PUEY UNGPHAKORN INSTITUTE
FOR ECONOMIC RESEARCH

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May 2018

Discussion Paper
No. 85

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Abstract

This paper examines the patterns of price adjustment at the micro level in order to further our understanding of price rigidity at the aggregate level. We highlight 5 stylized facts: 1) Prices change infrequently with a mean duration of approximately 4 to 7 months between price changes; 2) Price decreases are common accounting for roughly 45 percent of all price changes; 3) Price changes, both increases and decreases, are sizable compared to the prevailing inflation rate; 4) The size of price changes covaries strongly with the rate of inflation, whereas the fraction of items changing prices does not; and 5) There is significant dispersion in price levels as well as in the synchronicity of price changes across geographical regions. Based on a dynamic factor model, we also utilize prices at the disaggregated level to perform an inflation decomposition to understand the underlying driving factors of inflation. The key findings are: 1) Prices at the micro level are driven mainly by idiosyncratic shocks but these shocks become less important for CPI inflation at the aggregate level; 2) Pure inflation which drives long-term price movements in Thailand is responsible for approximately 10 percent of overall price movements; 3) More than half of all within-quarter fluctuations can be classified as relative price changes in response to aggregate shocks; 4) The short-run inflation-output tradeoff which appears weak in aggregate data becomes much stronger once volatile idiosyncratic price changes are removed.

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

JEL Classifications: C40, C25, D40, E31

*We are grateful to the participants at the Puey Ungphakorn Institute for Economic Research Seminar at the Bank of Thailand and discussion session at the Ministry of Commerce of Thailand for useful information and comments. Thanks to Chonnakan Rittinon for excellent research assistance. The opinions expressed in this paper are those of the authors and should not be attributed to the Puey Ungphakorn Institute for Economic Research or the Bank of Thailand.

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1 Introduction

During the recent period, there have been a number of fundamental changes in inflation dynamics in many countries including Thailand, making the behavior of inflation worldwide a puzzle. Inflation has been relatively low despite being subject to large and diverse shocks such as those driven from commodity price cycles. The sharp downturn in real activity during the Great Recession did not lead to a severe deflation as it did during the Great Depression of the 1930s, causing economists to question the validity of the short-run inflation-output tradeoff as captured by the traditional Phillips curve. Due to ongoing structural changes from forces such as globalization and the information technology revolution, fluctuations in inflation have also become more volatile and more persistent, as observed by recent sharp and prolonged movements of inflation from the central bank's inflation target.

A growing body of empirical research employ microeconomic price data to investigate the nature of price-setting which has helped economists better understand the overall behavior of inflation dynamics. A large theoretical literature has shown that the sources of price stickiness and alternative forms of nominal rigidities determines the response of the economy to a broad range of disturbances, which at the macroeconomic level is related to the degree of inflation persistence. Understanding inflation persistence is important towards the conduct of monetary policy. The degree of price rigidity, for example, is a critical determinant of the effectiveness of monetary policy as it influences the time it takes for inflation to move towards target in response to shocks. Empirical assessment of the nature of price setting as well as its underlying key drivers is therefore an important line of research that can further our understanding of inflation dynamics more generally.

This paper aims to exploit the richness of microeconomic price data to help further our understanding about inflation dynamics at the aggregate level. We do so in two parts. First, we examine the patterns of price adjustment at the micro level to establish key stylized facts. Among others, we analyse the frequency of price adjustment, the duration of price spells, the size of price changes, the heterogeneity in price setting, as well as the manner and extent to which price setting behavior depends on the rate of inflation. Given that we have price data across Thai provinces, geographical variations in price levels and dynamics are also investigated. Second, we utilize the method of Reis and Watson (2010) to perform a dynamic factor analysis of disaggregated prices to better understand the underlying sources of heterogenous 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. In doing so, we hope to gain a better understanding about what type of fundamental shocks matters for overall inflation, as well as gain insight on how the different components are related to other key macroeconomic variables in the economy such as real output.

Our work falls within the recent strand of literature that has emerged as statistical offices in various countries started to make available to researchers 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 rarer due to limited data availability, but examples can be found in Gouvea (2007) and Medina et al. (2007) for Brazil and Chile, respectively. The factor analysis for inflation builds on a large literature including Stock and Watson (1989), Ciccarelli and Mojon (2005), Boivin et al. (2009), and Reis and Watson (2010). The premise of the factor model is that the covariation among economic time series variables can be utilized to trace out a few underlying unobserved series or factors, which can help disentangle the common sources and drivers of price movements.

To our knowledge, this is the first paper to analyse 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 5 stylized facts:

1) Prices change infrequently. The mean 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 10.37 and 7.74 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.

5) There is significant dispersion in price levels as well as in the synchronicity of *price changes across geographical regions.* 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. Similarly, while product price changes tend to occur at different times across provinces, price changes for services are much more asynchronous than for goods.

For the factor analyses, the empirical findings can be summarized as follows: 1) lowered inflation in Thailand during the past few years can be explained by persistent downward pressures from favorable relative price shocks; 2) while disaggregate price series are mainly driven by idiosyncratic price fluctuations, these cancel out at the aggregate level, causing 70 percent of the movements in headline CPI inflation to be attributed to aggregate shocks; 3) the important driver of within-quarter fluctuations is the relative price component, which is responsible for slightly more than half of all inflation rate fluctuations; 4) food and energy price shocks are important drivers of the relative price index, while relative prices of services, durables and imports are also important; 5) pure inflation is excessively smooth and only explains approximately 10 percent of all within-quarter fluctuations of inflation; 6) the Phillips curve relation for Thailand is weak when examined with aggregate data, but once the pure and idiosyncratic components are removed, the Phillips correlation strengthens and becomes relevant for the relative price component of inflation.

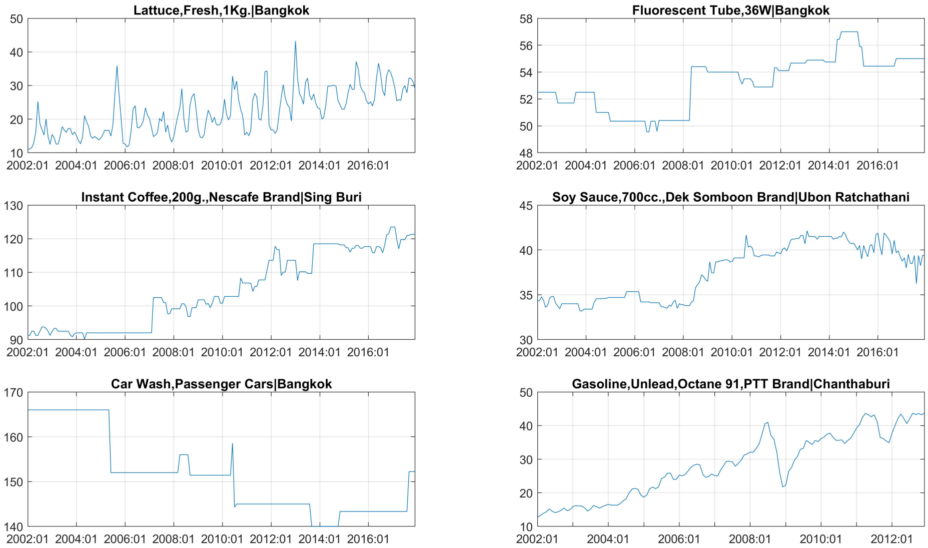
The rest of the paper is organized as follows. The next section outlines the microeconomic price data that underlies the study. Section 3 sets out details of the statistical measures used and the key stylized facts. Section 4 outlines the dynamic factor model and reports the findings from the factor analyses. 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). Recently, these micro prices have been made publicly available. 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 (here lettuce) is much more volatile than processed goods (here instant coffee) or services (here 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.

Figure 1: Examples of individual price trajectories



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 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.

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

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

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)

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

The ELIs can also be aggregated into various economic groups of interest as shown in Table 3. The first grouping is for products contained in core inflation, the second for services, the third for durables, and the last for those that fall under the government's price control regulation.[3] Again, the reason why approximately 15 percent of coverage is lacking for core, services and durables is because the housing rent ELI can be classified as these groups.

[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.

[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.

[3] Given the presence of control prices in Thailand, we will investigate whether and how price dynamics of products that fall within the control group differ from those that don't. However, note that the type of control implemented on the product (eg. control of sales price, storage amount or import/export logistics) and its degree (eg. high priority versus non-strict watch list) varies across products as well as across time. More details can be found at the Ministry of Commerce's Department of Internal Trade website.

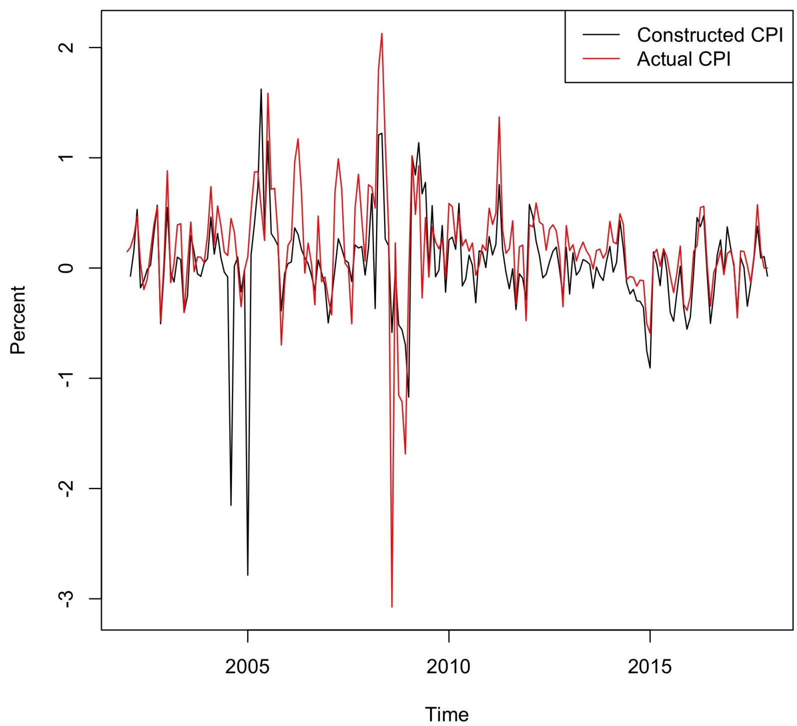
All in all, our micro price dataset provides a good representation of the overall CPI in Thailand. As shown in Figure 2, the constructed price index from our dataset tracks actual CPI well, with the exception of only a few periods. That said, we stress that our aim is not to replicate the CPI per se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

Table 3: Coverage of the Consumer Price Index by Economic Groups

	Dataset Share (ELI count)	Actual Share (ELI count)
Core	57.42 (307)	73.09 (312)
Control	31.85 (96)	31.85 (97)
Service	9.63 (80)	25.26 (83)
Durable	9.09 (46)	24.50 (47)
Total	84.33 (445)	100.00 (450)

Note: Reported are the dataset share and actual share of the CPI for each group in percent, calculated using 2011 expenditure share weights obtained from the Ministry of Commerce. Each group's corresponding ELI count are reported in parentheses.

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.

3 Stylized Facts

We summarize the patterns of price changes in Thailand into 5 stylized facts, established on the basis of various indicators including the frequency of price changes, the duration of price spells, the frequency of price increases and decreases, the size of price 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, economic sectors, as well as across time.

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.[4]

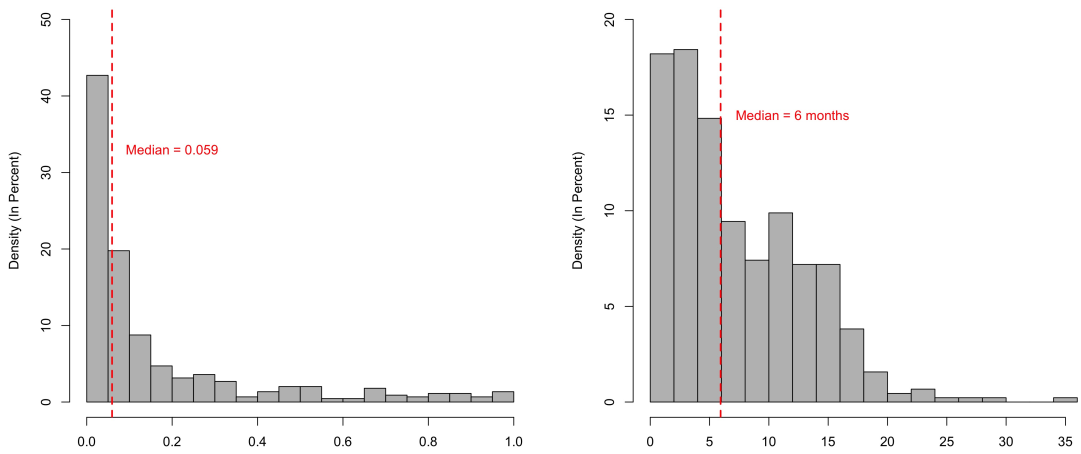
Alternatively, we can calculate the mean duration of price changes from the data directly by taking the average length of price spells that are associated with each price trajectory. Compared to the frequency approach, this method has the advantage of the mean duration being estimated directly from the 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-

[4]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.

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 0.6 and 0.17, 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 0.10 (price changes 10% of the time in a given period), while the plot on the right suggests that approximately half of all price spells last longer than 5 months.

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.

Aggregating statistics at the ELI level up by expenditure share weights, Table 4 shows the breakdown of price changes by product categories 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.

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 differences between their mean and median figures are not as pronounced as Thailand.[5] 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.

Table 4: 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

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.

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.[6]

When organized by sectors, Table 5 shows that the duration of price changes are significantly longer for core, service and durable 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. Somewhat surprisingly, control items exhibit slightly shorter duration than non-control items. But on inspection, it reflects the fact that control items tend to be those in certain product categories, such as food, whose price change more often by nature.

Overall, the degree of price rigidity in Thailand is high. Its consumption structure is characterized by a large share of food products, whose prices change frequently, and

[5]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.

[6]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. $E(1/F) \geq 1/E(F)$.

Table 5: Frequency and Duration of Price Changes by Economic Sector

	Mean Frequency	Implied Mean Duration	Empirical Mean Duration
Core	0.06	15.13	8.81
Non-core	0.50	1.44	2.47
Control	0.34	2.45	5.09
Non-Control	0.12	7.60	7.82
Service	0.04	22.76	10.30
Non-Service	0.22	3.94	6.33
Durables	0.07	14.38	8.07
Non-Durables	0.22	4.03	6.63
Total CPI	0.20	4.40	6.79

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.

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 this.

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. 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.

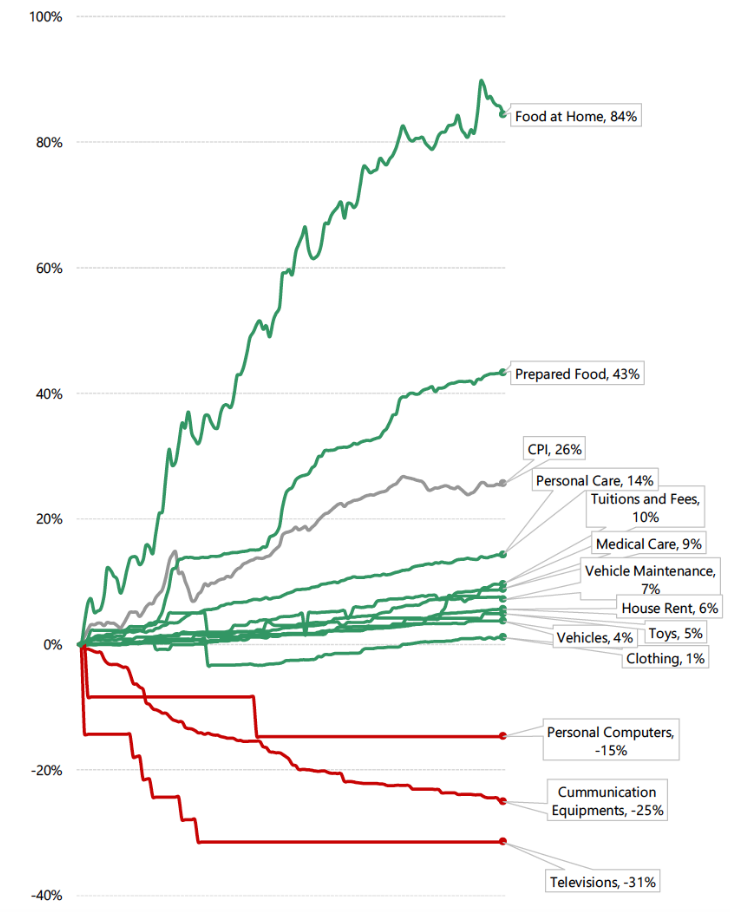
Fact 2: Prices decreases are common. On average, 45 percent of all price changes are price decreases. Thus downward price rigidity in Thailand does not appear to be a pervasive issue. This result is similar to those found for the US and the Euro area.

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, a resulting price increase can actually occur from underlying price changes in both directions. In an average month, we find that approximately 60 percent of all price changes are price increases while the remaining are price decreases.[7] Figure 4 shows that such relative price changes loom large. Over the ten

[7] This is the sample average of the blue line in Figure **??** but conditional on directional price changes.

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.

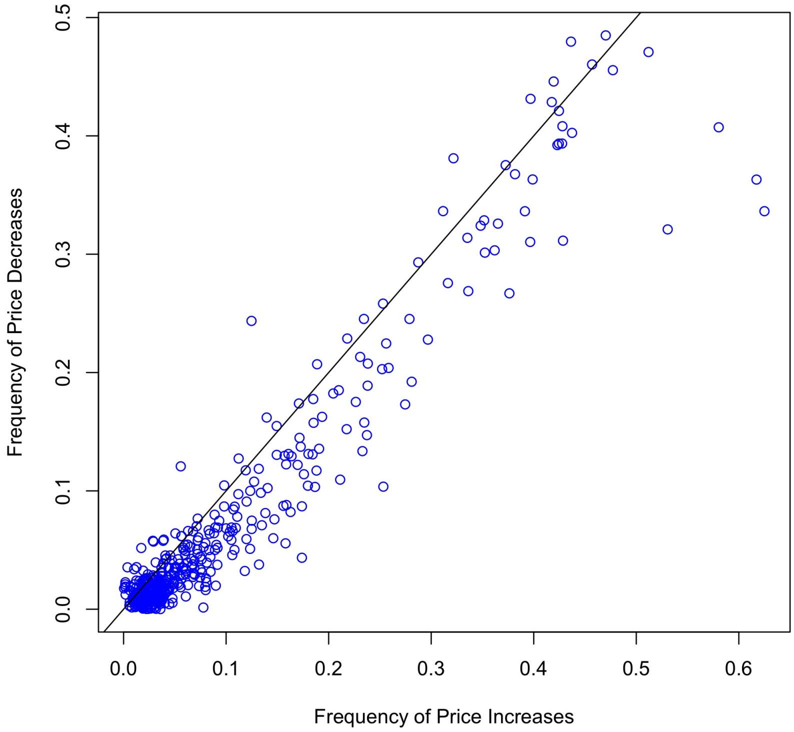
Figure 4: Percentage Change in Price Levels by Category (2006-2017)



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), for example 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.

Tables 6 and 7 shows the empirical duration of price increases and decreases by product categories and various 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.

The finding that overall price falls are common has important implications for the optimal inflation objective. 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 important reason for such an inflation buffer.

Table 6: 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

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.

Table 7: Empirical Mean Duration Increases and Decreases by Economic Sector

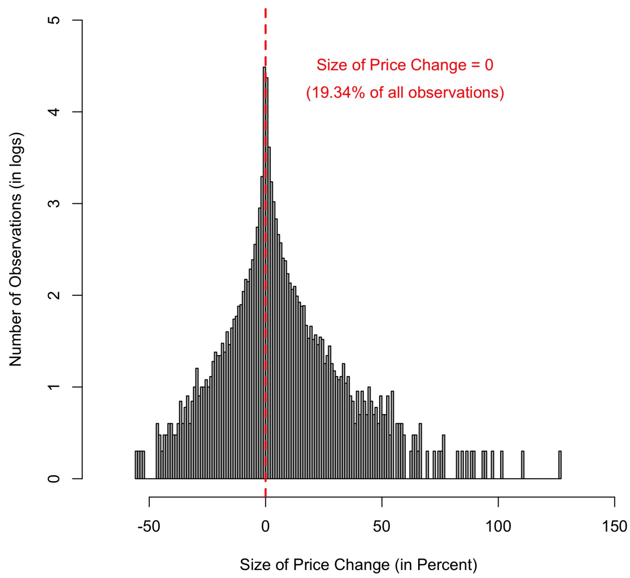
	Mean Duration Increase	Mean Duration Decrease	Fraction Increase
Core	11.74	15.10	66.66
Non-core	3.76	4.63	56.42
Control	6.96	8.12	53.16
Non-Control	10.55	13.95	59.63
Service	13.48	15.69	70.00
Non-Service	8.64	11.23	56.01
Durables	9.76	11.35	70.31
Non-Durables	9.12	11.78	57.28
Total CPI	9.73	12.29	56.41

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.

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).

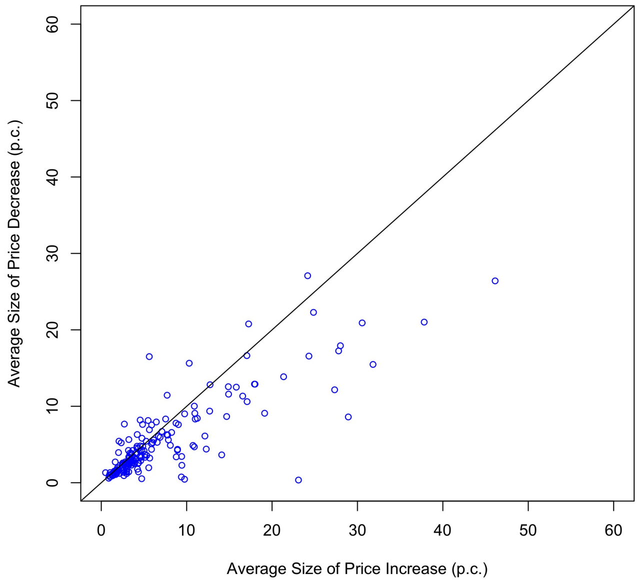
Figure 6 displays the distribution of the monthly size of price changes at the ELI level. The distribution is skewed towards larger monthly price increases. Given the high degree of overall price rigidity in Thailand, it is not surprising that 19 percent of all observations are those where the monthly 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. In our sample, price increases as well as decreases are sizeable 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%. This is reflected in Figure 7 which plots the average size of price increases and decreases for each ELI. Average monthly inflation, by contrast, stood at around 0.11 percent (or 1.26 percent annualized). 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.

Figure 7: Size of Price Increases and Decreases



Note: Plotted are the average size of price increases and decreases in percent for a particular ELI, computed based on the median population-weighted product, then aggregating up by 2011 expenditure share weights. The line through the origin is a 45 degree line.

Looking across categories and sectors, Tables 8 and 9 show 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.

With respect to broader groupings, price changes for products in core, services, non-durables, and those not under government regulation tend to be larger. Part of these differences again is related to differences in the frequency of price changes. While a negative correlation between size and frequency of price increases and decreases is not particularly apparent at the aggregate CPI level (0.02 and 0.17 for price increases and decreases respectively), the negative correlation is particularly strong for some sectors. For core and service sectors, it is as high as around -0.3. This suggests that for these goods whose prices change less frequently, the average size of change is larger.

Table 8: Size of Price Increase and Decrease by CPI Category

	Average Price Inc.	Median Price Inc.	Average Price Dec.	Median Price Dec.
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

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.

Table 9: Size of Price Increases and Decreases by Economic Sector

	Average Price Inc.	Median Price Inc.	Average Price Dec.	Median Price Dec.
Core	14.03	6.63	10.05	6.42
Non-core	5.35	3.78	4.57	3.45
Control	10.19	3.81	7.94	3.66
Non-Control	10.49	6.61	7.62	5.80
Service	32.95	31.60	16.55	13.61
Non-Service	8.84	4.97	7.14	4.69
Durables	4.92	4.33	6.76	8.12
Non-Durables	10.64	5.95	7.79	4.82
Total CPI	10.37	5.82	7.74	5.42

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.

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 is 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 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 10 contains summary statistics for CPI inflation and its intensive and extensive margin of price changes over the entire sample. In the sample, the monthly average inflation rate is 0.11 percent or 1.26 percent annualized. We can also see that 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) exhibits a much higher variation relative to its mean.

Table 10: Time Series Moments

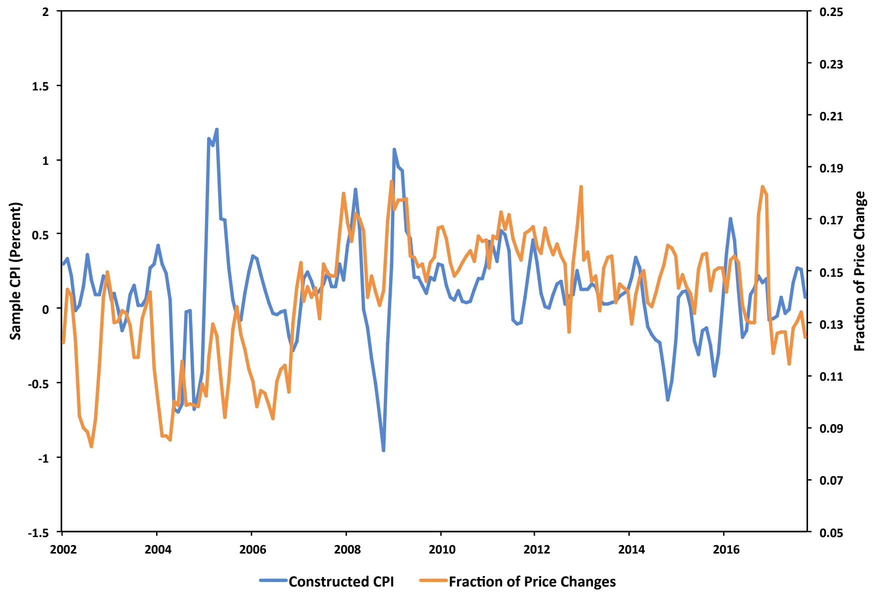
Variables	Mean(%)	Std dev(%)	Correlation with π
π_t	0.105	0.452	
fr_t	13.976	3.020	0.102
dp_t	0.749	3.259	0.976
fr_t^+	7.908	3.377	0.547
fr_t^-	6.066	2.957	-0.520
dp_t^+	4.538	3.067	0.570
dp_t^-	4.237	3.591	-0.544
pos_t	0.362	0.307	0.787
neg_t	0.257	0.283	-0.743

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 $\pi_t = pos_t - neg_t$.

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, the size of price changes or the intensive margin, drives inflation dynamics much more than the extensive margin. In other words, 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). These observations are illustrated more clearly in Figures 8 and 9. As shown, while the absolute size of price changes comoves closely with CPI inflation, 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 declines 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.

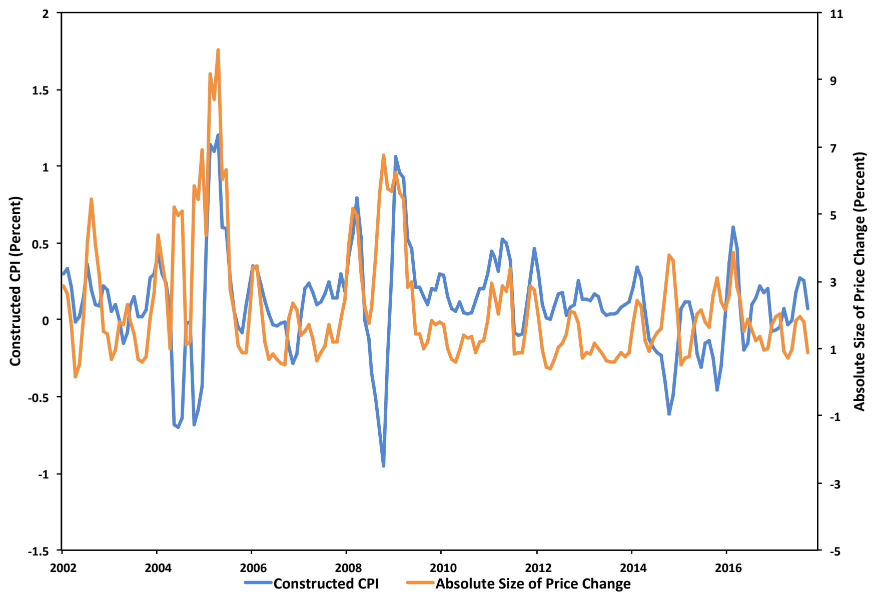
Looking at price increases and decreases separately, however, Table 10 shows that

Figure 8: CPI Inflation and Fraction of Price Changes



Note: Plotted is the three-month moving average of constructed CPI inflation from our dataset and the fraction of items with changing prices in each month.

Figure 9: CPI Inflation and Absolute Size of Price Changes



Note: Plotted is the three-month moving average of constructed CPI inflation from our dataset and the absolute size of price changes in each month.

variations in fraction are more correlated with inflation than its overall figure suggests. This implies that the observation 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. Finally, the last two lines of Table 10 show that variations in the intensive and extensive margins of price increases (pos_t) are more important for inflation than those for prices decrease (neg_t). This is not surprisingly for a country with generally positive inflation.

Instead of just the level of inflation, we can also look at the relative important 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.[8]:

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

Table 11 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 intensive margin 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. Also, not surprisingly, we find that the variance of price increases account for more of the total inflation variance than price decreases, especially in the post 2012 period.

Table 11: Variance Decompositions

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

[8]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:

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

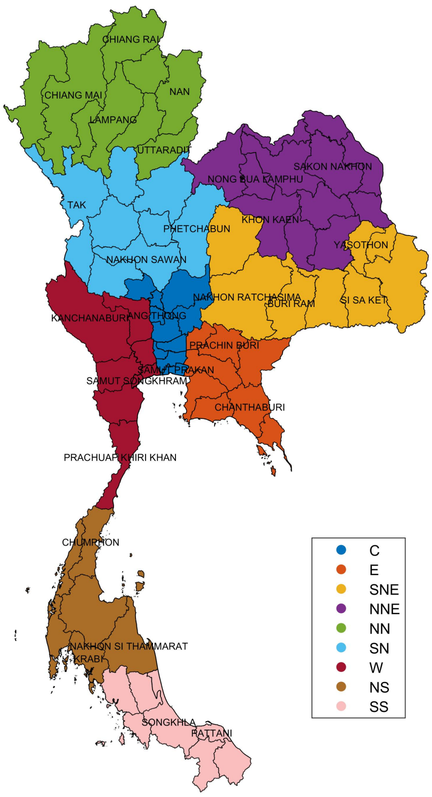
where $pos_t = fr_t^+ \cdot dp_t^+$ and $neg_t = fr_t^- \cdot dp_t^-$.

Fact 5: There is significant dispersion in price levels as well as in the synchronicity of price changes across geographical regions.

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 dispersion in price levels of the same product across locations; and ii) the synchronicity or extent to which prices of identical products changes at the same time in different regions.

In order to analyze geographical properties of prices, we need to construct a cross-provincial panel dataset. Unfortunately, most of products in the data do not exist in all provinces. Even the most popular product (green curry soup) is observed in only 71 provinces. Thus instead of focusing at the provincial level, we divide Thailand into nine regions as listed in Table 12. These correspond to broad regions as illustrated in Figure 10. 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 chose the most popular one to represent that ELI. All in all, we end up with a panel of 164 products across 9 regions.

Figure 10: Map of Thailand



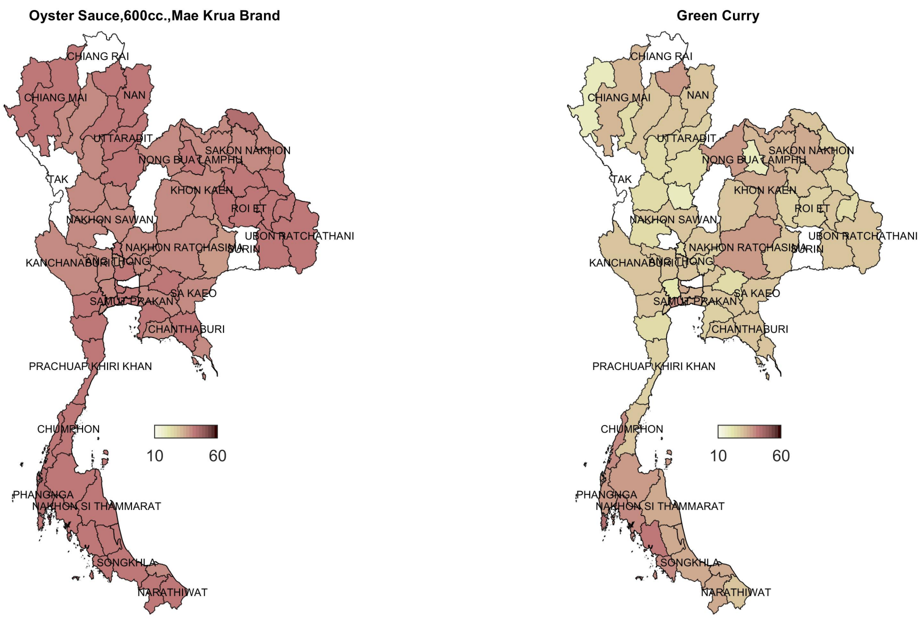
To get a flavor of the regional dispersion in price levels, Figure 11 shows the price

Table 12: 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

variation observed as of 2017M12 for two generic products, oyster sauce and green curry soup. The latter presumably embodies a greater share of non-traded component, which one would expect to vary more across regions. This is indeed the case, with the price of oyster sauce bounded in a relatively narrow range of between 37 to 45 baht while green curry soup ranges from 20 to 45 baht.

Figure 11: National Products



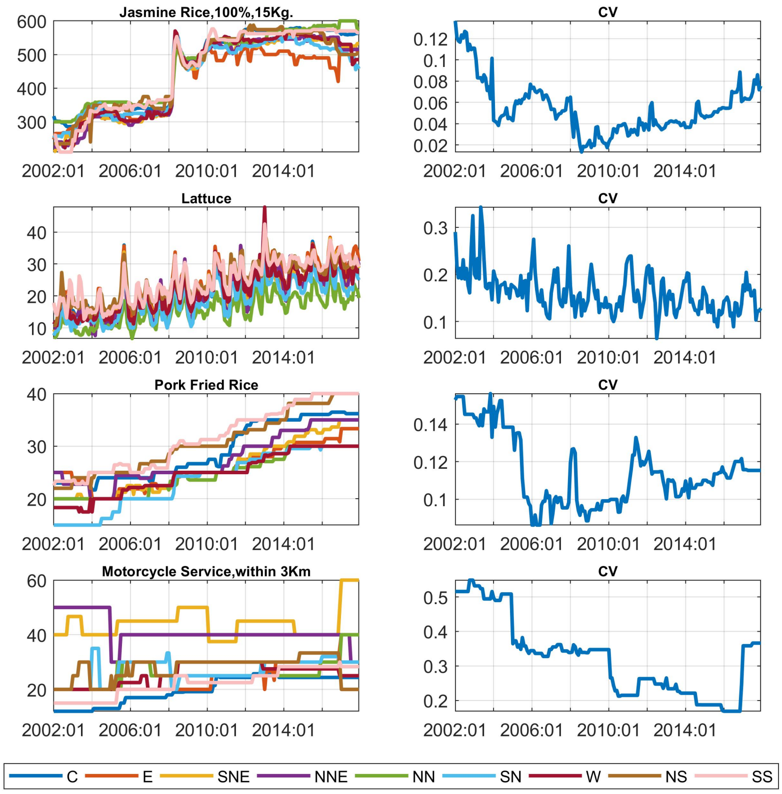
(a) Oyster Sauce

(b) Green Curry

Note: Oyster sauce and green curry are among the top 5 products in the dataset that cover the most number of provinces.

Looking also at the time variation in price dispersion across regions, Figure 12 shows movements in price levels across the nine regions for selected products (left-hand column). This regional dispersion can be summarized by 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 figure illustrates the large heterogeneity in degree of price dispersion across product categories as well as across time. Lettuce, for example, displays relatively low dispersion (average CV of 16.2 percent) whereas the price of motorcycle transport varies more substantially across regions (average CV of 32.3 percent). In both cases, regional price dispersion has declined steadily overtime. While quite variable, the dispersion of jasmine rice and pork fried rice, by contrast, display no apparent trend over time.

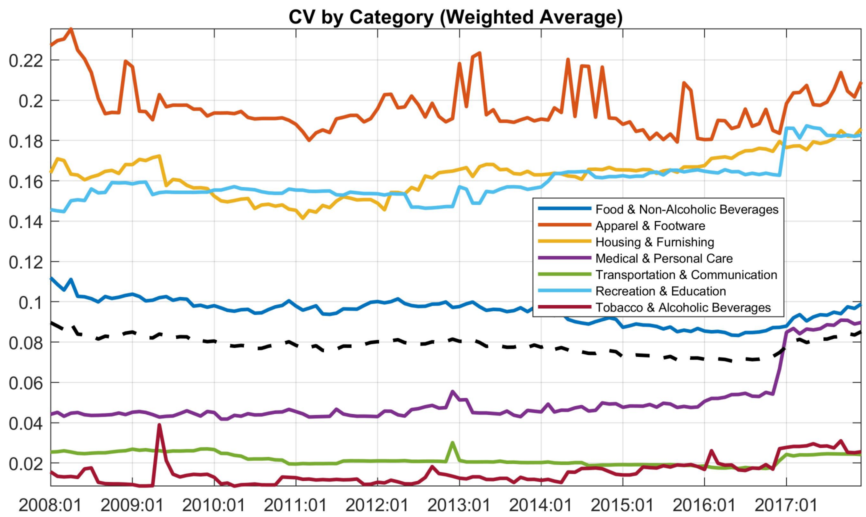
Figure 12: Coefficient of Variation



Note: We calculate coefficient of variation (CV) across regions at time t as $CV_t. = \frac{\sigma_t}{\mu_t}$ where σ_t and μ_t are the standard deviation and mean of the product's prices at time t respectively.

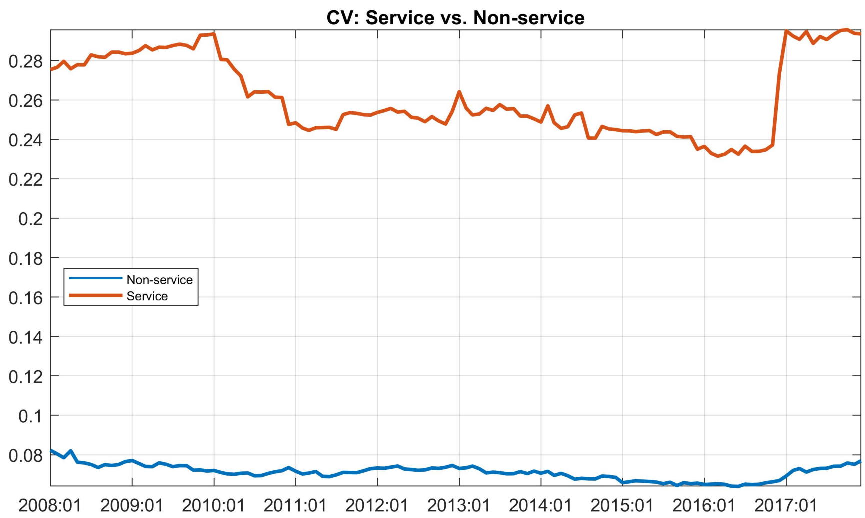
Figure 13 shows expenditure-weighted averages of the regional dispersion (the CV measure) in product prices by broad product categories. The dotted black line is the weighted average CV for all goods. At this level of aggregation, with perhaps the exception of recreation and education, regional price dispersion displays no trend over time. There are, however, sizable differences in dispersion across product groups. Apparel and footwear displays the highest dispersion, followed by housing and furnishing and recreation and education. At the other extreme, tobacco and alcoholic beverages and transportation and communication have the lowest dispersion. One 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. Figure 14 indeed shows that the dispersion for services prices is much larger. These observations are summarized in Table 13, which show the mean CVs over the whole sample period for the various product groupings.

Figure 13: Coefficient of Variation by Categories



Note: CV is aggregated up to the category level by using 2011 expenditure share weights.

Figure 14: Coefficient of Variation for Service and Non-service



To gauge the extent to which prices for the same product across regions change in a synchronous manner, 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. Note that in the case of perfect synchronization, FK=0. The last column of Table 13 shows this index for each product category. Synchronization is highest for food and beverages while they are lowest for transportation and communication. More generally, services synchronization is also much lower than for non-services.

Table 13: Summary Statistics by Product Category

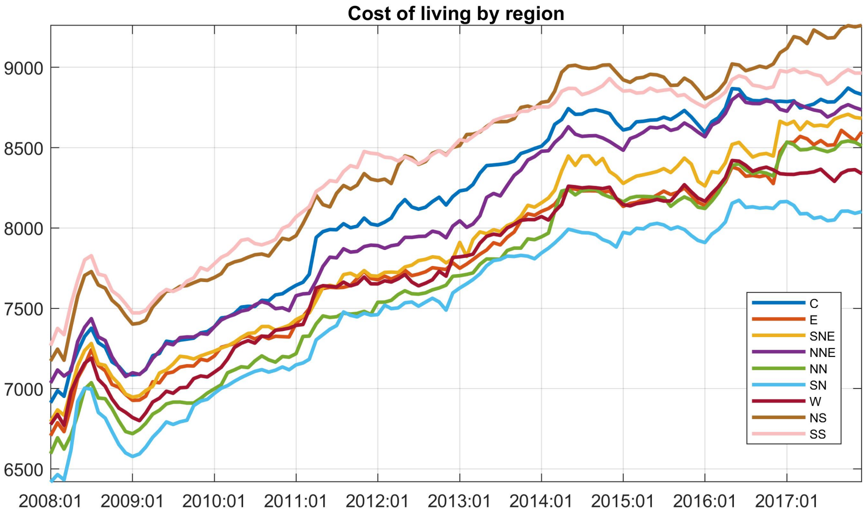
Category	Number of ELIs	Mean CV	FK
Food & Beverages (FB)	97	0.10	0.43
Clothing & Footwear (CF)	13	0.20	0.55
Housing & Furnishing (HF)	14	0.16	0.59
Health & Personal Care (HP)	16	0.05	0.68
Transportation & Communication (TC)	11	0.02	0.87
Recreation & Education (RE)	10	0.16	0.66
Tobacco &Alcoholic Beverages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

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

Finally, we can use our data to construct something akin to a cost of living index for each region. We combine our 164 ELIs together to make a hypothetical basket of consumption. Using average prices in 2011, the base year for CPI expenditure weights, as reference prices and 'central' as the reference region, we then calculate the quantity consumed for each ELI by dividing weights by reference prices. Applying each region's prices to the hypothetical basket, we obtain monthly regional expenses.

Figure 15 shows the cost of living for our nine regions. The dispersion of prices across regions is apparent in our constructed cost of living. This dispersion appears to have risen over time. As of mid-2016, the cost of living of the most expensive region was around 20 percent (or roughly 1300 baht) higher than that of the cheapest region. Overall, NS (northern parts of the south) and SS (southern parts of the south) are the most expensive regions, while SN (southern parts of the north) and W (west) have some of the lowest living expenses.

Figure 15: Cost of Living by Region



Note: The cost of living index is measured by monthly expenses that are based on 164 ELIs.

4 Factor Analysis of Microeconomic Prices

As evident from the stylized facts section, there is a great deal of heterogeneity in price setting, in terms of the frequency and size of price changes, as well as large degrees of price dispersion across geographical regions. In making sense of these diverse price movements, it would be important to gain a better understanding about the underlying sources of price movements.

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). As discussed in Reis and Watson (2010), absolute price changes are often seen as the price response to anticipated monetary and fiscal shocks, while relative price changes can 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.

In this section, we utilize the richness of disaggregated price movements to identify separate components of inflation that are driven by different fundamental shocks. We follow Reis and Watson (2010) and employ a dynamic factor model to distinguish between absolute and relative price movements as well as aggregate versus idiosyncratic price changes[9]. More specifically, we assume that the comovements of N individual price series can be decomposed as follows:

[9]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.

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

where π_t is an $N\times1$ 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. Accordingly, there are a total of k factors that are used to capture the common movements in disaggregated prices.

As pointed out by Reis and Watson (2010), an important challenge in the inflation decomposition of Eq. (1) is that a_t and R_t are not separately identified[10]. To overcome this problem, they 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 becomes 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.

4.1 Data Description and Estimation Methodology

We use quarterly ELI price series for the inflation decomposition given that microeconomic price data in the stylized fact section is noisy. While it is possible to construct ELI price series from the microeconomic data, we opt to use official chained price indices of goods and services at the ELI level instead, which is provided by the Ministry of Commerce. We compute quarterly inflation at the annual rate according to $\pi_{it} = 400 \times ln(P_{it}/P_{it-1})$, where P_{it} is the quarterly ELI price index for good i. The sample spans 2002Q2-2018Q2 and comprises of 225 ELIs[11].

Prior to estimation, we clean the data accordingly. First, several price series contain very few price changes which make it problematic for estimation. We therefore exclude

[10] To see this, for any arbitrary $(k-1)\times1$ 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'.

[11] Given that the CPI basket is redefined every several years, our dataset shortens as we extend the sample back. For example, the current CPI basket contains 425 items, but 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 items and model instability issues may arise if we choose to perform the inflation decomposition over pre and post inflation targeting regimes.

series with more than 30 quarters of zero price changes if it belongs in the service category, and more than 15 quarters of zero price changes if it belongs in the non-service category. Our criteria is more relaxed for the service-sector because price changes of service-related items are known to be sticky. Next, we remove series j if there exists another series i that satisfies $Cor(\pi_{it}, \pi_{jt}) > 0.99$ and $Cor(\Delta\pi_{it}, \Delta\pi_{jt}) > 0.99$ to remove collinear price series. Last, large outliers are replaced with centered seven-quarter local medians, which finally reduces the number of ELI series in the dataset to 179.

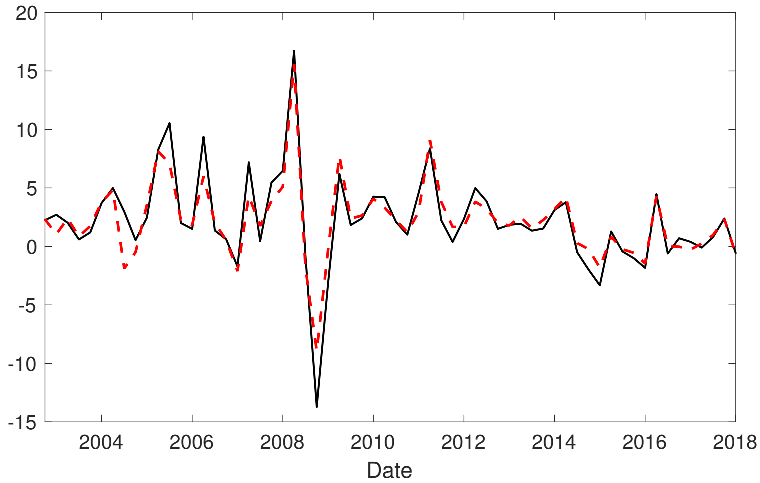
To get a sense of the data, Table 14 provides a sample summary of the price series grouped into categories as well as economic sectors. With 179 ELIs, our sample covers approximately 65 percent of the CPI. Coverage is lacking in some categories but these typically have low weight in the CPI except for transportation excluding fuel. Overall however, our sample provides decent coverage according to economic sectors. Also, according to Figure 15, when we compare the inflation rate as constructed by the ELI series against actual CPI inflation, our constructed price index tracks overall inflation well with the exception of only a few periods.

Table 14: Sample Coverage of the Consumer Price Index

	Actual	Our Sample
Category		
Raw Food	15.5 (127)	12.5 (72)
Food in Core	18.0 (48)	14.3 (27)
Clothing	3.1 (54)	1.1 (15)
Housing excl Gas	20.4 (58)	17.7 (26)
Healthcare	6.5 (63)	2.2 (17)
Transport excl fuel	17.9 (40)	7.7 (7)
Education & Recreation	6.0 (43)	0.8 (5)
Tobacco & Alcohol	1.2 (4)	1.2 (4)
Gas & Electricity	3.8 (4)	3.8 (3)
Fuel	7.7 (9)	3.3 (3)
Economic Sectors		
Service	38 (93)	21 (12)
Tradables	33 (209)	24 (93)
Durables	24 (47)	18 (23)
Total	100 (450)	64.4 (179)

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.

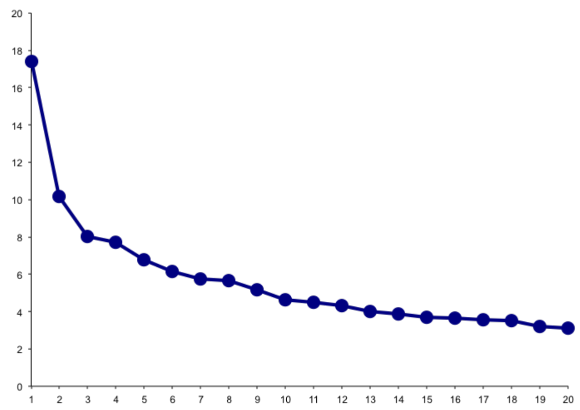
Figure 16: Constructed and Actual CPI Inflation



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.

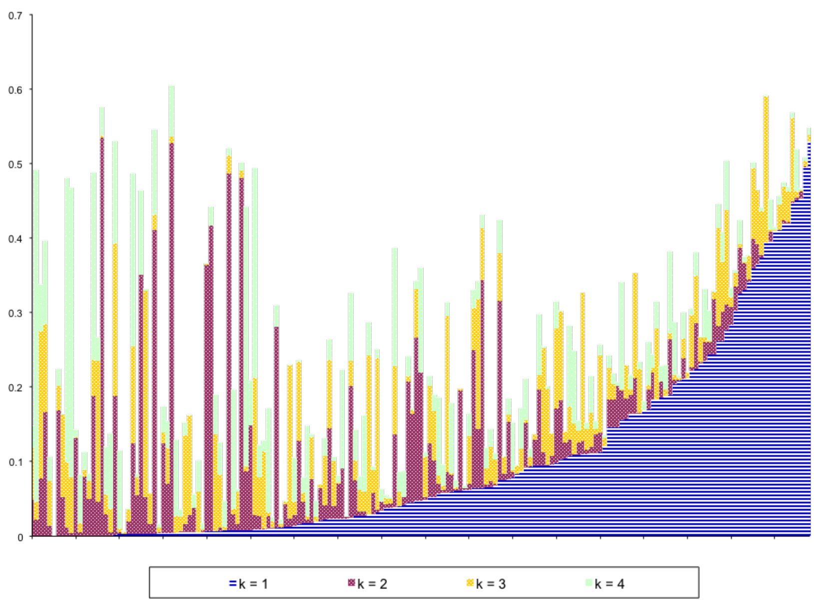
Next, to perform the inflation decomposition, we need to determine the number of common factors k. Choosing k involves a tradeoff because while a higher k can explain a larger share of the variance in the data, additional factors increases the complexity of the model and reduces the reliability and significance of parameter estimates. To guide our choice on k, we turn to a few statistical tests. First, we compute Bai-Ng estimators (Bai and Ng, 2002), which are based on the number of dominant eigenvalues of the covariance matrix of the data. The ICP1, ICP2, ICP3 Bai-Ng estimates are 1, 1 and 2 factors respectively. Next, we examine the largest 20 eigenvalues of the sample correlation matrix of the inflation data as shown in Figure 16, and while it is clear that there is one large eigenvalue, it is less clear whether 2 or 3 total factors are needed. Last, we calculate the fraction of variance explained by unrestricted factor models with 1-4 factors for the 179 inflation series. In Figure 17, the series are ordered 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 still 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 17: Eigenvalues of the Correlation matrix



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

Figure 18: 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 first factor for the 179 ELIs.

Once k is defined, we set up the empirical model for estimation. 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:

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

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

where 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 $var(\epsilon_t) = Q$.

Once parametric assumptions for the latent factors are made, the parameters of the model are estimated via maximum likelihood. However, numerically maximizing the likelihood function is computationally complex due to the large number of parameters (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 is the compute the latent factors using signal extraction formulae. This involves imposing certain restrictions such as those defined by Eqs. (2)-(3). For details on estimation, readers are referred to the Web Appendix of Reis and Watson (2010).

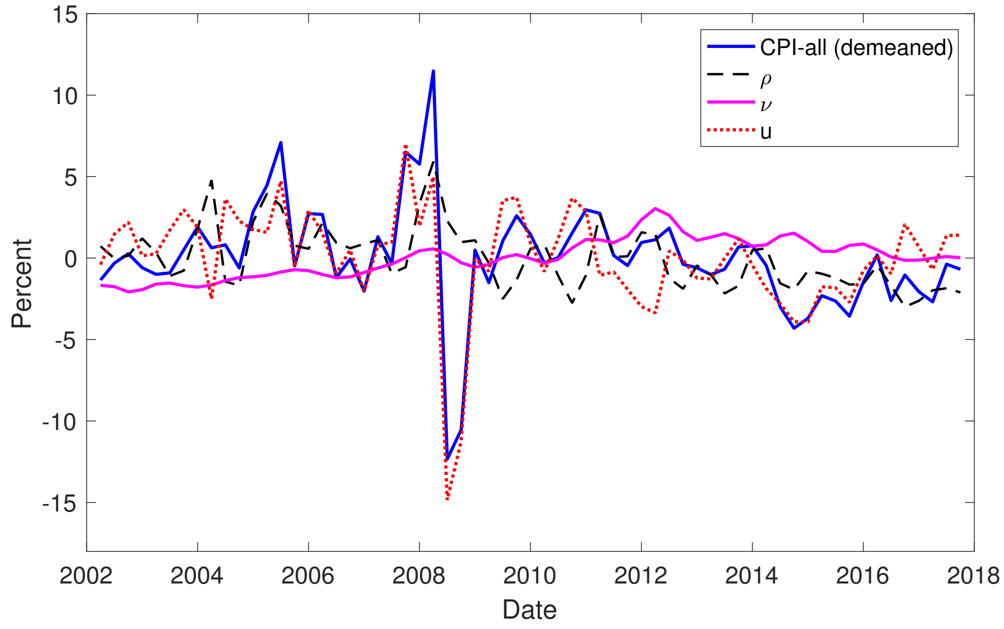
4.2 Empirical Results

Figure 18 shows the historical decomposition of CPI inflation into pure, relative and idiosyncratic components using 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. Upon close examination, the pure inflation component is slightly lower than the sample mean of headline inflation in the pre 2010 period, but became slightly higher in the period thereafter. This implies that the pure inflation component is not responsible for the current phenomenon of low CPI inflation rates for Thailand.

According to Figure 18, the relative price components (ρ_t and u_t) play a substantial role in explaining within-quarter price fluctuations. Large swings in the inflation rate during the Great Recession in 2008 can be attributed almost entirely to relative price fluctuations, although the idiosyncratic component appears to play a more substantive role. However, in the past few years, what appears to be driving inflation lower are favorable relative price changes that deliver macroeconomic wide effects in ρ_t, leading to surprisingly low and persistent inflation in spite of loose monetary policy conditions.

Next, we investigate the degree of inflation variability as explained by the three fac-

Figure 19: CPI Inflation Decomposition



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

tors. We follow Reis and Watson (2010) and compute canonical R^2 measures for inflation and its components at all and business cycle frequencies[12]. Table 15 reports both simple standard deviation measures as well as the fraction of these averaged canonical R^2 measures. First, for aggregate headline inflation, we observe that while the idiosyncratic component of inflation (u_t) is most volatile, it does not play a large role in explaining the overall movements of headline inflation. According to the R^2 measures, 11 percent of the movements in aggregate headline inflation is accounted for by pure inflation, 57 percent is explained by the relative price index and the remainder is driven by idiosyncratic shocks. This implies that macroeconomic wide shocks is responsible for a large share of roughly 70 percent of all inflation rate fluctuations while the idiosyncratic component explains only 30 percent. This finding holds for both all and business cycle frequencies[13].

The finding that aggregate shocks can explain a large proportion of inflation variance is consistent with, among others, Reis and Watson (2010) and Forbes et al. (2017). Based on the analysis for the US, Reis and Watson (2010) find that the aggregate component also explains around 70 percent of overall inflation fluctuations at all frequencies and 90 percent at business cycle frequencies. For the UK, Forbes et al. (2017) finds that up to 72 percent of the variation in five aggregate inflation series can be explained by just

[12] As described in more detail in their paper, Reis and Watson (2010) examine the relationship between y_t and x_t in $y_t = \delta(L)x_t + e_t$, via its R^2 measure over specific frequency bands of interest.

[13] We expected that the proportion of variation explained by the relative price component to increase at business cycle frequencies. However, note that these R^2 estimates are not exact and are associated with some error.

Table 15: Volatility and Fraction of Inflation Variability Explained by Its Components

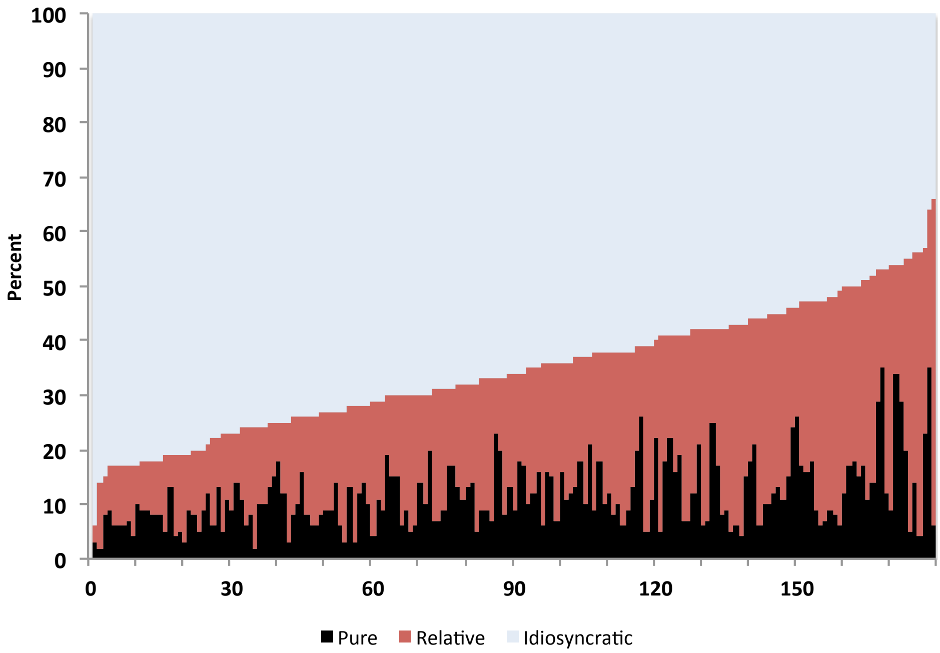
	Standard Deviation				R^2 (All freq)			R^2 (B-cycle freq.)		
	π_t	v_t	ρ_t	u_t	ρ_t	v_t	u_t	ρ_t	v_t	u_t
Aggregate Inflation Rates										
CPI Inflation	3.91	1.15	2.97	3.10	0.57	0.11	0.32	0.56	0.09	0.35
Disaggregated Series										
25th Percentile	1.57	1.15	0.88	2.02	0.15	0.07	0.78	0.10	0.02	0.88
Median	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.

one common principal component. There is also a large body of empirical evidence that dynamic factor models, with few number of factors (in our case 3) can account for a large share of the variability in macroeconomic variables (see Stock and Watson, 2005 and references therein).

Next, we investigate the distribution of variance and variance decompositions for disaggregated inflation series in the second panel of Table 15. The findings are quite different from the aggregate analysis. First, disaggregated inflation rates are much more volatile than aggregate series with a standard deviation that is on average almost three times as large. There is also considerable heterogeneity across the disaggregated series in terms of inflation volatility. Examining the R^2 measures, much of this volatility at the disaggregated level can be attributed to idiosyncratic disturbances. At the twenty-fifth and seventy-fifth percentiles, the relative price index accounts for only 10 to 46 percent of the business cycle variability of individual inflation rates, while pure inflation accounts for only 2 to 8 percent. On average, idiosyncratic components explain 65 percent of all inflation rate movements, which is almost double of what was reported for aggregate headline inflation. Figure 19 makes this point clear by plotting the fraction of variability explained by the components for the 179 ELIs. As shown, the area that corresponds to the idiosyncratic component is largest. Nonetheless, these noisy shocks at the goods level end up canceling each other out, thus we find that what matters for headline CPI at the aggregate level are rather relative price fluctuations in ρ_t that are driven by macroeconomic wide shocks. Similar findings are reported for the US (see Boivin et al., 2009; Reis and Watson, 2010).

Figure 20: 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.

Components of Inflation and Other Observables

A key input towards conducting monetary policy is to understand the source of changes in aggregate price movements. Table 16 examines the canonical R^2 correlation between the relative and pure price indices with several conventional measures. For the relative price index, food and energy prices explain approximately 40 percent of ρ_t at all frequencies. This share increases at business cycle frequencies for food, but surprisingly declines by half for energy, which may suggest that a sizable component of energy price movements are being passed through to the trend. When combining food and energy, together they explain only 60 to 70 percent of all relatively price changes. 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 ρ_t. Together, the five dimensional index (food, energy, services, durables, imports) can account for almost all relative price movements in Thailand.

In the bottom panel, we report the canonical R^2 measure between pure inflation and conventional monetary policy indicators. Theoretically, inflation is a monetary phenomenon in the long-run, suggesting a tight link between pure inflation and measures linked to monetary policy such as money growth, changes in the policy rate, and the term spread. Indeed, given that the relationship between these monetary policy indicators and

Table 16: The Components of Inflation and Other Observables

	Frequencies	
Observable	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.

pure inflation are close to zero at business cycle frequencies, we confirm the notion that pure inflation is a long-term construct. However, at all frequencies, we do not find a strong link between our monetary policy indicators and pure inflation. Nevertheless, small R^2 measures are 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 premiums.

The Phillips Correlation

For Thailand, Manopimoke (2018) shows that the slope of the Phillips curve, which captures the short-run relationship between inflation and real economic activity, has become muted in recent years. This finding is consistent with evidences for other countries (see IMF, 2006), and have led researchers to question the validity of the Phillips curve. A number of explanations have been proposed for the apparent flattening of the Phillips curve, mostly related to changes in the supply side of the economy, whether it be 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).

A recent line of research suggests that the apparent disappearance of the Phillips curve may in fact be a measurement problem. For example, Bullard (2018) uses the standard textbook New Keynesian framework to show that with improved monetary policy, the empirical Phillips curve can be zero even while the structural Phillips curve relation is still intact. This finding implies that economists can no longer look to find the 'true' inflation-output tradeoff from empirical Phillips curve slope estimates if monetary authorities are aggressive in fighting inflation. Stock and Watson (2018) argue that with substantial noise in major price indexes, the inflation-output relationship could 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.

The findings of Stock and Watson (2018) is not surprising in light of the evidence of large heterogeneity in price-setting as shown in the stylized fact section of this paper. For France and the US, Imbs et al. (2011) and Luengo-Prado et al. (2017) show that large heterogeneity in price setting is consistent with sectoral Phillips curves, where different sectors respond differently to marginal costs. They argue that ignoring such heterogeneity can result in misspecified aggregate Phillips curves with potentially large policy implications. In light of these evidences, utilizing disaggregated price data should help us gain a better understanding about the weak Phillips correlation for Thailand.

Based on a factor analysis of disaggregated price data, Reis and Watson (2010) show that the relative price component of inflation best captures the Phillips correlation. This is because it reflects how the various goods and services respond differently to aggregate shocks. To investigate whether the Phillips correlation is most relevant in the relative price component for Thailand, we compute R^2 coherence measures for inflation and various real economic activity variables in Table 17. First, we produce baseline estimates in Panel A, by examining the correlation between overall inflation and real activity variables at business cycle frequencies. We find that correlation between inflation and GDP is 0.23 at business cycle frequencies but is weak, being only marginally significant at the 10 percent level. The relationship between inflation and other components of GDP is stronger for investment and strongest for exports and imports, but nonetheless weak and not statistically significant for consumption and domestic demand. The finding that inflation is more responsive to the global component of real economic activity and less so with domestic economic conditions is in line with the findings of Manopimoke (2018). Based on an open economy New Keynesian Phillips curve framework, the author argues that the forces of globalization that accelerated since the year 2000 has enhanced the importance of global factors in driving short-run inflation rate movements in Thailand.

Table 17: Fraction of Variability of Real Variables Associated with CPI Inflation

Real Variable	Frequencies 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.

Next, we control for relative prices to investigate whether it will diminish the short-run relationship between inflation and real economic activity. Using food and energy as controls in Panel B reduces the strength of the Phillips correlation. Likewise, controlling for intertemporal relative prices (using changes in the policy rate) and the relative price of domestic and foreign goods (using the nominal effective exchange rate) in Panel C also reduces the Phillips correlation by a sizable degree as well. Finally in Panel D, when we control for the relative price factor ρ_t, the Phillips correlation disappears over business-cycle frequencies. The disappearance of the Phillips correlation when we control for relative prices suggest that the empirical short-run tradeoff between inflation and real economic activity is largely explained by relative price factors.

To illustrate the same point from a different perspective, we examine the correlation of the aggregate components (v_t and ρ_t) of inflation and real activity variables in Panel E. We find that by removing the noisy price fluctuations as driven by the idiosyncratic component, the Phillips relation becomes much stronger. The R^2 measure more than doubles for real GDP at business cycle frequencies, while the correlation for other real components also increase although to a lesser extent. Then, by controlling for the relative price index in Panel F, we again find that the Philips correlation disappears, as the squared coherence measure between pure inflation and real economic variables falls to zero. As such, these findings altogether implies that the Philips correlation, in which many economists have claimed to disappear during recent periods, is still intact, but may be difficult to detect since it is hidden in the relative price component of inflation.

5 Conclusion

The aim of this paper is to improve our understanding of the dynamics of individual price setting in Thailand and draw macro implications for monetary policy. Based on highly disaggregated price data, we have documented a number of stylized facts. These observations have important policy implications that deserve further research. The high degree of price rigidity, for example, 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. Moreover, high price rigidity indicates that firms' margins act as an important absorber of shocks to input costs.

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. At the same time, the large heterogeneity in price changes points to a significant contribution of relative price changes to overall inflation. The conduct of monetary policy would benefit from disentangling these movements from generalized price changes that are amenable to policy in the long run. Finally, we have documented the substantial dispersion in price levels for the same product and services across regions. The law of one price does not hold within the country. Further research to uncover the underlying drivers of these observations are welcome.

To disentangle the underlying key shocks driving heterogenous price movements, we employ a dynamic factor analyses to better characterize overall fluctuations in disaggregated prices. We find that while prices at the disaggregated level are mainly driven by idiosyncratic price shocks, at the aggregate level, headline CPI inflation is largely driven by changes in relative prices that are adjusting in response to aggregate demand and supply shocks. In fact, low and persistent inflation in Thailand during recent years can simply be explained by favorable relative price shocks. The pure inflation component on the other hand remains elevated, implying that the puzzling low inflation rates in Thailand as of late should not be viewed as permanent or long-term phenomenon. Last, we investigate the Phillips correlation which has been difficult to detect based on data at the macroeconomic level. Using disaggregated data to examine the Phillips correlation in the relative price component by removing volatile idiosyncratic price fluctuations as well as the excessively smooth component of pure inflation, we find that the Phillips correlation which captures the short-run inflation-output tradeoff for monetary policy strengthens significantly. These findings deliver important policy implications particularly for inflation control, and calls for more research along the lines of how relative price changes are important to overall inflation dynamics and the conduct of monetary policy.

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

5.1 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

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

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

5.2 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.

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