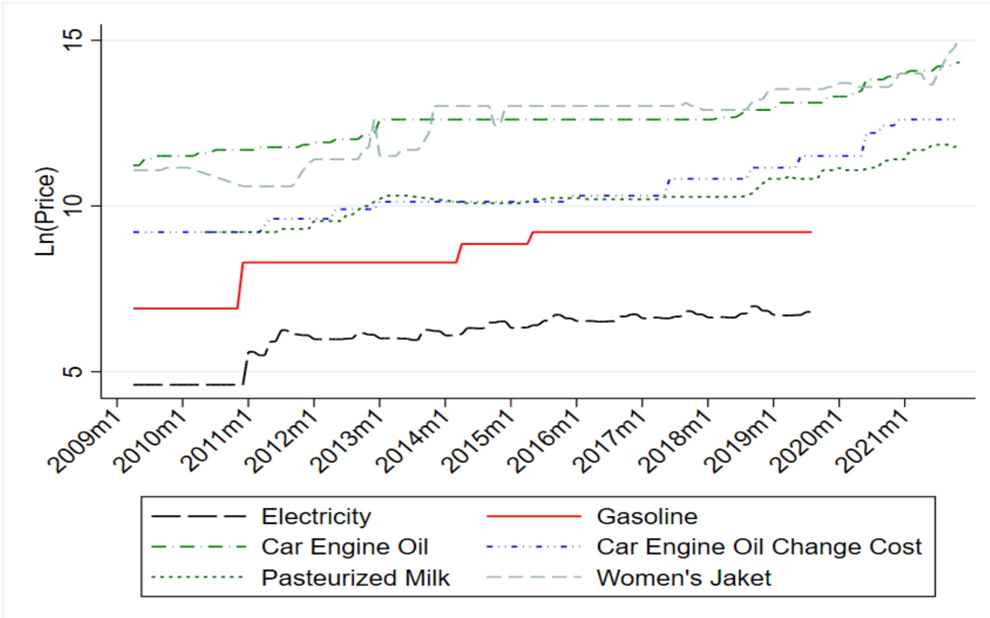
In certain cases, the government fully controls prices and meets demand as a monopolist, such as with utilities, bread, and internet, resulting is no unofficial market for these goods. Hence, SCI reports regulated prices in these markets, which change less frequently due to the government absorbing shocks, as these prices do not reflect typical market dynamics. However, when government resources can't meet demand at regulated prices, unregulated markets coexist, as seen with products like meat, fruits, and vegetables. While SCI claims its price quotes cover both regulated and unregulated markets, the observed prices supports this claim, showing more frequent changes in markets the government cannot fully control compared to fully regulated markets.

Figure 6 shows price trends for six products across six outlets. Gasoline and electricity prices are fully regulated by the government, while pasteurized milk and car engine oil prices are influenced by the government but not fully controlled due to unmet market demand. In contrast, the prices of women's jackets and car engine oil change services are set entirely by private sellers without government regulation.

The price trajectories of car engine oil and pasteurized milk more closely resemble those in unregulated markets than regulated ones. In regulated markets, like gasoline and electricity, prices remain fixed during inflation periods (2006–2014 and 2018–2022)[1]. In contrast, unregulated markets show gradual price increases during inflation. This evi-

[1]Electricity prices in Iran exhibit seasonal fluctuations, leading to a non-flat trend, unlike gasoline prices.

Figure 6: The price trajectory of six different price-outlets



Notes: This graph shows the price trajectory of six different product-outlets. To investigate the long-run behavior of pricing, we choose lengthy trajectories.

dence supports SCI's claim that their sample is not biased toward regulated prices.[1].

Appendix B. Data Appendix

Appendix B..1 Dataset structure and sample construction

- **Source and coverage**: We use monthly urban price quotes collected by the Statistical Center of Iran (SCI) between April 2006 and March 2022. The dataset covers 231 cities across all 31 provinces. In total, it includes over 34 million price quotes, more than 306,000 retail outlets, and 453 products classified according to the COICOP (1999) system. Product weights are based on the 2016 Household Income and Expenditure Survey (HIES).

- **Consumer basket weights**: According to the 2016 HIES, price quotes used in our analysis account for 66% of consumer expenditures, excluding housing rent. Figure 7 in this appendix shows the breakdown of weights by province and nationally.

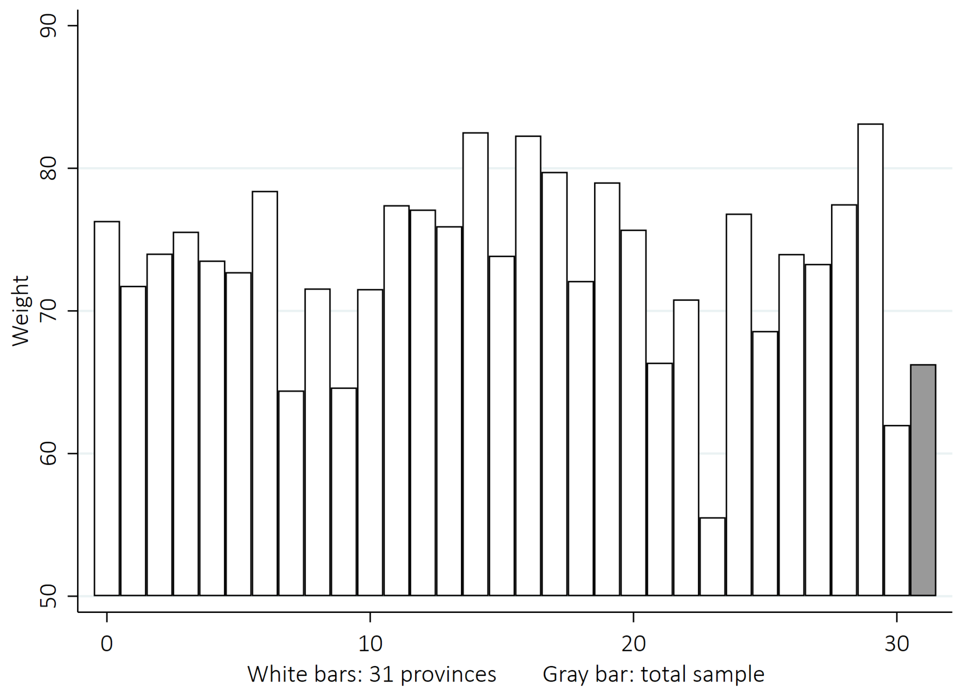
- **Examples of products**: Products include food, apparel, services, and durable goods

[1]This aligns with studies like Aparicio and Cavallo (2021), which find that price control cannot be applied broadly to most products.

such as pasteurized milk, women's jackets, car engine oil, and general practitioner visits.

- **Data cleaning**: We exclude observations flagged as unreliable by SCI, those with month-over-month price changes exceeding 900% or below 90%, and those with zero product weights. This cleaning reduces the sample from 37.9 million raw quotes to 34.3 million usable observations.

Figure 7: Weights of consumer baskets (excluding housing rent)



Notes: White bars represent provincial weights, and the gray bar represents the national weight. Weights are based on HIES 2016.

Appendix B..2 Macroeconomic variables

- **CPI**: We use the monthly urban CPI inflation rate (excluding housing rent) as reported by SCI.

- **FX**: From 2006 to 2022, Iran's economy operated under a dual FX system during certain periods. In this study, we focus on the USD cash price in the unofficial (non-regulated) market, as published by the Central Bank of Iran (CBI). CBI data are missing for April–September 2018; for these months, we use the monthly average of daily USD prices from a reliable website tracking currency and gold markets[1].

- **MBRI expected inflation**: From 2016 to 2022, MBRI conducted 18 surveys of professional forecasters on expected inflation and FX. We construct a 12-month expected inflation index using the implied duration from pricing frequency, with a maximum cap of 12 months. When the implied duration crosses calendar years, we compute a weighted average of the current and next year's forecast, based on the overlap. We then convert the annual expectation to a monthly rate using $(1+\pi_t^e)^{(1/12)}$.

Appendix C. Complementary evidence

In this appendix, we assess whether our main findings—particularly the interaction between inflation and FX depreciation—remain valid after controlling for a different expected inflation proxy, based on MBRI survey. this index index is constructed as described in Appendix B..

Table 5: Standardized regression results controlling for expected inflation (MBRI)

	Frequency of price changes				Absolute size of price changes			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
π_t	3.79***	3.40***	3.75***	-0.19*	0.69***	0.91***	1.08***	-0.08*
	(0.39)	(0.51)	(0.73)	(0.18)	(0.11)	(0.16)	(0.20)	(0.04)
π_t^2			-0.12	0.50***			-0.11*	0.25***
			(0.19)	(0.15)			(0.07)	(0.01)
Δe_t	0.02	-1.19**	-2.93***	3.78***	0.26	0.52	-0.00	1.18***
	(0.09)	(0.11)	(0.15)	(0.66)	(0.27)	(0.38)	(0.40)	(0.29)
$(\Delta e_t)^2$			1.04***	1.19***			0.18	0.38
			(0.11)	(0.47)			(0.12)	(0.39)
$\pi_t \cdot \Delta e_t$		1.55***	-0.02	-2.27***		-0.56	0.70	-1.39***
		(0.03)	(0.06)	(0.23)		(0.17)	(0.28)	(0.39)
π_t^e	1.91***	2.86***	3.15***	0.31***	1.11***	0.95***	0.98***	0.13***
	(0.54)	(0.53)	(0.52)	(0.07)	(0.21)	(0.23)	(0.23)	(0.02)
Constant	14.7***	15.1***	13.2***	14.8***	10.70***	10.66***	10.60***	10.73***
	(1.22)	(1.24)	(1.27)	(1.43)	(0.43)	(0.43)	(0.42)	(0.52)
Observations	7,797	7,797	7,797	7,797	7,452	7,452	7,452	7,452
R-squared	0.273	0.279	0.300	0.298	0.135	0.135	0.136	0.134

Notes: This table presents standardized coefficients from regressions of product-level frequency and absolute size of price changes on inflation, FX depreciation, expected inflation, and their interactions. Columns (1)–(4) correspond to the frequency of price changes, and columns (5)–(8) to the absolute size of price changes. The expected inflation variable (π_t^e) is based on MBRI survey data and converted to a monthly rate. All variables are standardized by their sample standard deviations, so coefficients reflect the effect of a one-standard-deviation increase. Standard errors are clustered at the product level and reported in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table 5 presents standardized regression results, where the coefficients measure the effect of a one-standard-deviation increase in each independent variable. Columns (1)–(4)

[1] https://english.tgju.org/

correspond to the frequency of price changes, and columns (5)–(8) to the absolute size of price changes. These results are comparable to columns (4)–(7) in Tables 3 and 4 in the main text.

We find that the key patterns discussed in the main results remain intact. Inflation has a strong and significant effect on both frequency and absolute size of price changes. FX depreciation alone has a small or insignificant effect, but its interaction with inflation is positive and significant for frequency (column 2), consistent with the complementarity mechanism. This effect vanishes when higher-order terms and expectations are added (column 4), but inflation and expected inflation remain jointly significant.

In columns (3) and (4), the squared terms of inflation and FX depreciation are included. The significance of these nonlinear terms shows that the marginal effect of each shock depends on its own size and on the presence of the other shock. The coefficient on expected inflation (π_t^e) is positive and significant throughout, but its inclusion does not eliminate the inflation–FX complementarity seen in earlier specifications.

Overall, these results confirm that the observed interaction between inflation and FX shocks is not merely the result of forward-looking pricing behavior. Instead, they support a model in which both inflation and FX jointly shape firms' price-setting decisions, particularly under high volatility.

Appendix D. Temporary price changes

In this section we calculate regular prices as Kehoe and Midrigan (2015) to measure the effect of temporary price changes. There is a great deal of concern in this literature regarding temporary price changes. In studying pricing behavior, it is necessary to identify which types of price changes are important and which types of price changes are being studied. Bils and Klenow (2004) show more than 22% of prices are changed each month, whereas Nakamura and Steinsson (2008) show more than half of price changes are related to sales. Changing prices temporarily is not limited to sales, and some price increases may be temporary as well. Kehoe and Midrigan (2015) introduce an algorithm designed to filter out temporary price increases and decreases. They discover that the frequency of regular price changes amounts to 6.9%.

This[1] algorithm is based on the idea that a price is a regular price if the outlet charges it frequently in a window of time adjacent to that observation. We start by computing for each period the mode of prices in a five-month rolling window which includes prices in

[1]We used the online appendix of Kehoe and Midrigan (2015) to write this paragraph.

Table 6: Simple vs regular frequency and absolute size of price changes during 2006-2022.

		Frequency		Size	
		Regular	Simple	Regular	Simple
Price Changes	Mean	0.11	0.24	26.74	14.71
	Sd	0.10	0.24	29.21	11.87
	Med	0.09	0.15	18.69	11.25
Price Increases	Mean	0.09	0.18	28.13	15.31
	Med	0.06	0.12	18.77	11.53
Price Decreases	Mean	0.02	0.06	16.98	7.29
	Med	0.00	0.00	13.77	5.34

Notes: This table gives weighted summary statistics of frequency and absolute size of price changes over 2006-2022 for simple price changes and regular price changes. We calculate regular price changes as Kehoe and Midrigan (2015). *Mean*, *Sd* and *Med* represent the weighted average, standard deviation and median of the statistics, respectively. *Price Changes* displays the total price changes, including price increases and decreases. *Price Increases* and *Price Decreases* provide statistics that focus on price increases and price decreases.

the previous two months, the current month, and the next two months. Then, based on the modal price in this window, we construct the regular price recursively as follows[1]:

- For initial period set the regular price equal to the modal price.
- For subsequent period, if observed price is equal to the modal price and at least one-third of prices in the window are equal to the modal price; then set the regular price equal to the modal price.
- Otherwise, set the regular price equal to the preceding period's regular price.

Table 6 presents summary statistics of regular price changes. This table also contains the summary reported in Table 1 to compare the behavior of regular prices and simple prices. According to table 6, the average frequency of regular price changes is 11 percent, while the average frequency of simple price changes is 24 percent. There is a smaller difference between average and median frequency of regular prices than simple prices, and median frequency is 9%. Frequency of price increases in regular has greater share than simple prices and majority of regular price changes are related to price increases.

According to table 6, the average absolute size of regular price changes is 26.74%, while for simple price changes it is 14.71%. The difference between absolute size of regular price changes and simple price changes can be seen for median size, price increases and decreases. According to Kehoe and Midrigan (2015), the mean size of regular price changes

[1] Kehoe and Midrigan (2015) provide a detailed exposition of their algorithm in the supplementary appendix available online.

and simple price changes are 11%. Furthermore, Nakamura and Steinsson (2010b) (the supplement to Nakamura and Steinsson (2008)) calculates regular price changes by Kehoe and Midrigan (2015) formula and finds that 220 out of 270 products have smaller mean size of regular price changes than simple price changes.

We can explain this difference between absolute price changes and simple price changes by referring to strategic complementarity. Nakamura and Steinsson (2010a) demonstrates that outlets consider strategic complementarity in pricing decisions, taking into account the pricing decisions of other outlets. A possible equilibrium in this environment is multi-step Pricing; if one outlet changes its price in one step and on a large scale, the others can change their prices in multi-steps and on a smaller scale and steal the market from the first outlet. Consequently, to change a price on a large scale, an outlet separates the process into multiple steps.

Kehoe and Midrigan (2015) algorithm to construct regular price achieves it by identifying the modal price within a five-month window of prices. Due to this, prices in the process of changing are not recognized as regular prices. Instead, the algorithm identifies the modal price as the price that remains stable and unchanged. When we consider these points, we can say that if an outlet wants to change its price on a large scale, it prefers to do it in multiple stages, and prices set in medium steps are not unchanged. Therefore, our algorithm does not consider them as regular price and the price of first and final steps are considered as regular price. Consequently, our algorithm captures the difference between the current outlet price level and the previous outlet price level and ignores transitory prices[1].

In table 7, we show the estimation of product level fixed effects using indices with regular price indices as equation 6. This table is comparable with Table 3 and 4. Table 7, panel A, column 1 indicates that a 1 percentage point increase in inflation increases the frequency of regular price changes by 1.5 percentage points. It is half of the coefficient in Table 3, which is 3 percentage points. The results show that the average frequency of regular prices changes is half that of simple prices changes (Table 6) and that its sensitivity to inflation is also half. Table 7 Panel A, columns 2 and 3, as Table 3, show that the FX has a small correlation with the frequency of regular price changes, relative to the inflation coefficient (column 2), and the FX is insignificant when competing with inflation (column 3). Column 4 shows that interaction term of inflation and FX is insignificant which differ from Table 3. We control for expected inflation in columns 5-8 using Alvarez et al. (2019), and despite a different scale than Table 3, Panel A, Columns 5-8, the coefficient pattern is

[1] It may be that Kehoe and Midrigan (2015) is not the right regular price filter for an economy with high inflation like Iran.

Table 7: Regulr prices vs macro variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Dependent variable: frequency of price changes								
					Exp.inf: Alvarez et al (2019)			
Inflation (inf.)	0.015***		0.015***	0.014***	0.013***		0.013***	0.013***
	(0.0008)		(0.0007)	(0.0008)	(0.0007)		(0.0007)	(0.0006)
FX growth (fx.)		0.002***	-0.000	-0.000		0.001***	-0.000	-0.001**
		(0.0001)	(0.0001)	(0.0002)		(0.0001)	(0.0001)	(0.0002)
Inf.*fx.				0.0001				0.0001
				(0.0001)				(0.0001)
Exp.inf					0.004***	0.010***	0.004***	0.004***
					(0.0008)	(0.0010)	(0.0009)	(0.0009)
Constant	0.085***	0.109***	0.085***	0.086***	0.080***	0.091***	0.080***	0.080***
	(0.0013)	(0.0002)	(0.0013)	(0.0013)	(0.0021)	(0.0019)	(0.0022)	(0.0021)
Observations	75,693	75,693	75,693	75,693	75,693	75,693	75,693	75,693
R-squared	0.059	0.014	0.059	0.059	0.061	0.028	0.061	0.061
F test	0	0	0	0	0	0	0	0
Panel B: Dependent variable: absolute size of price changes								
					Exp.inf: Alvarez et al (2019)			
Inflation (inf.)	1.70***		2.17***	1.96***	1.57***		1.97***	1.70***
	(0.221)		(0.255)	(0.269)	(0.223)		(0.253)	(0.270)
FX growth (fx.)		0.04	-0.23***	-0.37***		-0.11***	-0.27***	-0.45***
		(0.030)	(0.034)	(0.058)		(0.022)	(0.032)	(0.059)
Inf.*fx.				0.04***				0.04***
				(0.010)				(0.011)
Exp.inf					0.32	1.53***	0.72***	0.80***
					(0.258)	(0.266)	(0.254)	(0.258)
Constant	23.80***	26.86***	23.43***	23.78***	23.39***	24.11***	22.46***	22.77***
	(0.409)	(0.066)	(0.432)	(0.458)	(0.575)	(0.525)	(0.620)	(0.621)
Observations	70,146	70,146	70,146	70,146	70,146	70,146	70,146	70,146
R-squared	0.011	0.000	0.013	0.014	0.011	0.005	0.014	0.015
F test	0	0.228	0	0	0	0	0	0

Notes: We calculate regular price changes as Kehoe and Midrigan (2015). Frequency of price changes is calculated as the proportion of outlets that change their prices (equation 2). Absolute size of price changes is calculated as the average size of price changes condition on price change occurred (equation 4). All regressions include 453 products fixed effects. *Inflation* is calculated by the growth of the urban CPI (excluding housing rent). *FX growth* shows the growth of the USD cash price at the unofficial market. Both *inflation* and *FX growth* are monthly. Heteroscedasticity-robust standard errors are reported in parentheses. Observations are weighted by the importance weight. *, **and *** significant at 10, 5, and 1 percent levels.

similar.

In Table 7, Panel B, the absolute size of regular price changes is the dependent variable. This panel is comparable to Table 4. Column 1 indicates that a 1 percentage point increase in inflation increases the absolute size of regular price changes by 1.7 percentage points. It is 45% larger than the coefficient in Table 4, which is 1.18 percentage points. In column 2, FX coefficient is insignificant, while in Table 4 this coefficient is positive and significant. Other columns of Panel B are similar to Table 4.

In general, Table 7 Panel A and B show weaker relationships between pricing behavior and FX, but the strength of relationship between regular pricing behavior and inflation is the similar to 3 and 4. We explore more complementarity evidence in Appendix C, where we examine the impact of FX lags, inflation lags, and aggregate demand on our findings.