Thai Inflation Dynamics: A View from Micro CPI Data*

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Abstract

This paper utilizes disaggregated prices at the micro level to examine the patterns of price adjustment in Thailand. Among the key stylized facts, we found that the frequency of prices changes are generally low, price decreases are common, the size of price changes are large relative to the inflation rate, and there is significant dispersion in price levels as well as in the synchronicity of price changes across regions. Exploiting the richness of price changes at the goods-level, we conduct dynamic factor analyses to better understand the underlying sources of heterogeneous price movements, highlighting the importance of relative price changes in driving the bulk of overall CPI movements. Implications for monetary policy are drawn.

Keywords: Factor model, inflation, price rigidity, price setting, relative prices, Phillips curve.

JEL Classifications: C40, C25, D40, E31.

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1 Introduction

A growing body of empirical research employ micro price data to investigate the nature of price-setting, offering insights into the 'nuts and bolts' of overall inflation dynamics. Such work has helped differentiate among alternative microfoundations of price setting, which critically determine the dynamic behavior of macro models, particularly the impact of monetary policy (Dotsey and Wolman (2018) and Gautier and Le Bihan (2018)). At the same time, analyzing price dynamics from the ground up helps to understand the nature of shocks that drive aggregate price changes. Distinguishing between aggregate versus idiosyncratic demand and supply shocks is crucial towards formulating the appropriate policy response.

This paper aims to exploit the richness of micro price data to help further our understanding about inflation dynamics along these two dimensions. We do so in two parts. First, we examine the patterns of price adjustment at the micro level to establish 5 key stylized facts with respect to the frequency, direction, size, dispersion and synchronicity of prices changes, both across sectors as well as geographical areas. Much of the existing evidence on micro price dynamics has come from developed economies where, even there, significant differences across countries have been observed. We add to this literature evidence from Thailand, a small-open emerging market economy.

Second, we utilize the method of Reis and Watson (2010) to perform a dynamic factor analysis of disaggregated prices to better understand the underlying drivers of heterogeneous price movements. In particular, we decompose inflation into three components; *a pure component* which is driven by common shocks that affect all prices equiproportionally, *a relative component* which captures the disproportionate responses of prices to aggregate shocks, and *an idiosyncratic component* which reflect price movements of only a particular good or service. We establish 2 additional stylized facts about the type of fundamental shocks that drive price movements, and how the different inflation components are related to key macroeconomic variables in the economy such as real output.

Our work falls within the recent strand of literature that has emerged as researchers have gained access to large-scale datasets of individual prices that are regularly collected to compute consumer price indices. Bils and Klenow (2004) is an early example of this line of research for the US, with follow up work by Nakamura and Steinsson (2008). Altissimo et al. (2006) and Dhyne et al. (2005) summarizes the numerous studies undertaken in the Euro area countries. Studies in emerging markets are more scarce due to limited data availability, but examples can be found in Gouvea (2007) and Medina et al. (2007) for Brazil and Chile, respectively. As for the factor analysis for inflation, our work builds on a large literature including Stock and Watson (1989), Boivin et al. (2009), Ciccarelli and Mojon (2010), and Reis and Watson (2010). This line of work utilizes covariation among economic time series to trace out a few underlying unobserved series or factors that can help uncover the sources and drivers of common price movements.

To our knowledge, this is the first paper to analyze price adjustment in Thailand using micro-level price data. We make use of data released by the Ministry of Commerce on 8,317 individual products collected across 77 provinces in Thailand over a 15 year period starting in 2002 at monthly frequency (though data for many products do not exist over the entire sample and span only a subset of provinces). All in all, we have over 9 million observations. By using the same data that underlies the CPI, the quality of the data should be of a reasonable level and the findings can be directly related to overall price dynamics.

We highlight 7 stylized facts:

1) Prices change infrequently. The average duration that a price does not change is approximately 4 to 7 months. There is significant heterogeneity in the frequency and duration of price changes across CPI categories, economic sectors, as well as across time.

2) Prices decreases are common. On average, 45 percent of all price changes are price decreases. Thus downward price rigidity in Thailand does not appear to be a pervasive issue. This result is similar to those found for the US and the Euro area.

3) Price changes, both increases and decreases, are sizable compared to the prevailing inflation rate. The average size of price increases and decreases are 10.4 and 7.7 percent, respectively, compared to average monthly inflation rates of 0.11 percent (or 1.26 percent annualized).

4) The size of price changes covaries strongly with the rate of inflation, whereas the fraction of items changing prices does not. That is, with the number of products whose price change being roughly the same each month, the rate of inflation varies with the size of individual products' price changes (intensive margin), rather than variations in the number of products whose prices change (extensive margin). The intensive margin also contributes a much higher proportion to the overall variance of inflation. That said, the fraction of items changing prices does vary systematically with positive and negative inflation movements separately.

5) There is significant dispersion in price levels for identical products across geographical regions even as price changes tend to occur at the same time. Average dispersion is 8 percent and the degree of dispersion varies substantially across product groups with higher dispersion observed in services compared to non-service items. Product price changes across provinces do co-move to a significant degree, and is highest for transport and communication, reflecting the national nature of oil prices.

6) The bulk of overall price movements in the CPI are relative price changes. Aggregate relative price shocks account for 57 percent of total inflation rate variability, while another 32 percent is explained by idiosyncratic good-specific shocks. 'Pure inflation' explains only 11 percent of overall inflation variability.

7) The underlying drivers of aggregate price movements are related to well-known macroeconomic variables. The pure inflation component is correlated with factors related to monetary policy, particularly in the long-run. For the relative price component, traditional relative price factors such as food and energy price shocks can explain a large proportion of its movements. Its relation with real variables such as GDP is also strong at business cycle frequencies, providing empirical support for the Phillips curve.

Overall, the evidence provides support for price setting mechanisms that incorporate heterogeneity both in firm-specific shocks as well as in price adjustment costs with elements of state-dependent pricing features that compliment purely time-dependent ones as reflected in standard Calvo pricing models. The prevalence of negative price adjustments suggests no compelling reason to set higher inflation targets to compensate for downward price rigidity. Finally, the importance of relative price movements calls for caution in attributing CPI changes to inflation. Much of CPI movements, even over extended periods of time, may reflect fundamental relative price changes driven by structural demand and supply factors that, in and of themselves, are non-monetary in nature and hence do not warrant any monetary policy response.

The rest of the paper is organized as follows. The next section outlines the micro price data that underlies the study. Section 3 sets out details of the statistical measures used to study the patterns of price adjustments and discusses the first 5 key stylized facts. Section 4 outlines the dynamic factor model and reports 2 additional stylized facts. Section 5 concludes.

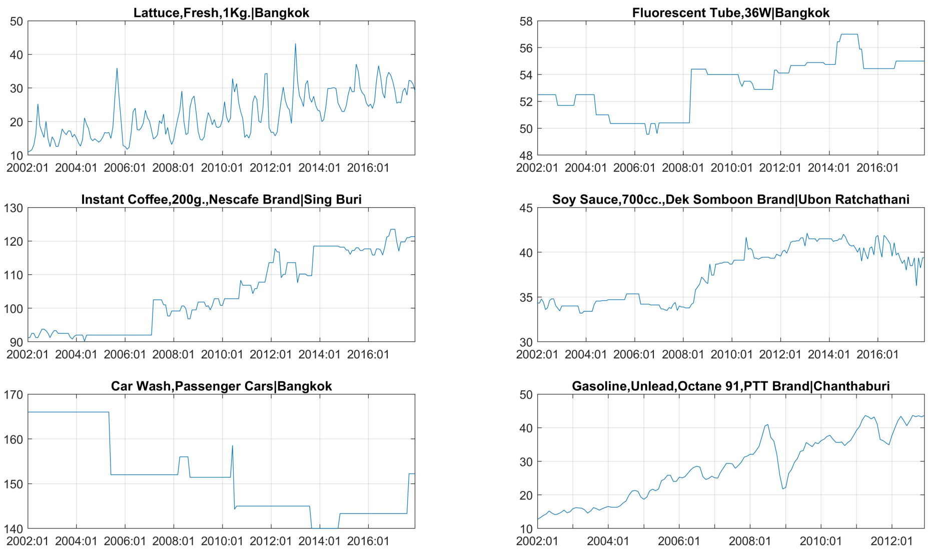
2 Microeconomic Price Data Overview

Each month, the Ministry of Commerce collects prices of thousands of individual goods across 77 provinces in Thailand that are used to construct the Consumer Price Index (CPI). The products are identified at a highly detailed level. For example, a 280cc bottle of Coca Cola sold in Bangkok. We will refer to this as an 'item', which represents a product-province pair with a unique specification of brand and/or packaging unit.

Figure 1 provides a plot of price trajectories for six selected items in the dataset. Focusing on the left-hand panel, for example, the product is 'Fresh lettuce', the unit specification is '1 kg.', and the province in which it was surveyed is 'Bangkok'. Note that there can be many items for the same product as the same product can be sampled across multiple provinces. Indeed, our dataset contains 8,317 unique products but 53,785 items. As can be seen in Figure 1, price trajectories varies significantly across product types. Prices of raw food (lettuce) is much more volatile than processed goods (instant coffee) or services (car wash). To preserve the information contained in the data at this highly granular level, we will compute all statistics at the item level and aggregate these up to broader levels in our summary measures.

The full dataset is an unbalanced panel with some missing and discontinued products. After cleaning the data according to a process outlined in Appendix A, we end up with a balanced panel containing 53,785 individual price trajectories that spans a period of

Figure 1: Examples of individual price trajectories



180 months between 2002M1-2017M12. To relate the items in our sample to the actual CPI, we can group them into 'Entry-Level-Items' (ELIs). ELIs are generic nationally representative products, aggregating over brands and locations, that enter the CPI with expenditure share weights as computed by the Ministry of Commerce. For example, the upper left hand corner item in Figure 1 belongs to the 'Lettuce' ELI, which accounts for approximately 0.05 percent of the CPI based on its 2011 expenditure share weight. These expenditure share weights can then be used to aggregate up statistics from the ELI to the CPI level. However, our dataset cannot replicate the CPI perfectly since our sample contains items that covers only 445 of the 450 ELIs used in official CPI figures. Nevertheless, this corresponds to a 84.3 percent coverage of the overall CPI. Table 1 summarizes our dataset.

Given that a single ELI classification contains many items, statistics at the ELI level are constructed by first computing statistics at the item level. Item-level statistics are then aggregated across provinces to the product level, and then finally across brands or characteristics to the ELI level using median population-weights across items and products respectively.[1] This approach ensures that information at the granular level of our data is preserved in calculating all of our aggregate statistical measures.

At a more aggregate level, ELIs can be grouped into 7 broad categories as shown in the top panel of Table 2. Overall, our dataset provides good coverage of the actual

[1]For official CPI construction, the Ministry of Commerce selects individual items to represent a particular ELI, but information on which items are chosen is not publicly available. The median population-weighted approach that we use thus mimics the method employed by the Ministry of Commerce as much as possible.

Table 1: Description of Dataset

Number of Items	53,785
Number of Products	8,317
Number of Entry Level Items	445
Number of Provinces	77
Sample Period	2002M1-2017M12

CPI. Except for housing and furnishing, all categories in our dataset provides more than 95 percent coverage of their actual share in the CPI. The reason why coverage for the housing and furnishing category is somewhat lacking is because we excluded the housing rent ELI which has a relatively high expenditure share weight of 15 percent.[2] In addition to the overall CPI, we also analyze core and service subcomponents. Dataset coverage for these groups is shown in the bottom panel of Table 2. Again, the reason why coverage is lacking for core and service goods is because the exclusion of the housing rent ELI.

Table 2: Coverage of the Consumer Price Index by Category

	Dataset Share (ELI Count)	Actual Share (ELI Count)
Food and Non-Alcoholic Beverages	33.48 (175)	33.48 (175)
Apparel and Footwear	3.03 (53)	3.06 (54)
Housing and Furnishing	8.73 (61)	24.14 (62)
Medical and Personal Care	6.54 (63)	6.54 (63)
Transportation and Communication	25.53 (47)	25.54 (49)
Recreation and Education	5.81 (42)	6.03 (43)
Tobacco and Alcoholic Beverages	1.20 (4)	1.20 (4)
Total	84.33 (445)	100.00 (450)
Core	57.42 (307)	73.09 (312)
Service	9.63 (80)	25.26 (83)

Note: Reported are the dataset share and actual share of the CPI for each category and economic groups in percent, calculated using 2011 expenditure share weights obtained from the Ministry of Commerce. The corresponding ELI count are reported in parentheses.

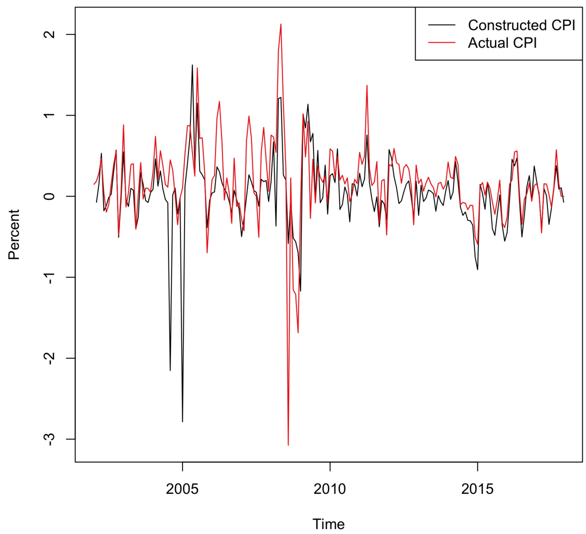
All in all, our micro price dataset provides a good representation of the overall CPI in Thailand. As shown in Figure 2, the constructed price index from our dataset tracks actual CPI well, with the exception of only a few periods. That said, we stress that our aim is not to replicate the CPI per se but to examine price-setting behavior at the micro level from a sample that is broadly representative of the consumption basket.

3 Patterns of Price Changes

We summarize the patterns of price changes in Thailand into 5 stylized facts, established on the basis of various unconditional statistics including the frequency of price changes, the duration of price spells, the frequency of price increases and decreases, the size of price

[2] All items in the housing rent ELI contain no price movements and are thus excluded from our dataset. To compute the official CPI index, the Ministry of Commerce uses housing rent price data from a different source which is not publicly available.

Figure 2: Constructed and Actual CPI Inflation



Note: Plotted is month-on-month actual CPI inflation compared to the constructed inflation series from our micro price dataset based on year 2011 expenditure share weights.

changes, and the degree of synchronization of price changes. Details for the computation of these indicators are outlined in Appendix B.

Fact 1: Prices change infrequently. The average duration that a price does not change is approximately 4 to 7 months. There is significant heterogeneity in the frequency and duration of price changes across CPI categories, as well as across economic sectors.

The frequency of price changes (f_j) is computed as the ratio of observed price changes to all observed price records. It is thus an average incorporating price changes of all firms where the product j has been recorded over the sample. The implied duration of price spells (i.e. the time span a price is unchanged) could be calculated as the inverse of the frequency of price changes $T = 1/f$. However, given the discrete nature of the data (ie. we observe one price change per month but do not know when in the month it changed nor whether there were more than one change in the month), this may not be the best representation of the underlying process. It is thus more appropriate to assume that prices can change at any moment. Baumgartner et al. (2005), Bils and Klenow (2004), and Baudry et al. (2004) show that unbiased estimates of the mean duration of price spells in continuous time under the assumption of a constant hazard rate (ie. assuming that the probability of a price change is constant within a month) can be calculated as $D_j = \frac{-1}{ln(1-f_j)}$. We adopt this measure for converting frequencies into implied mean duration.[3]

Alternatively, we can calculate the mean duration of price changes from the data directly by taking the average length of price spells that are associated with each price trajectory. Compared to the frequency approach, this method has the advantage of the mean duration being estimated directly from the empirical data and thus avoids relying on specific assumptions about the distribution of price changes over time. However, a major drawback is that it requires uncensored price spells only (eg. price spells that start and end with a change). Since it does not use all information that is available, it has been shown that this duration measure could be subject to some downward bias as longer price spells are likely to be discarded (see discussion in Baudry et al., 2004).

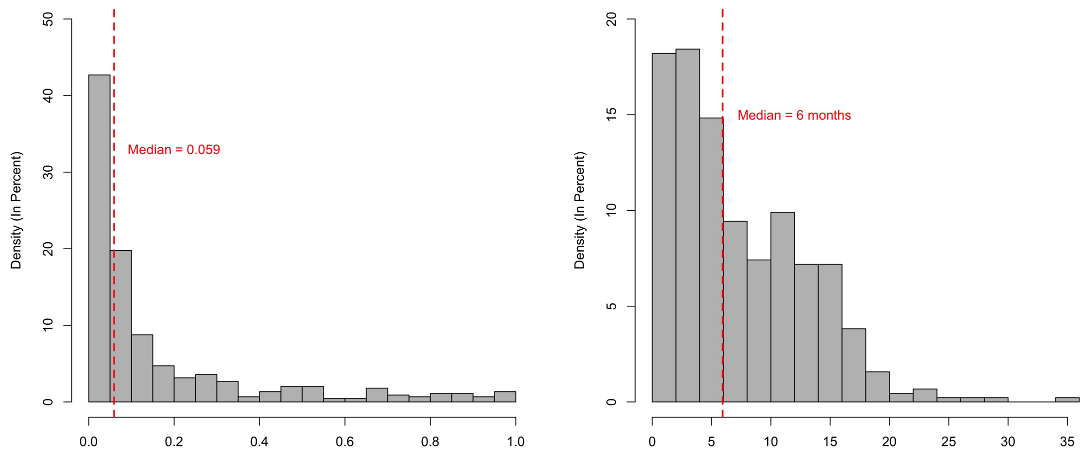
In light of these issues, we provide estimates of mean duration from both the frequency and empirical duration approaches. To get a sense of the underlying distribution of these measures, Figure 3 shows the distribution of the frequency and empirical duration of price changes at the ELI level. We stress again that these statistics are calculated in a bottom-up manner where the frequencies and empirical durations at the item level are successively aggregated up. As shown, both distributions are skewed, with most products exhibiting very low frequency of price changes or relatively high duration. The un-weighted median and mean frequency are 0.06 and 0.15, respectively. For the empirical duration, the un-weighted median and mean are 5.9 and 7.4, respectively. Based on the left plot, almost half of all price changes at the ELI level exhibit a frequency of less than 0.06 (price changes 6% of the time in a given period), while the plot on the right suggests that approximately half of all price spells last longer than 6 months.

Aggregating statistics at the ELI level up by expenditure share weights, Table 3 shows the breakdown of price changes by product categories and selected economic sector types in terms of mean frequency and duration. Overall, prices change infrequently in Thailand. For the CPI as a whole, prices do not change for approximately 4 and 7 months according to implied mean and empirical mean duration estimates respectively. However, note that there is a substantial degree of heterogeneity in the duration of price changes across CPI categories with, for example, prices for food and beverages changing much more often than those in apparel and footwear. In contrast, when organized by sectors, the duration of price changes are significantly longer for core and service goods. The difference in price rigidity between core and non-core goods is particularly large, reflecting the exclusion of volatile items from core in order to make it serve as a proxy for trend inflation.

We also report median frequency and duration of price changes by product categories in Table C1 of Appendix C. As shown, the mean frequency of price changes is more than twice the corresponding median frequency, reflecting the fact that the distribution of the frequency of price changes is very right-skewed. This is consistent with evidence in Nakamura and Steinsson (2008) and Klenow and Kryvtsov (2008) for the US, although

[3]Our main findings are based on mean rather than median duration to correspond to actual CPI calculations that are based on a weighted average of its underlying components.

Figure 3: Distribution of the Frequency and Empirical Duration of Price Changes



(a) Frequency (b) Empirical Duration

Note: Plotted is the distribution of frequency and empirical duration of price changes at the ELI level (unweighted) based on the median population-weighted product.

Table 3: Frequency and Duration of Price Changes by Category

	Mean Frequency	Implied Mean Duration	Empirical Mean Duration
Food and Non-Alcoholic Beverages	0.23	3.91	5.37
Apparel and Footwear	0.03	29.37	13.42
Housing and Furnishing	0.13	7.37	6.37
Medical and Personal Care	0.07	13.03	8.68
Transportation and Communication	0.29	2.86	7.14
Recreation and Education	0.04	22.88	8.33
Tobacco and Alcoholic Beverages	0.11	8.70	7.15
Total CPI	0.20	4.40	6.79
Core	0.06	15.13	8.81
Non-core	0.50	1.44	2.47
Service	0.04	22.76	10.30
Non-Service	0.22	3.94	6.33

Note: All frequencies are reported in percent per month and durations are reported in months. Mean frequency denotes the average of frequency of price changes at the ELI level weighted by their corresponding 2011 expenditure share weights. Implied mean duration is equal to $-1/ln(1-f)$ where f is the mean frequency of price change. Empirical mean duration is the average of price spell lengths at the ELI level aggregated up by their 2011 expenditure share weights.

differences between their mean and median figures are not as pronounced as Thailand.[4] Examining further, the discrepancy that appears at the aggregate level comes from the skewed distributions of food and non-alcoholic beverages and transportation and communication, particularly because these categories hold a relatively high weight in the overall CPI basket. In contrast, empirical mean and median duration measures are roughly similar, implying relatively symmetrical distributions for empirical duration across CPI categories.

To compare our results with previous studies for other countries, we refer to Table 1 of Klenow and Malin (2010) which offers a comprehensive list of mean frequencies across countries. The mean frequency of price changes in Thailand is similar to that of advanced economies such as France (0.19) and the UK (0.19) but lower than in Japan (0.23) and the US (0.26-0.36). Countries such as Italy (0.10) and Germany (0.11) have very rigid prices, whereas emerging nations with high average inflation rates such as Mexico (0.29), Brazil (0.37) and Chile (0.46) change prices most frequently.[5] Overall, the degree of price rigidity in Thailand is high, especially compared to other emerging market countries. For emerging market nations, its consumption structure is characterized by a large share of food products, whose prices change frequently, and a smaller share of services, whose prices change infrequently. The finding of high degree of price stickiness with significant heterogeneity across products/sectors is in line with results from other countries.

There are many possible reasons for our findings of price rigidity and heterogeneity in price-setting. In terms of price stickiness, a stable macroeconomic environment with well-anchored expectations of price stability limits the need to change prices. At the same time, structural factors may also prevent firms from changing prices. These include the desire to preserve long-term relationships with customers, explicit contracts which are costly to renegotiate, and coordination problems arising from the fact that firms prefer not to change prices unless their competitors do so. Thus firms' margins act as an important absorber of shocks to input costs. With respect to heterogeneity across product/sectors, one important factor is the variability of input costs. For example, previous work suggests that prices tend to change less frequently for products with a larger share of labour input and with a smaller share of intermediate energy inputs. Higher levels of competition has also been found to be associated with less price stickiness. Thus differences in production and market structures can help to account for differences in the level of price rigidity across product and sectors.

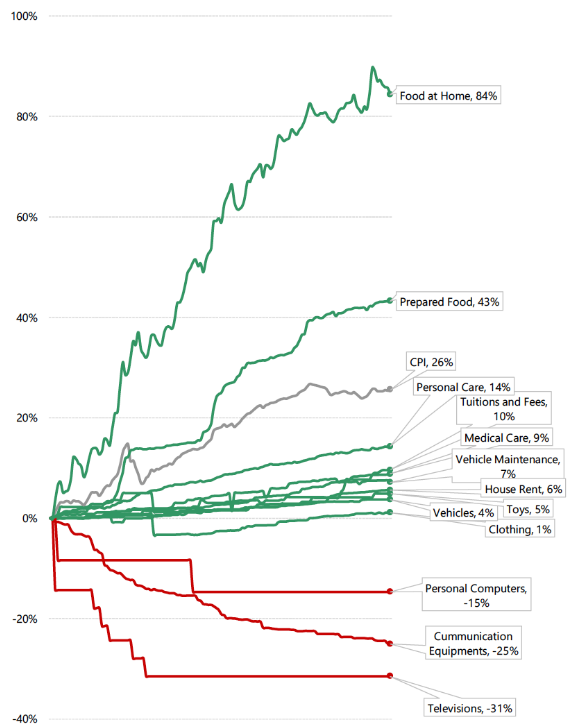
[4]Mean and median frequency of price changes for the US are 0.21 and 0.28 (Nakamura and Steinsson, 2008), and 0.27 and 0.36 (Klenow and Kryvtsov, 2008) respectively. These calculations are based on posted prices which typically have higher frequency than regular prices as they include sales.

[5]It is difficult to compare mean duration across countries because implied mean duration is typically either computed as the implied duration of the average frequency of price change or the average of the implied duration of price changes. In this paper we use the former approach which will always be smaller or equal to the latter due to Jensen's inequality ie. $E(1/F) \geq 1/E(F)$.

Fact 2: Prices decreases are common. On average, 45 percent of all price changes are price decreases. Thus downward price rigidity in Thailand does not appear to be a pervasive issue. This result is similar to those found for the US and the Euro area.

Most macroeconomic models assume that price changes are the result of aggregate shocks. Thus inflation is defined to be a generalized increase in prices. For the fraction of producers changing prices at any given time, prices are typically assumed to either go up or go down together. However, in the data, approximately 60 percent of all price changes in an average month are price increases while the remaining are price decreases. Figure 4 shows that such relative price changes loom large. Over the ten year period until 2017 during which cumulative CPI inflation amounted to 26%, prices of items in the food at home category increased by over 80% whereas electronic products such as televisions, computers, and cell phones have seen continuous price declines. We return to the role of relative prices in more detail below.

Figure 4: Percentage Change in Price Levels by Category (2006-2017)

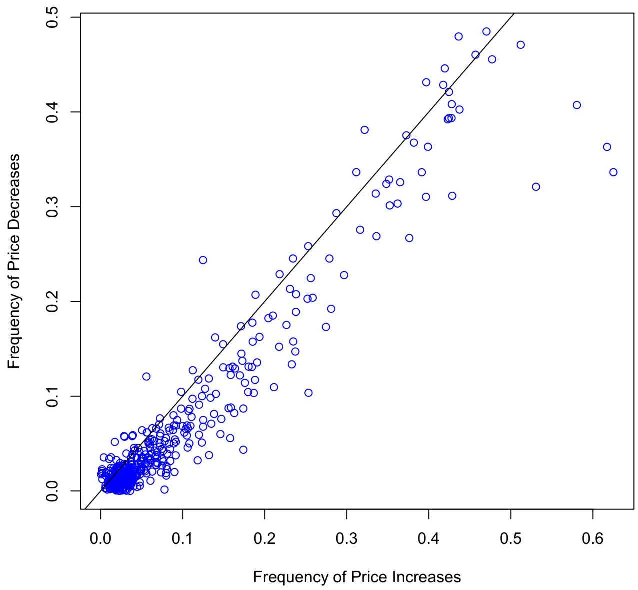


Sources: CEIC, Ministry of Commerce, authors' calculations.

In macroeconomic analysis, it is also generally presumed that prices are rigid downwards. Figure 5 shows that this is far from being realistic. The figure plots for each ELI the frequency of price increases and decreases. If an ELI lies on the 45 degree line, then over the sample it has the same number of price increases as decreases. As can be seen, while the frequency of price decreases for most ELIs is lower than that of price increases, they are quite close. In fact, the overall weighted median fraction of price increases is

56.4 percent, implying that approximately 45 percent of price changes are price decreases. This finding is consistent with the evidence reported elsewhere. For the US, Nakamura and Steinsson (2008) found that one-third of non-sale price changes are price decreases (see also Klenow and Krysvtov (2008)). Altissimo et al. (2006) and Dhyne et al. (2005) document similar evidence for countries in the Euro area.

Figure 5: Frequency of Price Increases and Decreases



Note: Plotted is the frequency of price increases (decreases) for a particular ELI (unweighted) over the sample period, calculated based on the median population-weighted product.

Table 4 shows the empirical duration of price increases and decreases by product categories and economic groupings. The first observation to note is that, in general, the duration of price increases are lower than price decreases. This implies that while price decreases are pervasive, for a given good, price increases more frequently. This is particularly the case for food and non-alcoholic beverages and tobacco and alcoholic beverages where the mean duration of price increases is much shorter than that of decreases. In terms of price declines, transportation and communication, recreation and education and housing and furnishing are at the lower extreme with durations of around 10 months, while at the other extreme, apparel and footwear has an empirical duration of 18 months. Core and service goods also show relatively high duration of price declines at around 15 months.

The finding that overall price falls are common has important implications for the optimal inflation target. It has been argued that downward nominal price rigidities that are not matched by similar upward rigidities may justify a higher inflation objective in order to facilitate relative price adjustments. Our findings do not suggest that this is an

Table 4: Empirical Mean Duration of Price Increases and Decreases by Category

	Mean Duration Increase	Mean Duration Decrease	Fraction Increase
Food and Non-Alcoholic Beverages	7.94	13.38	57.28
Apparel and Footwear	18.08	18.85	66.66
Housing and Furnishing	8.69	10.90	56.55
Medical and Personal Care	11.28	13.94	59.32
Transportation and Communication	10.59	10.26	52.79
Recreation and Education	11.59	10.58	64.28
Tobacco and Alcoholic Beverages	10.68	17.26	82.22
Total CPI	9.73	12.29	56.41
Core	11.74	15.10	66.66
Non-core	3.76	4.63	56.42
Service	13.48	15.69	70.00
Non-Service	8.64	11.23	56.01

Note: Mean duration increases (decreases) are in months and is based on calculating the average length of price spells between increases (decreases) for each ELI based on the median population-weighted product, then aggregating up by 2011 expenditure share weights. Fraction increase is calculated as the fraction of mean frequency increases over the sum of mean frequency price changes.

important reason for such an inflation buffer.

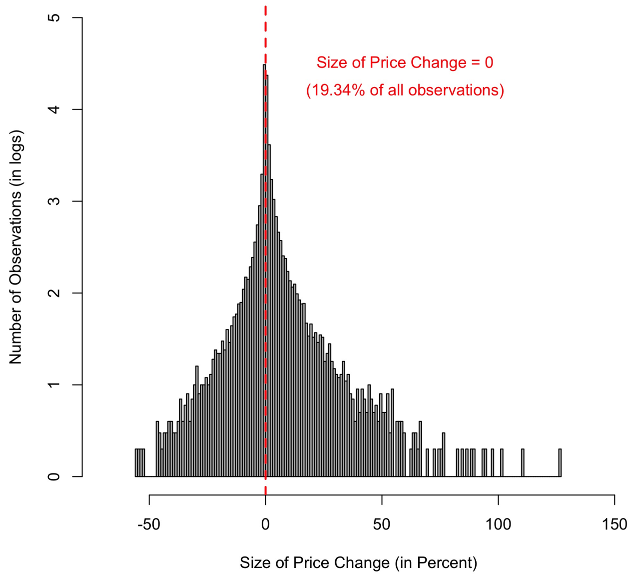
Fact 3: Price changes, both increases and decreases, are sizable compared to the prevailing inflation rate. The average size of price increases and decreases are 10.4 percent and 7.7 percent, respectively, compared to average monthly inflation rates of 0.11 percent (or 1.26 percent annualized).

Figure 6 displays the distribution of the monthly size of price changes at the ELI level. The distribution is skewed towards larger monthly price increases. Given the high degree of overall price rigidity in Thailand, it is not surprising that 19 percent of all observations are those where the monthly size of price changes are zero. One would also expect, given this rigidity, that the size of price changes might be relatively large when prices do eventually change. This is indeed the case. According to Table 5, price increases as well as decreases are sizable compared to the inflation rate. The average consumer price increase is found to be in the order of 10.37%, while the average price decrease only slightly smaller at 7.74%. Although smaller, median price increases and decreases are still sizable at 5.82 and 5.42 percent respectively. Average monthly inflation, by contrast, is just 0.11 percent (or 1.26 percent annualized).[6]

Looking across categories and sectors, Table 5 shows that there is significant heterogeneity in the relative size of price increases and decreases. Price increases tend to be larger than price decreases across all product categories. Recreation and education and apparel and footwear display the largest percentage change in prices. These product categories also happen to be highly rigid groups (high duration of price change) consistent with the idea that for products whose prices change rarely, when the change eventually happens, they tend to be large. This is confirmed in the broader groupings, where price

[6] Our finding that price increases are larger than price decreases contrasts with evidence from Dhyne et al. (2005). For the Euro area, they find that the magnitude of price decreases are 10 percent on average, while the size of price increases are only 8 percent.

Figure 6: Distribution of Size Changes



Note: Vertical axis shows the number of observations that are transformed by the function $log_{10}(x+1)$ where x is the number of observations. The horizontal axis shows the monthly size of price changes (unweighted) for each ELI as well as time period in percent. Size changes at the ELI level is based on the median population-weighted product.

changes for core and service goods tend to be larger. Again, this reflects the negative correlation between size and frequency of price increases and decreases (around -0.3 for both core and services) – for goods whose prices change less frequently, the average size of change is larger.

The stylized facts highlighted so far point to a large degree of heterogeneity in the frequency of price changes across goods as well as the concurrency of large positive and negative price changes intermixed with many small ones. Taken together, they suggest large differences in either firm-specific shocks or in underlying price setting friction, be it in the form of 'menu costs' or the opportunity to change prices (Calvo parameter). A satisfactory model of price setting would need to incorporate heterogeneity along one or many of these dimensions (eg. Dotsey and Wolman (2018), Gautier and Le Bihan (2018)).

Fact 4: The size of price changes covaries strongly with the rate of inflation, whereas the fraction of items changing prices do not. Variations in the size of price changes also contributes to the bulk of the overall variance of inflation.

Given the granularity of the data, we are able to decompose the inflation process and ask whether changes in the inflation rate are due to changes in the number of products whose prices adjust or simply changes in the size of individual products' price changes. Following Klenow and Kryvtsov (2008) monthly inflation can be decomposed into the

Table 5: Size of Price Increase and Decrease by CPI Category

	Mean Increase	Median Increase	Mean Decrease	Median Decrease
Food and Non-Alcoholic Beverages	6.84	6.20	5.66	5.42
Apparel and Footwear	14.11	11.28	14.14	10.93
Housing and Furnishing	16.42	3.58	12.87	3.55
Medical and Personal Care	10.80	10.18	7.91	4.61
Transportation and Communication	16.02	3.55	8.31	3.44
Recreation and Education	29.78	32.30	20.47	17.31
Tobacco and Alcoholic Beverages	4.96	3.67	1.97	1.12
Total	10.37	5.82	7.74	5.42
Core	14.03	6.63	10.05	6.42
Non-core	5.35	3.78	4.57	3.45
Service	32.95	31.60	16.55	13.61
Non-Service	8.84	4.97	7.14	4.69

Note: Mean and median size of price increases and decreases are in percent and are based on calculating the average size of price increases for each ELI based on the median population-weighted product, then aggregating up by 2011 expenditure share weights.

fraction of items with price changes (fr_t), the extensive margin, and the average size of those price changes (dp_t), the intensive margin. Namely,

$$\pi_t = \sum_i \omega_{it}(p_{it} - p_{it-1}) = \underbrace{\sum_i \sum_t \omega_{it} I_{it}}_{fr_t} \cdot \underbrace{\frac{\sum_i \sum_t \omega_{it}(p_{it} - p_{it-1})}{\sum_i \sum_t \omega_{it} I_{it}}}_{dp_t}$$

where the first term fr_t is the fraction of items changing prices in each month t, and the second term dp_t is the magnitude of price changes occurring in month t, both computed by taking the weighted average across ELIs.

This can be further decomposed into

$$\pi_t = fr_t^+ \cdot dp_t^+ - fr_t^- \cdot dp_t^-$$

where fr_t^+ and fr_t^- denotes the fraction of price increases and decreases, respectively, and dp_t^+ and dp_t^- denote the size of price increases and price decreases, respectively. That is, inflation is the net result of price increases and decreases driven by changes in the fraction of products whose price change weighted by the size of those changes.

Table 6 contains summary statistics for CPI inflation and the intensive and extensive margins of price changes. In the sample, the monthly average inflation rate is 0.11 percent or 1.26 percent annualized. The fraction of items changing prices (fr_t), the extensive margin, is relatively stable over time with the standard deviation being small relative to its mean. On the other hand, the size of price changes (dp_t), the intensive margin, exhibits a much higher variation relative to its mean.

Not only are the size of price changes more volatile, they are also almost perfectly correlated with inflation with a correlation coefficient of 0.98. The fraction of price changes, by contrast, has a much lower correlation with inflation. Overall, with the number of products whose price change being roughly the same each month, the rate of inflation varies with the size of individual products' price changes (intensive margin), rather than

Table 6: Time Series Moments

Variables	Mean(%)	Std dev(%)	Correlation with π
π_t	0.105	0.452	
fr_t	13.976	3.020	0.102
dp_t	0.749	3.259	0.976
fr_t^+	7.908	3.377	0.547
fr_t^-	6.066	2.957	-0.520
dp_t^+	4.538	3.067	0.570
dp_t^-	4.237	3.591	-0.544
pos_t	0.362	0.307	0.787
neg_t	0.257	0.283	-0.743

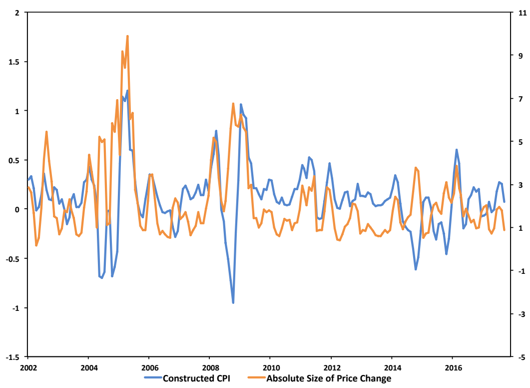
Note: The entries are means, standard deviations, and cross-correlations across time of the monthly values of each variable. The variables π_t = inflation, fr = the fraction of items with changing prices, dp_t = the size of price changes, fr_t^+ =the fraction of items with rising prices, fr_t^- = the fraction of items with falling prices, dp_t^+ = the size of price increases, $dp-_t$ = the absolute size of price decreases, $pos_t = fr_t^+ \cdot dp_t^+$ and $neg_t = fr_t^- \cdot dp_t^-$. Note that $\pi_t = pos_t - neg_t$.

variations in the number of products whose prices change (extensive margin).

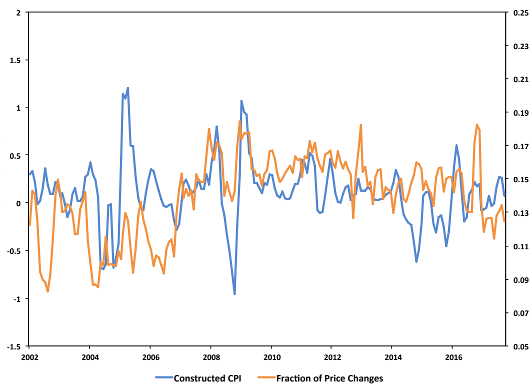
Figure 7 illustrates these points more clearly. As shown in Panel a, while the absolute size of price changes tracks CPI inflation closely, Panel b shows that the fraction of price changes do not. This is because while the fraction of price changes did climb higher when inflation surged during the onset of the global financial crisis period in 2007, other periods of high inflation did not necessarily correspond to higher fraction of price changes. Also, as inflation declined rapidly in 2015, the fraction of price changes fell back only gradually.

Our results on how inflation is related to price changes at the intensive and extensive margins are similar to Klenow and Krysvtsov (2008) and Nakamura and Steinsson (2008) for the US as well as Vilmunen and Laakkonen (2005) and Dhyne et al. (2005) for the Euro area. For example, Klenow and Krysvtsov (2008) find that over 1988-2004, the correlation between the fraction of price changes and inflation is only 0.25 while the average size was volatile and had an almost perfect correlation with inflation (0.99).

Figure 7: CPI Inflation and Absolute Size and Fraction of Price Changes



(a) Absolute Size



(b) Fraction

Note: Plotted is the three-month moving average of constructed CPI inflation from our dataset (left axes in percent) and the absolute size of price changes and fraction of items changing prices in each month (right axes in percent).

Looking at price increases and decreases separately, however, Table 6 shows that variations in fraction are more correlated with inflation than its overall figure suggests. This implies that although the extensive margin plays a relatively small role in overall inflation, it does vary systematically with the inflation rate. When inflation rises, the number of products whose price increase does rise and the number of products whose price decrease falls. Thus the extensive margin appears to be important when looking at the rise and fall of inflation separately although their effects cancel each other out at the aggregate level. Finally, the last two lines of Table 6 show that variations in the intensive and extensive margins of price increases (pos_t) are as important for inflation than those for prices decreases (neg_t). Compared with findings for the US, this observation is similar to Klenow and Krystov (2008) but contrasts with those of Nakamura and Stensson (2008), whom only find a significant relation between inflation and those of price increases.

Instead of just the level of inflation, we can also look at the relative importance of the intensive and extensive margins on the variance of inflation. Taking the variance of a first-order Taylor series expansion of $\pi_t = fr_t \times dp_t$ around the sample means $\bar{fr}$ and $\bar{dp}$ gives the following decomposition of inflation variance.[7]:

$$var(\pi_t) = \underbrace{var(dp_t) \cdot \bar{fr}^2}_{\text{IM term}} + \underbrace{var(fr_t) \cdot \bar{dp}^2 + 2 \cdot \bar{fr} \cdot \bar{dp} \cdot cov(fr_t, dp_t) + O_t}_{\text{EM term}}.$$

Table 7 reports the variance decompositions results, showing the intensive (IM) and extensive (EM) margin contributions to CPI inflation variance over the sample. To mitigate the period with large swings in inflation which could cause size changes to be very large, we exclude the 2007M1-2009M12 time period. This splits the sample into two, where in both subsamples, the EM and IM margins are more or less relatively stable over time, with the IM accounting for a much higher proportion of overall inflation variance. That is, the variability of inflation is largely due to variations in the size of price changes of individual products rather than variations in the number of products whose prices are changing, which is a similar finding to Klenow and Kryvtsov (2008) for the US. When viewing price increases and decreases separately, we find that the variance of price changes in both directions account for relatively equal proportions of the total inflation variance, although price increases may have become relatively more important during the post 2010 period.

The observation that overall inflation is driven by the intensive margin with the frac-

[7]In the above expression, the higher order terms (O_t) and the covariance terms are small, thus the quantitatively important terms are the variance terms. Note that following a similar procedure, the variance decomposition for price increases and decreases can be computed as:

$$var(\pi_t) = \underbrace{var(pos_t) - cov(pos_t, neg_t)}_{\text{POS term}} + \underbrace{var(neg_t) - cov(pos_t, neg_t)}_{\text{NEG term}}$$

where $pos_t = fr_t^+ \cdot dp_t^+$ and $neg_t = fr_t^- \cdot dp_t^-$.

Table 7: Variance Decompositions

Sample	IM term	EM term	POS term	NEG term
2002M1-2007M1	0.25	0.05	0.13	0.16
(percent)	(83.03)	(16.97)	(45.02)	(54.98)
2010M1-2017M12	0.10	0.01	0.07	0.04
(percent)	(91.01)	(8.99)	(63.90)	(36.10)

tion of items changing prices relatively constant lends support to time-dependent Calvo-type frictions. Yet the fact that when one looks at price increases and decreases separately, the fraction of items changing prices seems to vary systematically with inflation also suggests that firms' price setting are state-dependent to some degree. Taken together, it is suggestive of the potential for pricing models that combine both features to better replicate the data.

Fact 5: There is significant dispersion in price levels for identical products across geographical regions even as price changes tend to occur at the same time.

Given price data across Thailand's provinces, we are able to investigate the geographical dimension of micro prices. We are primarily interested in two aspects: i) the synchronicity or extent to which prices of identical products change at the same time in different regions; and ii) the dispersion in price levels of the same product across locations.

In order to analyze the geographical property of prices, we need to construct a cross-provincial panel dataset. Unfortunately, most of the products in the data do not exist in all provinces. Thus instead of focusing at the provincial level, we divide Thailand into nine broad regions as listed in Table 8. Given these nine regions, we then identify 1,017 products that are observed in all regions, which together span 164 ELIs. For ELIs where more than one product is observed, we rank those products by the total number of population in provinces where the product exists and choose the most popular one to represent that ELI. All in all, we end up with a panel of 164 products across regions.

Table 8: Regions of Thailand

Central	Bangkok, Samut Prakan, Nonthaburi, Pathum Thani, Phra Nakhon Si Ayutthaya, Ang Thong, Lopburi, Sing Buri, Chainat, Saraburi
Eastern	Chonburi, Rayong, Chanthaburi, Trat, Chachoengsao, Prachinburi, Nakhon Nayok, Sa Kaeo
South North-eastern	Nakhon Ratchasima, Buriram, Surin, Sisaket, Ubon Ratchathani, Yasothon, Chaiyaphum, Amnat Charoen
North North-eastern	Bueng Kan, Nong Bua Lamphu, Khon Kaen, Udon Thani, Loei, Nong Khai, Maha Sarakham, Roi Et, Kalasin, Sakon Nakhon, Nakhon Phanom, Mukdahan
North Northern	Chiang Mai, Lamphun, Lampang, Uttaradit, Phrae, Nan, Phayao, Chiang Rai, Mae Hong Son
South Northern	Nakhon Sawan, Uthai Thani, Kamphaeng Phet, Tak, Sukhothai, Phitsanulok, Phichit, Phetchabun
Western	Ratchaburi, Kanchanaburi, Suphan Buri, Nakhon Pathom, Samut Sakhon, Samut Songkhram, Phetchaburi, Prachuap Khiri Khan
North Southern	Nakhon Si Thammarat, Krabi, Phang Nga, Phuket, Surat Thani, Ranong, Chumphon
South Southern	Songkhla, Satun, Trang, Phatthalung, Pattani, Yala, Narathiwat

To gauge the extent to which prices for the same product change in a synchronous manner across regions, we make use of the Fisher Konieczny (2000) index calculated for each product as:

$$FK = \frac{\sqrt{s^2_{p_t}}}{\sqrt{\bar{p}(1-\bar{p})}}$$

where p_t is the proportion of regions that changes the price of the product between $t-1$ and t, $\bar{p}$ and $s^2_{p_t}$ are the mean and variance of p_t respectively. In the case of perfect synchronization, FK=1, while it takes on a value of 0 in the case of perfectly staggered price changes. Table 9 shows the calculated FK index for each product category. Synchronization is highest for transportation and communication and is lowest for food and beverages. The higher figure for the former (FK=0.87) is due to the inclusion of energy prices in this category, and is consistent with the finding of Dias et al. (2004) which also finds the FK index in the energy sector for Portugal to be as high as 0.82. As a whole, the FK index for Thailand (0.57) is on the high side, especially when compared to the Euro area. Dhyne et al. (2006) reports a FK index that ranges between 0.13 for Germany and 0.48 in Luxembourg.

Table 9: Summary Statistics by Product Category

Category	Number of ELIs	FK	Mean CV
Food & Beverages (FB)	97	0.43	0.10
Clothing & Footwear (CF)	13	0.55	0.20
Housing & Furnishing (HF)	14	0.59	0.16
Health & Personal Care (HP)	16	0.68	0.05
Transportation & Communication (TC)	11	0.87	0.02
Recreation & Education (RE)	10	0.66	0.16
Tobacco &Alcoholic Beverages (TA)	3	0.66	0.02
Total	164	0.57	0.08
Service	14	0.47	0.26
Non-service	150	0.57	0.07

Note: FK is the Fisher and Konieczny (2000) index and mean CV is the simple mean of CV over time. Calculations are as described in the text.

Turning to the geographical dispersion of price levels, we focus on the coefficient of variation (CV), which is simply the ratio of the standard deviation of a product's price across regions relative to its mean. The last column of Table 9 shows the expenditure-weighted averages of the regional price dispersion (mean CVs) for different product categories. For the entire sample, the average CV is 8 percent. There is some heterogeneity in price dispersion across product categories with the CV measure being highest for clothing and footwear at 20 percent. At the other extreme, tobacco and alcoholic beverages and transportation and communication have the lowest dispersion, which are sectors with generally high levels of price synchronization. A key reason for price dispersion is differences in input costs and the role of non-traded components across regions. One way to capture this is to look at price dispersion for service versus non-services in the bottom panel of Table 9, where the dispersion for service prices are much larger at 26 percent.

4 A Factor Analysis of Price Movements

Our findings thus far suggest that there is a great deal of heterogeneity in price setting. To make sense of these diverse price movements, and especially how they relate to overall changes of the CPI as well as key macro variables, we estimate the dynamic factor model of Reis and Watson (2010) and decompose inflation into 3 separate components – pure, relative, and idiosyncratic to be defined precisely below – using micro price data. We then relate these components to a set of macroeconomic variables. In the next subsections, we briefly describe the empirical model and estimation methodology, then summarize our findings into 2 additional stylized facts.

4.1 Empirical Model and Estimation Methodology

A longstanding discussion about the causes of inflation emphasizes the distinction between generalized price changes that affect all goods in equal proportions (absolute price changes), and price changes that only happen to some goods relative to others (relative price changes) (see Vining and Elwertowski, 1976; Humpage, 2008). Absolute price changes are often seen as the price response to anticipated monetary and fiscal shocks, while relative price changes stem from unanticipated policy shocks, exchange rate shocks, as well as other demand and supply-side shocks that cause the prices of some goods to change in different proportion to others. Distinguishing among these disparate sources of shocks driving overall CPI movements is of immense importance for the conduct of monetary policy.

To make the distinction between absolute and relative price movements, Reis and Watson (2010) propose that the comovements of N individual price series can be decomposed as follows:

$$\pi_t = \mathbf{1}a_t + \Gamma R_t + u_t \tag{1}$$

where π_t is an $N\times 1$ vector of inflation series for N goods; a_t is the absolute price component that captures price changes that are common and equiproportional to all goods; R_t is the relative price component that reflects the effect of aggregate shocks on all goods in different proportions; and u_t is the idiosyncratic price component that captures only goods-specific relative price changes. With a_t being the absolute price component, $\mathbf{1}$ is a $N \times 1$ vector of ones. For R_t, the disproportionate effects of aggregate shocks on price movements is summarized by the $N \times (k-1)$ matrix Γ, where there are a total of k factors which capture the common movements in disaggregated prices. Note that the decomposition in Eq. (1) not only makes the distinction between absolute (a_t) and relative price movements (R_t and u_t), but also separates price changes that are driven by aggregate (a_t

and R_t) versus idiosyncratic shocks (u_t)[8].

An important challenge in estimating Eq. (1) is that a_t and R_t are not separately identified. To see this, for any arbitrary $(k-1) \times 1$ vector α, we have $\mathbf{1}a_t + \Gamma R_t = \mathbf{1}(a_t + \alpha' R_t) + (\Gamma - \mathbf{1}\alpha')R_t$, so that (a_t, R_t) cannot be distinguished from $((a_t + \alpha' R_t), R_t)$. In other words, we cannot distinguish absolute changes in prices from changes in 'average relative prices'. To overcome this problem, Reis and Watson (2010) suggest to focus on two independent components instead:

$$v_t = a_t - E[a_t | \{R_t\}_{t=1}^{T}] \tag{2}$$

$$\rho_t = E[F_t | \{R_t\}_{t=1}^{T}] \tag{3}$$

where 'pure' inflation v_t can be interpreted as the common component in price changes that has an equiproportional effect on all prices and is uncorrelated with changes in relative prices at all dates, while the relative price index ρ_t captures all aggregate movements in goods' price changes that are associated with some change in relative prices at some date.

Then, Eqs. (1)-(3) can be summarized by the following specification:

$$\pi_{it} = a_t + \gamma_i R_t + u_{it} \tag{4}$$

where the latent components are defined as:

$$\phi(L) \begin{pmatrix} a_t \\ R_t \end{pmatrix} = \epsilon_t \tag{5}$$

$$\beta_i(L) u_{it} = c_i + e_{it}. \tag{6}$$

and the innovations e_{it}, $e_{jt_{j \neq i}}$, and ϵ_t are mutually and serially uncorrelated with mean zero and variances $var(e_{it}) = \sigma_i^2$ and $var(\epsilon_t) = Q$.

To estimate the empirical model, we use quarterly ELI inflation series because data at the item level is too noisy for the inflation decomposition. While it is possible to construct the ELI inflation series by aggregating up price changes at the item level, we opt for using official chained price indices of goods and services at the ELI level provided by the Ministry of Commerce instead. Quarterly inflation at the annual rate is computed according to $\pi_{it} = 400 \times ln(P_{it}/P_{it-1})$, where P_{it} is the quarterly ELI price index for

[8]Bryan and Cecchetti (1994) also estimate a dynamic factor model but only separate absolute from relative price changes. Boivin et al. (2009) only distinguishes between aggregate and idiosyncratic price movements.

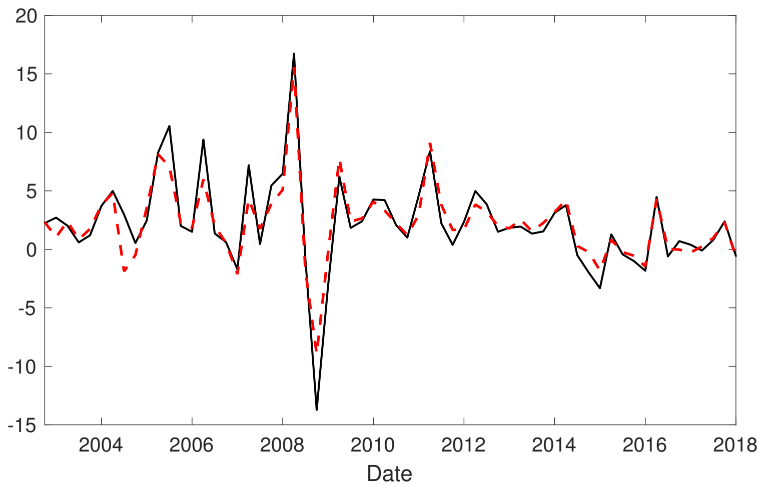
good i. Our dataset spans 2002Q2-2018Q2 and comprises of 225 ELIs[9]. After cleaning the data according to the approach outlined in Appendix D, we are left with a sample containing 179 ELIs. Table 10 provides an overview of the dataset, and Figure 8 shows that despite the total coverage of our dataset being only 64 percent of the overall CPI basket, our constructed series track actual CPI inflation well.

Table 10: Sample Coverage of the Consumer Price Index

	Dataset Share (ELI Count	Actual Share (ELI Count
Food and Non-Alcoholic Beverages	26.8 (99)	33.5 (175)
Apparel and Footwear	1.1 (15)	3.1 (54)
Housing and Furnishing	21.5 (29)	24.2 (62)
Medical and Personal Care	2.2 (17)	6.5 (63)
Transportation and Communication	11(10)	25.6 (49)
Recreation & Education	0.8 (5)	6.0 (43)
Tobacco & Alcohol	1.2 (4)	1.2 (4)
Total	64.4 (179)	100 (450)

Note: Reported are the actual and sample shares of the CPI in percent, calculated using 2011 expenditure share weights obtained from the Ministry of Commerce. The number of ELIs that fall within each group are reported in parentheses.

Figure 8: Constructed and Actual CPI Inflation



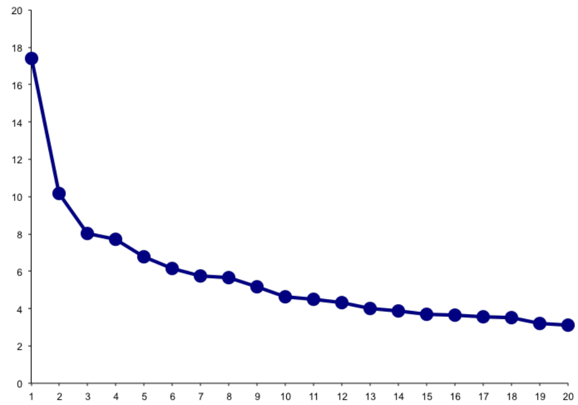
Note: Plotted is quarter-on-quarter actual CPI inflation (solid line) compared to the constructed inflation series from our dataset with 179 ELIs (dashed line) based on year 2011 expenditure share weights.
Source: Thai Ministry of Commerce, authors' calculations.

To estimate the empirical model, a key parameter that we first need to determine is the number of common factors k that best describes the dataset. Choosing k involves a

[9]The CPI basket is redefined every several years and therefore when choosing the dataset for estimation, there is a tradeoff between a longer dataset and the number of ELIs that can be included. More specifically, the most current CPI basket contains 425 items, but as we try to extend the dataset back, we lose items as we try to match identical goods in the 2013-2016, 2009-2012, 2005-2008, and 2002-2004 baskets. We choose to start our sample in 2002 as extending further back to 1998 leaves us with only 194 ELIs and model instability issues may arise if we choose to perform the inflation decomposition over pre and post inflation targeting regimes.

tradeoff, a higher k can explain a larger share of the variance in the data, but additional factors increases the complexity of the model and reduces the reliability and significance of parameter estimates. To guide our choice of k, we turn to a few statistical tests. Based on the largest 20 eigenvalues of the sample correlation matrix, it is clear that there is one large eigenvalue, but it is less clear whether 2 or 3 total factors are needed (see Figure 9). Various Bai-Ng estimators (Bai and Ng, 2002), which are similarly based on the number of dominant eigenvalues suggest 1-2 factors. We also calculate the fraction of variance explained by an unrestricted factor model based on 1-4 factors for the 179 inflation series. In Figure 10, we order the series by the fraction of variance explained by the 1-factor model. As shown, the second factor seems to improve the fit for several series but it is unclear whether additional factors are necessary. Taking all results into consideration, we use 3 factors (1 factor for a_t and 2 factors for R_t) to be on the cautious side.

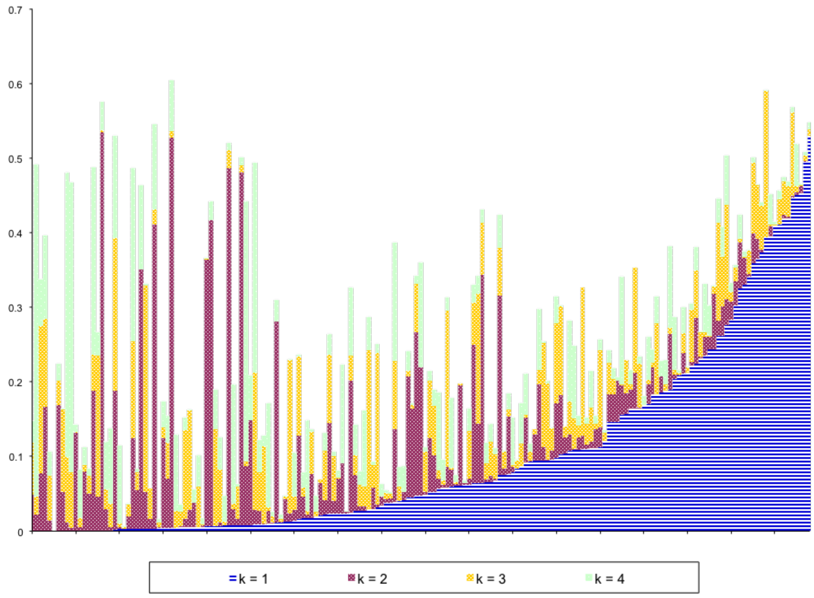
Figure 9: Eigenvalues of the Correlation matrix



Note: Plotted are the eigenvalues of the correlation matrix of inflation rates in the dataset.

Once k is defined, we then set up the empirical model for estimation. The parameters of the empirical model as described by Eqs. (4)-(6) are estimated via maximum likelihood. However, numerically maximizing the likelihood function is computationally complex due to the large number of parameters involved (179 price series with $k = 3$ factors with latent factors following VAR(4) and autoregressive processes). Therefore, we estimate the parameters using an expectation-maximization (EM) algorithm computed by Kalman smoothing in the E-step and linear regression for the M-step. Then, the final step of estimation involves computing the latent factors using signal extraction formulae. In doing so, certain restrictions such as those defined by Eqs. (2)-(3) are imposed upon the model. For details on estimation, readers are referred to the Web Appendix of Reis and Watson (2010).

Figure 10: Number of Factors



Note: Plotted is the fraction of sample variance of inflation explained by k factors, where k varies from 1 to 4. The horizontal axis is ordered by the fraction of variance explained by the 1-factor model for the 179 ELIs.

4.2 Empirical Findings

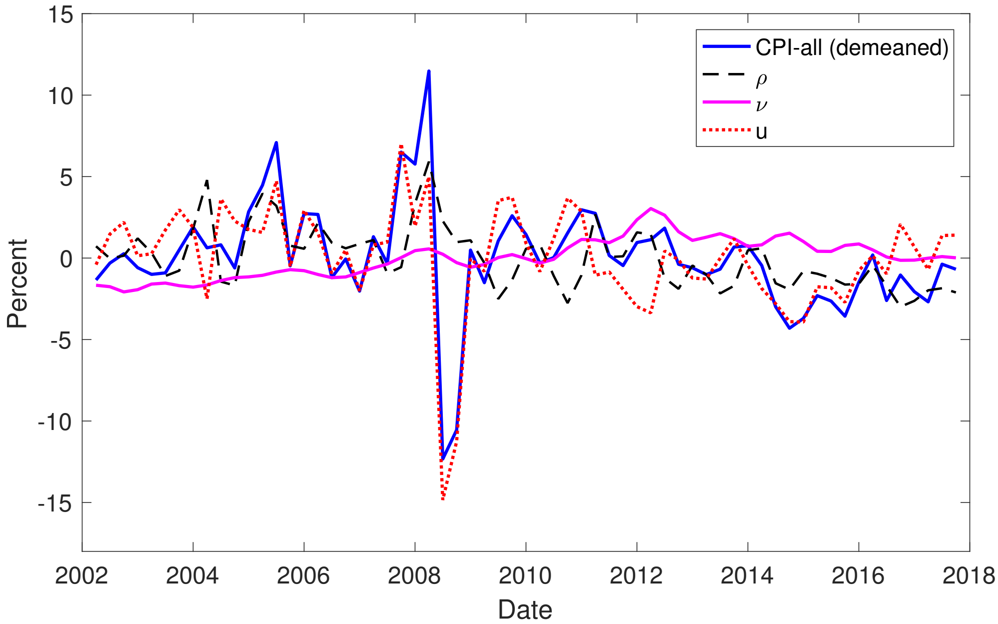
Fact 6: The bulk of overall price movements in the CPI are relative price changes. Aggregate relative price shocks account for 57 percent of total inflation rate variability, while another 32 percent is explained by idiosyncratic good-specific shocks. 'Pure inflation' explains only 11 percent of overall inflation variability.

Figure 11 displays the historical decomposition of Thai CPI inflation into pure, relative and idiosyncratic components based on 179 (demeaned) ELI price series. Overall, the trajectory of the pure inflation component (v_t) is smooth and more or less tracks the sample mean of headline CPI inflation. In contrast, the aggregate and idiosyncratic relative price components (ρ_t and u_t) are quite volatile. For example, large swings in the inflation rate during the Great Recession period can be attributed almost entirely to relative price fluctuations. Also, in the past few years, the component of inflation that appears to be driving inflation lower despite loose monetary policy conditions is ρ_t, the aggregate relative price component.

We next investigate the importance of the different inflation components in overall inflation variability more formally. In doing so, we utilize canonical R-squared measures.[10] Over the entire sample period, Table 11 shows that the standard deviation of overall CPI

[10]The canonical R^2 is used to measure the degree of correlation between specific variables of interest over the frequency domain. See Reis and Watson (2010) for more details on calculations of the canonical R^2 measure.

Figure 11: CPI Inflation Decomposition



Note: Based on the decomposition of inflation into pure (ν), relative (ρ) and idiosyncratic components (u).

inflation is 3.91. While ρ_t and u_t are indeed both volatile, according to the canonical R^2 measures reported in Table 11, only ρ_t plays a key role in explaining overall inflation variability. More specifically, up to 57 percent of all fluctuations in the CPI inflation rate can be attributed to the aggregate relative price component. The pure inflation component on the other hand, accounts for only 11 percent of the variation, whilst the idiosyncratic component explains the remaining 32 percent. This finding also holds at business cycle frequencies.

Table 11: Volatility and Fraction of Inflation Variability Explained by Its Components

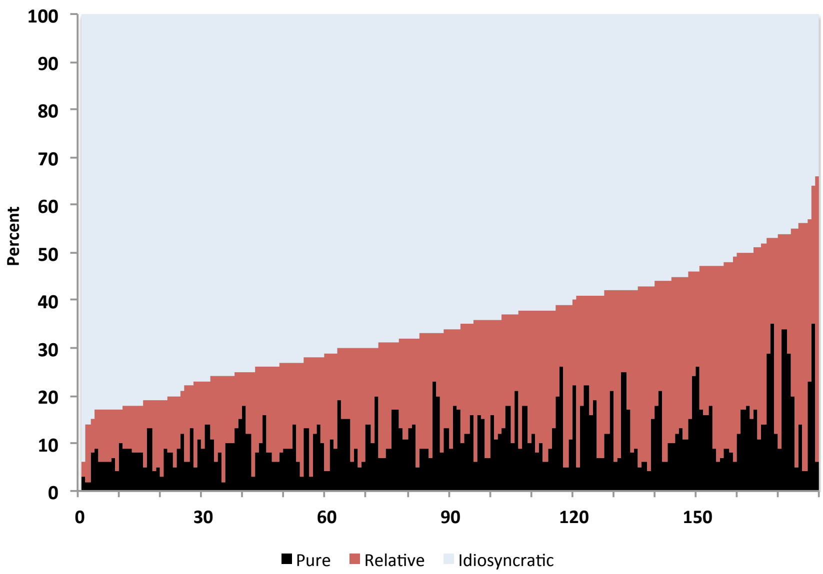
	Standard Deviation				R^2 (All freq)			R^2 (B-cycle freq.)		
	π_t	v_t	ρ_t	u_t	ρ_t	v_t	u_t	ρ_t	v_t	u_t
Aggregate Inflation Rates										
CPI Inflation	3.91	1.15	2.97	3.10	0.57	0.11	0.32	0.56	0.09	0.35
Disaggregated Series										
25th Percentile	1.57	1.15	0.88	2.02	0.15	0.07	0.78	0.10	0.02	0.88
Median	2.98	1.15	1.47	4.13	0.21	0.10	0.69	0.23	0.04	0.73
75th Percentile	7.71	1.15	3.64	9.85	0.30	0.15	0.55	0.46	0.08	0.62
Average	13.04	1.15	6.34	12.59	0.23	0.12	0.65	0.29	0.06	0.65

Note: Inflation is quarter-on-quarter changes of the headline consumer price index. Disaggregated inflation rates are the quarter-on-quarter changes corresponding to the 179 individual price series. Reported are the standard deviations and average squared canonical coherence R^2 measure over all and business cycle frequencies, where business cycle frequencies are defined over the $\pi/32 \leq \omega \leq \pi/6$ domain.

At the disaggregated level, individual price series are also driven by relative price changes. However, these price changes are driven by idiosyncratic rather than aggregate price shocks. According to the second panel of Table 11, disaggregated inflation rates are much more volatile than aggregate inflation series, with the average standard deviation being almost three times as large. Based on the canonical R^2 measures, much of this volatility can be attributed to idiosyncratic disturbances. On average, the idiosyncratic component explains as high as 65 percent of all disaggregated inflation rate movements, which is almost double of what was reported for aggregate headline inflation. The importance of the idiosyncratic component for the 179 ELI series can be seen more clearly in Figure 12. As shown, the area that corresponds to the idiosyncratic component is quite large although its contribution varies across goods.

The finding that idiosyncratic shocks are important for individual price series but relative price movements that stem from macroeconomic-wide shocks matter most for overall CPI are consistent with the findings of Boivin et al., (2009), Reis and Watson (2010) and Forbes et al. (2018), among others. Based on the analysis for the US, Boivin et al. (2009) show that sector-specific shocks account for 85 percent of monthly fluctuations in inflation. At the aggregate level, Reis and Watson (2010) show that the relative price component explains up to 70 percent of inflation rate fluctuations at all frequencies and 90 percent at business cycle frequencies. For the UK, Forbes et al. (2018) finds that up to 72 percent of the variation in five aggregate inflation series can be explained by just one common principal component.

Figure 12: Fraction of Variability Explained by Inflation Components



Note: Plotted is the fraction of sample variance of inflation at the ELI level explained by pure, relative and idiosyncratic components. The horizontal axis is ordered by the fraction of variance explained by the sum of the pure and relative components for 179 ELIs.

The importance of relative prices in driving overall CPI movements raises two key policy challenges. The first has to do with measurement. How to separate changes in the CPI driven by structural demand and supply factors, which in and of themselves warrant no policy response, from those that arise from monetary factors? While the latter will be embodied in the 'pure' component of CPI changes, which we have seen is quite small, both sets of factors will also show up in relative prices. Teasing out the policy-relevant part of CPI changes is critical yet difficult. Adam and Weber (2017), for example, show that in the presence of firm-specific productivity trends, overall prices may trend up or down independently of monetary policy. Thus there may be a something akin to a 'natural rate of CPI change' to be distinguished from overall inflation.

The second, related, challenge concerns policy control. To the extent that a substantial part of CPI variations reflect relative price changes driven by structural factors – such as favorable supply-side shocks related to globalization and technological innovation or the more traditional Balassa-Samuelson effect driven by productivity differentials – monetary policy has little control over these trends. Yet inflation-targeting frameworks may not be sufficiently nuanced to accommodate such changes as they are typically anchored to the CPI often with a relatively short horizon. This not only poses communication challenges but may also result in excess policy activism as central banks attempt to counter such trends.

Fact 7: The underlying drivers of aggregate price movements are related to well-known macroeconomic variables. The pure inflation component is correlated with factors related to monetary policy, particularly in the long-run. For the relative price component, traditional relative price factors such as food and energy price shocks can explain a large proportion of its movements. Its relation with real variables such as GDP is also strong at business cycle frequencies, providing empirical support for the Phillips curve.

Given the importance of the relative price component (ρ_t) in explaining CPI movements, we explore its behavior in more detail, linking it first to traditional relative price factors. According to the canonical R^2 measures in the top panel of Table 12, food and energy price shocks appear to be important in explaining ρ_t, as both of their correlations with ρ_t are as high as 40 percent at all frequencies, and increases to 64 percent at business cycle frequencies for food. Surprisingly, this share declines by half for energy at business cycle frequencies, which may suggest that a sizable component of energy price movements are being passed through to price changes at lower frequencies or trend inflation. Combining food and energy, both factors explain around 60 - 70 percent of all relatively price fluctuations. The remaining share may be explained by other relative price factors such as services, durables and imports, which as shown, also play a key role in explaining aggregate relative price fluctuations. When examining the five dimensional index (food, energy, services, durables, imports), these factors can account for almost all relative price movements in Thailand, especially at business cycle frequencies.

Next, we examine the drivers of pure inflation. Although pure inflation plays a less important role when compared to the relative price component in explaining within-

Table 12: The Components of Inflation and Other Observables

Observable	Frequencies All	B-Cycle
Relative-price index ρ_t		
Food	0.40 (0.12)	0.64 (0.25)
Energy	0.40 (0.12)	0.23 (0.19)
Food, Energy	0.60 (0.09)	0.73 (0.16)
Services	0.55 (0.11)	0.61 (0.17)
Durables	0.51 (0.11)	0.52 (0.17)
Imports	0.29 (0.09)	0.48 (0.23)
Food, Energy, Services, Durables, Imports	0.85 (0.04)	0.93 (0.04)
Pure inflation v_t		
Δ M1	0.26 (0.06)	0.08 (0.07)
Δ Policy Rate	0.10 (0.04)	0.02 (0.05)
Term spread (10Y-3m)	0.09 (0.06)	0.06 (0.08)

Note: Reported are the average squared canonical coherence R^2 measure for inflation and its components at all and business cycle frequencies, where business cycle frequencies are defined over the $\pi/32 \leq \omega \leq \pi/6$ domain. Standard errors are in parentheses. The relative price series are computed by subtracting headline CPI inflation from the actual series. The term spread is calculated as the difference between 10 year and 3 month nominal bonds.

quarter price fluctuations, pure inflation is still an important component of inflation because it reflects generalized price changes that affects all goods. According to Reis and Watson (2010), pure inflation also has a close interpretation to trend inflation, which reflects underlying price pressures that persists over the long-term horizon. As such, pure inflation should have a close link to monetary policy, thus we examine how pure inflation relates to measures linked to monetary policy such as money growth, changes in the policy rate, and the term spread.

Based on the canonical R^2 measures in the bottom panel of Table 12, we indeed find that pure inflation is a long-term construct, given that its correlation with monetary factors are all close to zero at business cycle frequencies. When examined at all frequencies, we only find a modest link between pure inflation and our monetary policy indicators. Small R^2 measures are nevertheless not surprising given that empirically, the link between money growth, nominal interest rates and inflation are typically found to be unstable and weak (see Mishkin, 1992; Stock and Watson, 1999). Also, as discussed in Blough (1994), the link between the term spread and inflation is an indirect one, thus often information content in the term spread for inflation may be confounded by market expectations about future term short rates and variation in liquidity or term premia.

Finally, we examine the correlation between the aggregate inflation components and real macroeconomic variables. Doing so not only allows us to study how different types of price movements are related to innovations from real variables, but it also allows us to re-examine the Phillips curve in a different light. It has been observed for many countries, including Thailand, that inflation and output correlation has become muted in recent years, casting doubt on the channel in which monetary policy can affect the macroeconomy (see IMF, 2006; Manopimoke, 2018). Explanations for the disappearance of the Phillips correlation typically involve changes in supply side factors such as ongoing structural changes in globalization (Borio and Filardo, 2007) or changes in the response of inflation expectations to recent persistent swings in oil prices (Coibon and Gorodnichenko, 2015).

Panel A of Table 13 reports the R^2 coherence measures for inflation and various economic activity variables. The weak Phillips curve relation is apparent, with a relatively weak correlation between inflation and GDP at business cycle frequencies of 0.23 and only marginally significant at the 10 percent level. Looking at the separate components of real GDP, we find that the correlation becomes even weaker for consumption, but is stronger for exports and imports. The fact that inflation appears to be more responsive to the global component of economic activity is consistent with the findings of Manopimoke (2018).

Table 13: Fraction of Variability of Real Variables Associated with CPI Inflation

	Frequencies	
Real Variable	All	B-Cycle
Panel A. Headline CPI Inflation		
GDP	0.21 (0.10)	0.23 (0.13)
Consumption	0.06 (0.03)	0.11 (0.09)
Investment	0.31 (0.11)	0.38 (0.15)
Domestic Demand	0.16 (0.10)	0.23 (0.13)
Exports	0.26 (0.09)	0.46 (0.12)
Imports	0.44 (0.10)	0.44 (0.14)
Panel B. CPI Inflation Controlled for Food and Energy		
GDP	0.08 (0.04)	0.01 (0.02)
Consumption	0.11 (0.05)	0.03 (0.03)
Investment	0.05 (0.03)	0.14 (0.11)
Domestic Demand	0.08 (0.04)	0.06 (0.08)
Exports	0.09 (0.04)	0.02 (0.03)
Imports	0.12 (0.05)	0.05 (0.06)
Panel C. CPI Inflation Controlled for Change in Policy Rate and Nominal Exchange Rate		
GDP	0.09 (0.04)	0.16 (0.14)
Consumption	0.10 (0.04)	0.10 (0.08)
Investment	0.09 (0.05)	0.07 (0.06)
Domestic Demand	0.07 (0.04)	0.08 (0.07)
Exports	0.11 (0.05)	0.11 (0.08)
Imports	0.13 (0.05)	0.11 (0.08)
Panel D. CPI Inflation controlled for Relative price index		
GDP	0.07 (0.03)	0.06 (0.04)
Consumption	0.03 (0.03)	0.01 (0.01)
Investment	0.10 (0.04)	0.03 (0.03)
Domestic Demand	0.08 (0.04)	0.02 (0.02)
Exports	0.03 (0.02)	0.08 (0.04)
Imports	0.05 (0.03)	0.03 (0.04)
Panel E. Aggregate inflation components v_t and ρ_t		
GDP	0.36 (0.11)	0.48 (0.19)
Consumption	0.14 (0.07)	0.13 (0.14)
Investment	0.32 (0.13)	0.39 (0.20)
Domestic Demand	0.20 (0.09)	0.25 (0.18)
Exports	0.46 (0.10)	0.58 (0.25)
Imports	0.52 (0.10)	0.51 (0.24)
Panel F. Pure inflation v_t		
GDP	0.06 (0.05)	0.01 (0.04)
Consumption	0.07 (0.05)	0.02 (0.03)
Investment	0.07 (0.06)	0.09 (0.10)
Domestic Demand	0.07 (0.07)	0.05 (0.08)
Exports	0.10 (0.04)	0.00 (0.01)
Imports	0.04 (0.03)	0.05 (0.08)

Note: Reported are the average squared canonical coherence over all and business cycle frequencies where business cycle frequencies are defined over the $\pi/32 \leq \omega \leq \pi/6$ domain. Standard errors in parentheses.

Given that the Phillips curve arises primarily because of nominal rigidities, with a subset of producers changing prices at a given point in time, it is fundamentally a relation between aggregate demand and relative prices. We indeed find this to be the case. First, by controlling for relative factors such as food and energy (Panel B), exchange rates (Panel C), and finally the relative price component from the inflation decomposition (Panel D), the strength of the Phillips correlation diminishes to a considerable degree, and is not statistically different from zero in many cases. Looking at the correlation between economic activity and the aggregate component of prices changes (v_t and ρ_t), we find that the Phillips correlation more than doubles for real GDP and also increases for other real variables at business cycle frequencies (Panel E). This suggests that idiosyncratic price fluctuations (u_t) act to mask the overall relationship which becomes much clearer once their effects are stripped out. Finally, Panel F confirms that the pure inflation component is hardly related to economic activity at all implying that it is the relative price component that drives the inflation-output relation.

The above findings are similar to Reis and Watson (2010) for the US. It implies that the Phillips curve is still intact, but may be confounded by noisy idiosyncratic price movements. Also, the excessively smooth pure inflation component may also make the Phillips correlation that is hidden within the relative price component difficult to detect. As such, the Phillips curve puzzle appears to be a measurement problem. This line of reasoning has also been advocated in other recent work. For example, Stock and Watson (2018) argue that with substantial noise in major price indexes, the inflation-output relationship could simply be masked in the data. They use sectoral inflation data to show that there are indeed some sectors that are still cyclically sensitive, and those tend to be sectors where prices are not set in international markets but locally. In light of these evidences, utilizing disaggregated price data is key towards helping us gain a better understanding about the empirical relevance of the Phillips curve.

5 Conclusion

This paper has shown that a bottom-up perspective of inflation utilizing micro price data offers a number of important insights into price dynamics at the macro level. Underlying the movements in aggregate price measures, such as the CPI, is a rich and highly heterogeneous set of individual price changes that reflect an agglomeration of idiosyncratic and common factors. We have documented a number of stylized facts that have implications for both modeling as well as policy.

The large degree of heterogeneity, the co-occurrence of large and small price changes in both directions, and the systematic variation in the number of items changing prices as inflation increases and decreases, suggests that a satisfactory model of price setting at a minimum should incorporate heterogeneous firms facing different shocks and costs of changing prices, and incorporate both time and state-dependent pricing elements. At the same time, the importance of relative prices in overall price dynamics implies that inflation analysis using macro models with a single good is unlikely to be sufficient. Moreover, it points to the need for models to take into account non-monetary factors that may drive trend inflation.

A number of policy implications also deserves highlighting. The generally high degree of price rigidity suggests that the impact of nominal shocks, such as monetary policy shocks, may be quite long-lived. It also implies that the responsiveness of prices to economic developments may not be that high so that for a given reduction in inflation, say, a much larger output gap is needed. In other words, the 'sacrifice ratio' may be high. In addition, the fact that price decreases are almost as prevalent as price increases implies that central banks may not need to set a higher inflation target to compensate for significant downward rigidity in prices. Finally, the outsize role of relative price changes in overall price dynamics highlights the importance of disentangling structural drivers from monetary ones in conducting policy. Central banks should not try to counter factors it cannot control, though we do find supportive evidence that their control has not diminished as much as it may seem as the Phillips curve still stands once noisy idiosyncratic price changes are filtered out.

Appendix A

The full dataset available from the Ministry of Commerce website is comprised of 24,460 products over 77 provinces. Naturally, the number of items (i.e. product $\times$ province) grows over time. Roughly, there were about 10,000 items in 2002 and 60,000 items in 2017. To exclude anomalies, we select only price trajectories that satisfy following conditions:

- The price data must be observed continuously for at least 2 years.
- The item must have at least 2 price changes.
- The sizes of price changes must be in the range of -70 and 230 percent.
- The item must belong to the CPI basket.

Appendix B

B1. Frequency and Implied Duration

Frequency is defined as the fraction of times prices were changed. For each item j, it is calculated as the ratio between the number of times a price change was registered and the sum of the number of times that prices changed plus the number of times prices remained fixed:

$$F_j = \frac{NI_j = 1}{NI_j = 1 + NI_j = 0}$$

where the indicator variable I_j is calculated as:

$$I_j = \begin{cases} 1 \text{ if } P_{j_t} \neq P_{j_{t-1}}, \\ 0 \text{ otherwise.} \end{cases}$$

The same formula can be used to calculate upward and downward price adjustments separately:

$$I_j^+ = \begin{cases} 1 \text{ if } P_{j_t} > P_{j_{t-1}}, \\ 0 \text{ otherwise} \end{cases}$$

$$F_j^+ = \frac{NI_j^+ = 1}{NI_j^+ = 1 + NI_j^+ = 0}$$

and

$$I_j^- = \begin{cases} 1 \text{ if } P_{j_t} < P_{j_{t-1}}, \\ 0 \text{ otherwise} \end{cases}$$

$$F_j^- = \frac{NI_j^- = 1}{NI_j^- = 1 + NI_j^- = 0}.$$

B2. Average size of price changes

For each item j, the average size of price increases and decreases can be calculated as:

$$\Delta_j^+ = \frac{\sum_t I_j^+(\frac{P_{j_t} - P_{j_{t-1}}}{P_{j_{t-1}}} \times 100)}{NI_j^+}$$

$$\Delta_j^- = \frac{\sum_t I_j^-(\frac{P_{j_{t-1}} - P_{j_t}}{P_{j_{t-1}}} \times 100)}{NI_j^-}.$$

Appendix C

Table C1: Frequency and Implied Duration of Price Changes by Category

	Median Frequency	Implied Median Duration	Empirical Median Duration
Food and Non-Alcoholic Beverages	0.09	10.16	3.67
Apparel and Footwear	0.03	30.58	13.22
Housing and Furnishing	0.13	7.15	5.01
Medical and Personal Care	0.05	21.59	6.30
Transportation and Communication	0.07	14.36	6.11
Recreation and Education	0.04	22.90	9.22
Tobacco and Alcoholic Beverages	0.09	10.48	6.23
Total CPI	0.08	12.36	6.05

Note: All frequencies are reported in percent per month and durations are reported in months. Median frequency denotes the median of frequency of price changes at the ELI level weighted by their corresponding 2011 expenditure share weights. Implied median duration is equal to $-1/ln(1-f)$ where f is the median frequency of price change. Empirical median duration is the median of price spell lengths at the ELI level aggregated up by their 2011 expenditure share weights.

Appendix D

The full dataset from the Ministry of Commerce over 2002Q2-2018Q2 comprises of 225 ELIs. Some price series contain very few price changes which make it problematic for estimation. We therefore exclude series with more than 30 quarters of zero price changes if it belongs to the service category, and more than 15 quarters of zero price changes if it belongs to the non-service category. We relax our criteria for the service-sector because price changes of items in this sector are known to be sticky. Next, to remove collinear price series, we remove a series j if there exists another series i that satisfies $Cor(\pi_{it}, \pi_{jt})$ >0.99 and $Cor(\Delta\pi_{it}, \Delta\pi_{jt})$ >0.99. Last, large outliers are replaced with centered seven-quarter local medians. After the cleaning process, the number of ELI series in the dataset is reduced to 179.

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