Decoding the Low Inflation Conundrum with Online and Offline Price Data*

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Abstract: The behavior of Thai inflation as of late has been puzzling, particularly due to the persistent declines in the level of the aggregate inflation rate. We exploit the richness of cross-sectional online and offline price data at the disaggregated level to disentangle and understand the key sources of generalized price movements. We find that the drivers of overall price fluctuations in Thailand has undergone two major changes. Prior to the year 2000, fluctuations in inflation were largely driven by permanent shocks due to the lack of a well-defined inflation target. Since then, permanent shocks played a small role in explaining overall inflation rate fluctuations. Instead, persistent declines in inflation during the post 2010 period can be largely attributed to the changing nature of transitory shocks from the raw food sector. Furthermore, while disaggregate prices can be largely explained by idiosyncratic price movements, we find that aggregate shocks explain as much as 70% of overall inflation rate fluctuations, of which the majority can be characterized as relative price changes. Finally, to investigate how aggregate inflation dynamics may evolve in the future, we analyze the nature of price-setting for a subset of online goods. We find that while online prices change more frequently than offline prices, they nevertheless exhibit considerable cross-sectional dispersion and low degrees of price synchronization. However, with enhanced competition from a growing e-commerce sector, prices may become more flexible and less dispersed. Our findings help address key challenges that policymakers face in today's low inflation era and also brings with it a deeper understanding of Thai inflation dynamics more generally.

Keywords: disaggregated prices, factor model, inflation, online prices, price setting, price rigidity, relative prices, signal-extraction, trend inflation.

JEL Classifications: C25, C33, C40, D40, E31.

*The authors are grateful to Piti Disyatat, Krislert Samphantharak, Nada Wasi, Pucktada Treeratpituk, Suphanit Piyapromdee, Nuwat Nukhwun and Surach Tanboon for helpful comments and discussions. We are also thankful to Priceza and members of the inflation team at the Bank of Thailand for the use of their data. The views expressed in this paper are those of the authors and do not necessarily reflect the position of the Bank of Thailand. Corresponding Author: Dr. Pym Manopimoke, Address: 273 Samsen Road, Phra Nakhon, Bangkok 10200, Thailand. E-mail: pymm@bot.or.th.

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1 Introduction

The previous chair of the Federal Reserve, Janet Yellen, stated in a recent remark that "[t]he biggest surprise in the US economy this year has been inflation" (Yellen, 2017). During the recent period, there have been a number of fundamental changes in inflation dynamics in the US as well as many countries across the globe, including Thailand, making the behavior of inflation 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.

The nature of changing inflation dynamics poses a new set of questions and challenges for policymakers in Thailand. Will low and persistent inflation be a permanent feature of the economy, and what is the outlook for the future direction of Thai inflation? Does the volatility that we observe in inflation reflect temporary price movements around a fairly stable trend, or does it reflect permanent shifts in the low-frequency trend component of inflation? Is the Phillips curve relation no longer useful to policymakers in gauging short-term price pressures, or is the relation still present but merely hidden in noisy price fluctuations? Also, many have conjectured that the rising dominance of e-commerce in the retail sector have exercised strong downward pressures on prices. Is the nature of goods being sold on the Internet different from brick and mortar stores and what are the implications for aggregate inflation dynamics in Thailand?

This paper attempts to answer these questions in order to improve our understanding of Thai inflation dynamics, and provide important insights for how monetary policymakers should respond to deviations of inflation from target. We examine Thai price dynamics in two separate sections of this paper, using different disaggregated datasets and econometric approaches. In the first part of this paper, we employ disaggregated inflation data that underlies the consumer price index (CPI) as collected by the Thai Ministry of Commerce from brick and mortar stores (we henceforth refer to this as offline data) to analyze the historical behavior of Thai inflation during the past two decades. Doing so however, is not possible without a good estimate of the true underlying rate of inflation, as movements in this persistent component of inflation is needed to determine the long-run level of inflation, to analyze inflation persistence, as well as to effectively identify the cyclical component of inflation that is relevant to studying the short-run Philips curve relation.

In order to estimate the true underlying rate of inflation, we follow two approaches that have been successful in the US, but have not yet been carefully applied to Thailand. The first is the multivariate unobserved components model with stochastic volatility and outlier-adjustments (MUCSVO) as developed by Stock and Watson (2016), which utilizes information in disaggregated inflation series to help extract the 'signal' or the permanent trend component of inflation from temporary price movements in the data, also referred to as the 'noise' or the cycle. This method builds on a longstanding literature that uses times series smoothing methods to solve the signal extraction problem (see Nelson and Schwert; 1997. Atkeson and Ohanian, 2001; Stock and Watson, 2007; Cecchetti et al., 2007; Cechetti et al. 2017). The novelty of the MUCSVO approach as compared to existing ones is its effective use of information in disaggregated data to help extract the trend, as well as allowing for time-variation in the smoother to depend on the ratio of permanent shocks to the trend and transitory shocks to the cycle. Accordingly, the model is flexible and becomes suitable for the task of real-time estimation of the trend, especially in the presence of ongoing structural breaks.

The second approach relies on the dynamic factor model of Reis and Watson (2010), whom leverage information in hundreds of goods-level price data to extract the underlying rate of inflation as the component of price changes that are equiproportional across all items. They call this component pure inflation, which is the common component of inflation that is independent of changes in relative prices. This notion of pure inflation dates back to the famous price experience of Hume (1752), and since the nature of relative price fluctuations are typically transitory, pure inflation has a similar interpretation to trend inflation. The method of utilizing factor models on large-scale price datasets to identify the common component of inflation has been used in various other studies for the use of inflation forecasting, investigating inflation persistence as well as assessing macroeconomic relationships as implied by theory (see Cristadoro et al., 2005; Amstad and Potter, 2007; Del Negro, 2006; Altissimo, et al., 2009; Boivin et al., 2009).

In the second section, we turn to analyze a separate set of questions that are relevant for understanding the future of inflation dynamics in Thailand. During the last decade, e-commerce has gained an increasing share of the retail sector in Thailand. Therefore, we employ a novel dataset obtained from a price comparison website that contains millions of daily micro-level price series at both the goods and stores level (we henceforth refer to this as online data), to examine the patterns of price adjustment of goods that are sold on the Internet. Among others, we are interested in analyzing how the unique landscape and features of the online market may have important bearings on the frequency of price adjustment, the duration of price spells, the size of price changes, as well as the degree of price dispersion and synchronization. Our analysis for Internet prices is similar in spirit to Lünnemann and Wintr and Gorodnichenko et al. (2017) that carry out studies for the Euro Area and the US. We view that while the evolution of online prices may not have current implications for aggregate inflation due to e-commerce still being in its nascent stages, understanding the dynamics of online price-setting behavior is of prime importance to help prepare central bankers for the not-so-distant future where e-commerce becomes the key force in retail.

While the past decade has seen a burst of studies that use disaggregated price data to study many issues related to inflation, they typically focus on the experiences of advanced economies. Perhaps due to limited data availability, studies on emerging markets are rare, and to our knowledge, only two studies utilizes disaggregated price data to understand Thai inflation dynamics. The first is Manopimoke and Limjaroenrat (2017), who also applies the Stock and Watson (2017) MUCSVO model to sectoral inflation data, but their focus is different from ours as they are interested in the issue of inflation measurement and forecasting. Our study on the other hand, estimates the MUCSVO model to identify the trend component of inflation to better understand the various puzzles associated with the recent behavior of inflation. Apaitan et al. (2018) utilizes micro-level price data to study the patterns of price adjustment such as size and frequency of price changes in the offline market, whereas our study focuses on the online market. Nevertheless, the findings of Apaitan et al. (2018) is useful for our study towards providing a baseline set of estimates to examine the differences between the micro price-setting behavior of online and brick and mortar stores. To our knowledge, our paper is the first systematic study that provides an empirical assessment of the pattern of price adjustments for Internet prices in an emerging country.

As a preview of our findings, the key findings in the first section are as follows: (i) since the adoption of the inflation targeting framework, the variability of permanent shocks declined substantially, causing a significant decline in inflation persistence. Measures of the underlying rate of inflation also became exceptionally smooth and stable despite large and volatile relative price shocks; (ii) since 2010, inflation persistence in Thailand increased from shifts in the signal-to-noise ratio due to a substantial reduction in the volatility of transitory shocks; (iii) lowered inflation in Thailand during the past few years can be explained by both a declining trend as well as persistent downward pressures from changes in relative prices, especially those of the raw food component; (iv) core inflation is not trend inflation since food and energy price sectors that are often excluded from measures of core explain approximately 15 percent of trend inflation rate movements. Food and energy components combined can also only explain approximately 70 percent of inflation fluctuations at business cycle frequencies; (v) most of the within-quarter variations of inflation are relative price changes while the underlying rate of inflation can only account for approximately 10 percent of variations. Over the longer one-year-horizon however, half of the fluctuations in inflation can be accounted for by the trend; (vi) while disaggregate price series are mainly driven by sector-specific noise, these cancel out at the aggregate level, causing 70 percent of the movements in headline CPI inflation to be attributed to aggregate shocks; (vii) the Phillips curve relation for Thailand is still intact, but a decomposition of inflation is needed to find this correlation in the common relative price component of inflation.

For the second section, our findings can be summarized into the following stylized facts: (i) On average, prices of online goods change as often as once every 1-3 months; (ii) price decreases are as common as price decreases even with sales removed; (iii) price synchronization for an identical product across sellers in online markets are extremely low; (iv) the degree of price dispersion for homogenous goods in online markets across sellers can be quite substantial, with the source of price dispersion being related to the heterogeneity of store characteristics; (v) for broad product groups that can be matched online and offline, online prices are lower, more flexible, and exhibit smaller price changes. Via more formal regression analysis, we also find that the effects of competition makes prices more flexible and reduces the degree of price dispersion.

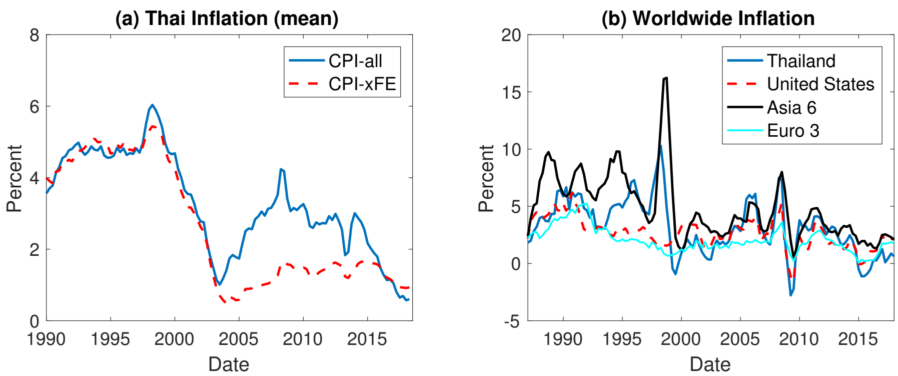
The rest of this paper is structured as follows. In the first section, we provide key stylized facts for the changing behavior of Thai inflation dynamics. Then, we outline the model specification, describe the data, and discuss how the empirical findings obtained by applying the Stock and Watson (2016) and Reis and Watson (2010) frameworks to Thai data can help us better understand the recent behavior of Thai inflation. In the second section, we first provide an overview of the e-commerce market in Thailand as well as discuss how and why the nature of price adjustments in the online market may be different from traditional offline stores. Then, we discuss the related literature, describe the dataset and present our empirical findings. The last section concludes and discusses monetary policy implications.

2 Decoding Inflation with Offline Data

2.1 Changing Inflation Dynamics in Thailand

Since the Bank of Thailand (BOT) adopted an explicit inflation targeting framework in May 2000, the level of inflation in Thailand declined substantially[1]. As shown in Figure 1a, the five year rolling average of Thailand's annual headline and core inflation decelerated sharply since the early 2000s, and headline inflation appears to have fallen further during the recent period after increasing during the Great Recession period due to large shocks to food and energy prices. The behavior of low inflation in Thailand is not country-specific but is an experience shared with many countries around the world. According to Figure 1b, currently headline inflation in Thailand is as low, if not lower, than advanced economies in Europe and the US, as well as other neighboring countries in Asia. Since 2010, quarterly headline inflation in Thailand averaged at 0.6 percent, down almost 2 percentage points from a decade earlier.

Figure 1: Thailand Inflation Mean and Worldwide Inflation Rates



Note: On the left-hand-side panel, inflation is quarter-on-quarter changes in the headline consumer price index (CPI-all) and core inflation is CPI-all excluding food and energy (CPI-xFE). The mean is calculated as a five-year moving average where the horizontal axis marks the end date of the rolling sample. For the right-hand-side panel, we use year-on-year changes in quarterly inflation to smooth out large fluctuations. Asia 6 is the simple average of inflation in China, Indonesia, Korea, Malaysia, the Phillipines and Singapore, and Euro 3 is the simple average of inflation in France, Germany, and the United Kingdom.
Source: Thai Ministry of Commerce, IMF International Financial Statistics Database, authors' calculations.

Given that inflation is ultimately a monetary phenomenon, lowered inflation rate levels have often been attributed to improved monetary policy, particularly

[1]From May 2000-December 2008, BOT used quarterly average of core inflation as the monetary policy target, setting the target range at 0-3.5 percent. Starting in 2009, the inflation target range narrowed by 0.5 percent on each side. Then in 2015, the BOT established a new monetary policy target based on the average of headline inflation at 2.5 percent with a tolerance band of 1.5 percent. The rationale for adopting headline inflation as the policy target is mainly for facilitating the central bank's communication with the public.

since the sharp declines in inflation globally corresponded to a period in which a number of countries, including Thailand, adopted the inflation targeting framework. However, the monetary policy explanation alone may not be able to fully account for the changed behavior in inflation, especially in the short to medium term. Given that the shift towards low inflation has been a worldwide phenomena coupled with growing evidence of high synchronicity between international inflation rates (see Ciccarelli and Mojon, 2010; Neely and Rapach, 2011; Manopimoke, 2015), a number of authors turn to the globalization hypothesis towards explaining the changed behavior of inflation.

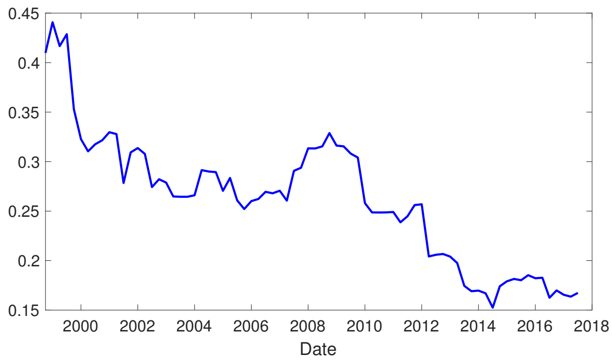
According to the globalization hypothesis, the integration of goods, factors and financial markets have been argued to help mute inflationary pressures around the world through a series of favorable external shocks. For example, the integration of low cost countries such as China and India into world trade systems can help depress trade prices and increases the share of imports in domestic demand (IMF, 2006; Kohn, 2006). Enhanced international competition through the forces of globalization also help restrain markups and producer prices, ultimately lowering inflation (Neiss, 2001; Binici et al., 2012). Furthermore, globalization has been shown to lead to a dramatic increase in the use of imported intermediaries in domestic production, and the information, communications and technology (ICT) revolution has made a great unbundling of production into global value chains possible. Not only has this been shown to increase the sensitivity of domestic inflation to global factors while reducing the role of domestic ones, but it has enhanced the intensity of shock spillovers (Auer and Mehrotra, 2014). As a result, structural changes that stem from globalization forces not only can help lower inflationary trends, but can also strengthen global inflationary cycles.

Manopimoke (2018) finds evidence in support of the globalization hypothesis for Thailand[2]. Based on a New Keynesian Phillips curve, the author reports that apart from the adoption of an inflation targeting framework which has helped significantly reduce the inflation trend, global supply and demand conditions have also played a key role since the year 2000 in driving short-run inflation rate movements in Thailand. Interestingly, this phenomenon occurred while the sensitivity of Thai inflation to domestic economic conditions declined dramatically, thus lending support to the globalization hypothesis. The weakening inflation-output trade off that Manopimoke (2018) reports for Thailand is an occurrence also known as the

[2]Empirical evidence for other countries have been mixed. Inconsistencies in findings are in large part due to different time periods of study, different empirical frameworks employed, as well as difficulties in measuring short-run global pressures on inflation. See Borio and Filardo, 2007; Ihrig et al. 2010; Bianchi and Civelli, 2015).

flattening of the Phillips curve, which has been observed in many countries and can explain why inflation in many countries have remained rather subdued despite the dramatic decline in growth during the downturn of the Great Recession (IMF, 2006; Borio and Filardo, 2007; Bullard, 2012). In this paper, we replicate the flattening Phillips curve phenomenon by estimating a reduced form Phillips curve with time-varying coefficients and GARCH disturbances to capture stochastic volatility (see Appendix A for details on model specification). As shown in Figure 2, the coefficient that captures the link between inflation and the domestic output gap for Thailand weakened by more than half over the entire sample period.

Figure 2: Time-varying Slope of a Reduced Form Phillips Curve for Thailand

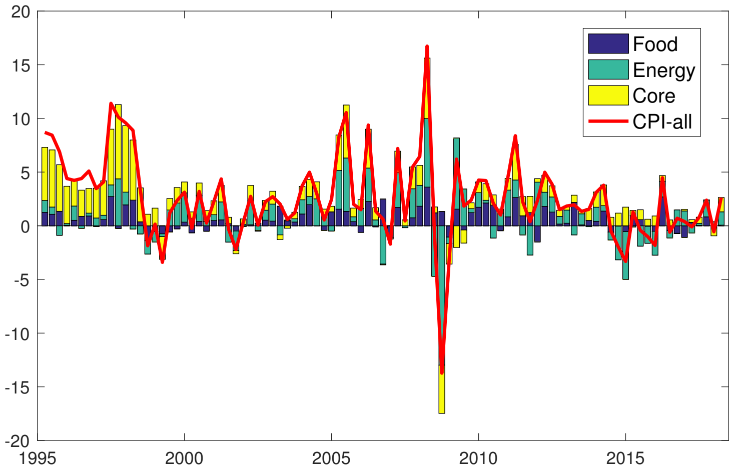


Note: Plotted is the time-varying slope of an estimated reduced form Phillips curve with GARCH disturbances. The model is estimated using quarter-on-quarter headline CPI data for the 1995Q2-2018Q2 time period. The output gap measure are Bank of Thailand's internal estimates.
Source: Bank of Thailand, authors' calculations.

So far, we have illustrated that the changed behavior in Thai inflation during past decades involved a lowered rate of inflation as well as a flattened Phillips curve relation. Other notable changes include changing volatility and inflation persistence. A quick glance at Figure 3 reveals that changes in inflation volatility during the mid 2000s have been substantial. Headline inflation reached almost 17 percent in 2008Q2, only to decline to -14 percent half a year later. Also, there have been periods in which inflation deviated persistently from the BOT's 2.5 percent inflation target. Last year was the third consecutive year in which the annual average inflation rate breached the BOT's lower inflation targeting band. Examining Figure 3 again, these changes may have something to do with the changing nature of relative price shocks. It is interesting to note that in the pre 2000 period, core components of inflation dominated overall price movements whereas relative price changes in food and energy exerted a leading role in the period thereafter.

We examine the changes in volatility and persistence more formally in Table 1. As shown in the first row, the standard deviation of headline inflation increased

Figure 3: Headline CPI Inflation and Contribution from Broad Sectors



Note: Plotted is quarter-on-quarter CPI inflation and contributions from core, food and energy components based on their time-varying expenditure share weights.
Source: Ministry of Commerce, authors' calculations.

after the year 2000, but reduced significantly after 2010. In the second row, we show that inflation persistence, usually interpreted as the duration it takes for the effect of shocks to dissipate, has undergone significant changes as well[3]. First, we find that our measure declined dramatically after the adoption of the inflation targeting framework in the year 2000, which may suggest that the BOT's explicit commitment to stabilizing inflation has helped reduce persistent deviations of headline inflation from its target by anchoring long-term inflation expectations. Interesting however, inflation persistence has risen again during recent years.

Autocorrelations in the change of inflation rates at various lags are also reported in the final rows to provide additional information on whether there is persistence in how inflation changes in each quarter as opposed to whether there is persistence in the levels. As shown, we find that the vast majority of autocorrelations are negative, indicating that positive surprises to inflation are followed by negative movements

[3]There are different ways to measure persistence such as taking the sum of coefficients or the largest root in an autoregressive (AR) process, calculating the half-life defined as the number of periods in which inflation remains above 0.5 following a unit shock, or examining impulse response functions based on fitting a particular model (see Pivetta and Reis (2007), Kang et al. (2009) and references therein). We choose to measure persistence as the sum of coefficients in an AR process or order k i.e. $\gamma = \sum_{i=1}^{k} \theta_i$ where θ_i are the autoregressive coefficients. The rationale is that for a stationary inflation process, the cumulative effect of a shock on inflation is given by $1/(1-\gamma)$, and thus a larger γ corresponds to a higher level of persistence. To choose k, we use the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), which yielded a range of measures for k that are less than or equal to 4 depending on the subsample involved. To ensure consistency, we choose $k = 4$. Note that the results are robust to taking the largest autoregressive root of the AR(4) process as a measure of persistence as well.

Table 1: Volatility and Persistence of Headline CPI Inflation

	Before 2000	2000-2010	After 2010
Volatility	2.852	3.663	1.964
Persistence	0.329	0.005	0.629
Autocorrelations			
Lag 1	-0.435 (0.001)	-0.164 (0.282)	-0.229 (0.163)
Lag 2	0.197 (0.001)	-0.157 (0.324)	-0.181 (0.201)
Lag 3	-0.102 (0.002)	-0.177 (0.299)	0.005 (0.361)
Lag 4	-0.159 (0.003)	-0.089 (0.400)	-0.313 (0.126)
Lag 5	0.051 (0.006)	-0.033 (0.535)	0.149 (0.150)
Lag 6	-0.206 (0.004)	0.090 (0.609)	0.253 (0.091)
Lag 7	0.226 (0.002)	0.086 (0.675)	-0.015 (0.141)
Lag 8	-0.224 (0.001)	-0.126 (0.679)	-0.154 (0.149)

Note: Reported in the first row are the standard deviations of seasonally-adjusted annualized quarter-on-quarter headline CPI inflation. Persistence in the second row is calculated as the sum of the coefficients in a fitted autoregressive model of order 4. The final rows are autocorrelations for the change in inflation series with p-values in parentheses.

in subsequent quarters (and vice versa). Consistent with persistence in the levels, persistence in $\Delta\pi_t$ are lower during 2000-2010 suggesting that shocks during this period were highly transitory. More specifically, the impact of shocks in this period decayed to zero within a year compared to other periods where the effect of the initial shock is only halved by two years. Interestingly, while persistence in the levels were higher in the post 2010 period, innovations around its trend were not as large when compared to the pre 2000 period. This finding suggests that the adoption of the inflation targeting framework has helped stabilize movements of inflation around its long-run level.

To summarize, this section shows a number of stylized facts for Thai inflation over the past two decades. First, we show that apart from observed declines in the level of inflation, Thai inflation has also been quite volatile and the degree of persistence in Thai inflation has been increasing in recent years. We also show that the Phillips curve relationship that is widely used to capture the link between inflation and real economic activity in the short-run has weakened, while changes in relative prices such as food and energy may have played a more important role in driving inflation dynamics as of late. In the next sections we decompose inflation into its various components to gain a better understanding of changes in inflation behavior as highlighted by these key stylized facts.

2.2 Trend-Cycle Decomposition

Based on micro-founded theoretical models, a longstanding tradition is to separately analyze inflation in two components. The first is some type of Phillips curve relation in which measures of economic slack (as captured by an unemployment gap or output gap) puts pressure on inflation in the short-run. The second component involves some role for inflation expectations. This framework has been exceptionally useful towards analyzing the dynamic properties of inflation such as inflation persistence, as well as understanding the source of movements in inflation over the short and long-term horizons (see Fuhrer, 2009).

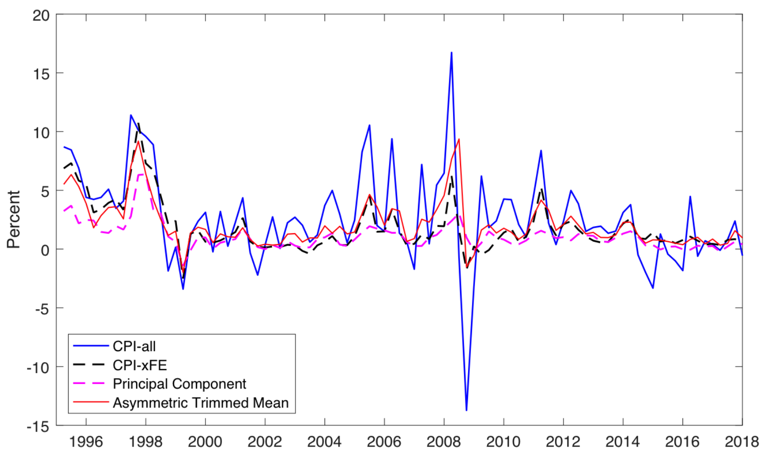
An important contribution by Stock and Watson (2007) was to propose a less theoretical but parsimonious model for the inflation process by suggesting that inflation could be well characterized by a model that decomposes inflation into a slow-moving trend component and short-lived fluctuations around the trend, often referred to as the transitory cycle[4]. Trend inflation are driven by persistent movements in inflation typically seen as resulting from permanent monetary policy shocks. The cycle component on the other hand is often seen as resulting from temporary price movements that are often driven by supply-side shocks. Since monetary policy effects the economy with a lag and these shocks tend to dissipate on its own over the short-run, it has been argued that policymakers should not react to such shocks as they will risk destabilizing the economy. As such, it is of prime importance that policymakers distinguish the 'signal' (trend) from the 'noise' (cycle) in order to 'look through the cycle' and only respond to persistent inflation deviations from target.

Typically, economists use core inflation as a measure of trend inflation, obtained by excluding from headline inflation food and energy sectors because they are known to be driven by large and volatile shocks (see Bryan and Cecchiti, 1994; Wynne, 2008). While this measure has gained popularity particularly because it is straightforward to compute and transparent in the manner in which it can be communicated to the public, it has been criticized on the grounds that the chosen set of excluded components are fixed, even when their influences vary across time periods. This may cause economists to 'throw away' important information that may help measure the trend, especially since food and energy price changes have become more persistent recently. Along the same line of reasoning, sectors that end up being included in core inflation may also be too volatile, thus imparting too much non-persistent variation in trend inflation.

[4]This technique performs a trend-cycle decomposition for inflation based on a statistical approach with the use of only univariate data. It is also possible to perform a trend-cycle decomposition for inflation based on theoretical relationships and the use of other macroeconomic data. For example, Kim et al. (2014) and Morley et al. (2015) performs a trend-cycle decomposition for inflation based on a bivariate unobserved components model of inflation and real activity variables that is consistent with the New Keynesian Phillips curve (NKPC). Manopimoke (2018) develops and estimates a similar framework for Thailand while allowing for regime-switching in NKPC parameters.

Figure 4 plots headline and core inflation in Thailand alongside other popular measures of trend inflation as monitored by the Bank of Thailand. A few observations emerge. First, it is interesting to note the fundamental shift in the relationship between headline and the various measures of trend around the year 2000. In the earlier period, headline generally moved in line with trend inflation. However, in the period thereafter, headline and trend measures diverged. Second, trend inflation estimates in the post 2000 period are more smooth relative to headline, most likely due to the adoption of an inflation targeting framework which helped anchor long-term inflation expectations. Last, since the year 2000, headline inflation remained higher than selected trend measures for prolonged periods, except for some brief periods of sharp downturns. Given that trend inflation is supposed to represent the underlying long-run rate in which headline inflation will revert to after the effects of temporary price shocks dissipate, the sustained divergence between headline and trend measures raises concerns about the validity of using core inflation as a representative measure of trend inflation in Thailand.

Figure 4: Selected Measures of Trend Inflation



Note: Displayed above are quarter-on quarter inflation series computed from the Thai consumer price index (CPI-all). Trend inflation measures include: (1) headline inflation excluding raw food and energy components, denoted CPI-xFE; (2) trend inflation constructed from extracting the common component of sectoral inflation series via principal components analysis; and (3) an asymmetric trimmed mean measure of trend inflation constructed by removing 12 and 6 percent of the items with the largest relative price changes from the lower and upper end of the price distribution respectively (see Bryan and Ceccetti, 1994).

As mentioned earlier, to understand the underlying behavior of Thai inflation dynamics, we need a good measure of trend inflation. This section applies the multivariate unobserved components model with stochastic volatility and outlier adjustment (MUCSVO) as developed by Stock and Watson (2016) to sectoral Thai inflation data to extract measures of the underlying trend. The MUCSVO model is an extension of the abovementioned Stock and Watson (2007) model. However, the authors show that the MUCSVO model imporoves upon the original model as well as other benchmark measures such as core inflation by delivering trend estimates that are smoother, more precise, and are able to forecast average inflation over the 1-3 year horizon more accurately both in-sample and out-of-sample. This is because in contrast to the construction of core inflation, the MUCSVO model does not impose which nonpersistent components to remove from the trend, but instead leaves it up to the data to decide what proportion of persistent price movements of a particular sector should pass-through to the trend. The weight of each sector's contribution to the trend is also allowed to vary over time depending on the the signal-to-noise ratio of the persistent to non-persistent shocks affecting that sector, thus making it particularly flexible and well-suited for modeling inflation dynamics that may be susceptible to structural changes.

2.2.1 Model Specification

Consider the following MUCSVO model as proposed by Stock and Watson (2016):

$$
\begin{aligned}
\pi_{i,t} &= \alpha_{i,\tau,t}\tau_{c,t} + \alpha_{i,\varepsilon,t}\varepsilon_{c,t} + \tau_{i,t} + \varepsilon_{i,t} && (1)\\
\tau_{c,t} &= \tau_{c,t-1} + \sigma_{\Delta\tau,c,t} \times \eta_{\tau,c,t} && (2)\\
\varepsilon_{c,t} &= \sigma_{\varepsilon,c,t} \times s_{c,t} \times \eta_{\varepsilon,c,t} && (3)\\
\tau_{i,t} &= \tau_{i,t-1} + \sigma_{\Delta\tau,i,t} \times \eta_{\tau,i,t} && (4)\\
\varepsilon_{i,t} &= \sigma_{\varepsilon,i,t} \times s_{i,t} \times \eta_{\varepsilon,i,t} && (5)\\
\alpha_{i,\tau,t} &= \alpha_{i,\tau,t-1} + \lambda_{i,\tau}\zeta_{i,\tau,t} \text{ and } \alpha_{i,\varepsilon,t} = \alpha_{i,\varepsilon,t-1} + \lambda_{i,\varepsilon}\zeta_{i,\varepsilon,t} && (6)\\
\Delta ln(\sigma^2_{\varepsilon,c,t}) &= \gamma_{\varepsilon,c}\nu_{\varepsilon,c,t}, \qquad \Delta ln(\sigma^2_{\Delta\tau,c,t}) = \gamma_{\Delta\tau,c}\nu_{\Delta\tau,c,t}, && \\
\Delta ln(\sigma^2_{\varepsilon,i,t}) &= \gamma_{\varepsilon,i}\nu_{\varepsilon,i,t}, \qquad \Delta ln(\sigma^2_{\Delta\tau,i,t}) = \gamma_{\Delta\tau,i}\nu_{\Delta\tau,i,t}, && (7)
\end{aligned}
$$

where the disturbance terms $\eta_{\tau,c,t}, \eta_{\varepsilon,c,t}, \eta_{\tau,i,t}, \eta_{\varepsilon,i,t}, \zeta_{i,\tau,t}, \zeta_{i,\varepsilon,t}, \nu_{\Delta\tau,c,t}, \nu_{\varepsilon,c,t}, \nu_{\Delta\tau,i,t}, \nu_{\varepsilon,i,t}$, are i.i.d. standard normal.

This model expresses the rate of sectoral inflation π_{it} as the sum of a latent common factor for trend inflation $\tau_{c,t}$, a latent common transient component $\varepsilon_{c,t}$, and sector-specific trends and transient components, $\tau_{i,t}$ and $\varepsilon_{i,t}$ (Eq. 1). According to Eqs. (2) and (4), the trend components follow a martingale process and the transitory components are serially uncorrelated processes as specified by Eqs. (3) and (5). The factor loadings on the common trend and transient components, $\alpha_{i,\tau,t}$ and $\alpha_{i,\varepsilon,t}$, evolve over time as a random walk as in Eq. (6). Eqs. (2)-(5) allow stochastic volatility in the latent common and sector-specific components, where the stochastic volatility processes evolve according to a logarithmic random walk as in Eq. (7). Given the existence of large outliers in sectoral inflation series, outliers in the transitory disturbances of the common and sector-specific components are accounted for through the random variables $s_{c,t}$ and $s_{i,t}$ in Eqs. (3) and (5). Following Stock and Watson (2016), large infrequent spikes in the price level that are two to ten times as large are labelled as outliers[5].

We are interested in the measure of trend inflation. The MUCSVO trend depends on the estimates of the common and sector-specific trend components as follows:

$$\tau_t = \sum_{i=1}^{n} W_{it}(\alpha_{i,\tau,t}\tau_{c,t} + \tau_{i,t}) \tag{8}$$

where n denotes the number of sectors, W_{it} is the expenditure share weight of sector i in total headline inflation, and $\alpha_{i,\tau,t}\tau_{c,t} + \tau_{i,t}$ denotes the overall sectoral trend.

2.2.2 Data Description and Estimation Methodology

The dataset consists of quarterly observations on ten components of inflation that are used to construct the CPI. The sample spans 1995Q1-2018Q2 which is the longest series available for sectoral inflation data from the Thai Ministry of Commerce. The ten components of are raw food, food in core, clothing, housing excluding gas and electricity, gas and electricities, healthcare, transportation excluding fuel, fuel, recreation and education, and tobacco and alcohol. Sectoral inflation rates are calculated as the quarter-on quarter log changes in the seasonally-adjusted sectoral price indices, where the quarterly index is constructed from taking the quarterly average of monthly data. More specifically, we compute the inflation series for sector i as $\pi_{it} = ln(CPI_{i,t}/CPI_{i,t-4}) \times 400$ where $CPI_{i,t}$ is the quarterly price index of inflation sector i. A plot of the ten inflation series are as shown in Panels (a) of Figures B1-B10 in Appendix B. Finally, actual expenditure share weights that are used to aggregate the sectoral series are also obtained from the Thai Ministry of Commerce.

To get a sense of the high degree of heterogeneity in sectoral inflation series, Table 2 reports the standard deviation and persistence of the ten sectors over three subsamples. Despite the expenditure shares of these sectoral inflation series being relatively constant (see Table 3), we find significant time variation in their volatility

[5]Typically, outliers are adjusted prior to model estimation based on the econometrician's judgment. The MUCSVO provides a model-based treatment of outliers by allowing large and infrequent one-time shifts in the cyclical common and sector-specific components to occur with probabilities p_c and p_i respectively. In the identification of outliers, we experimented with a range of reasonable parameter values and found the results to be relatively robust to these alternate specifications.

as well as their persistence, highlighting the importance of allowing for time-varying coefficients in the MUCSVO model. Also, the summary statistics highlight that simply excluding food and energy price sectors to arrive at a measure of core inflation may not be entirely appropriate. Based on standard deviation measures, it is clear that food and energy components are most volatile, but other sectors such as tobacco and alcohol and transportation excluding fuel have also been equally volatile during some periods as well. Also, the persistence of food and energy components are not necessarily the lowest among sectors, especially in the post 2010 period. As a result, excluding them to construct core inflation could be throwing away important information towards measurement of the trend.

Table 2: Standard Deviation and Persistence of Sectoral Inflation Series

	Standard Deviation			Persistence		
	Before 2000	2000-2010	After 2010	Before 2000	2000-2010	After 2010
Raw Food	11.35	7.71	5.77	0.29	0.31	0.46
Food in Core	4.03	3.50	3.11	0.58	0.68	0.56
Clothing	3.71	1.69	0.58	0.19	0.12	0.29
Housing x Gas	2.27	1.23	0.79	0.08	0.04	0.61
Healthcare	3.36	1.00	0.40	0.28	0.24	0.34
Transport x Fuel	3.44	7.27	0.95	-0.05	0.20	-0.46
Recreation & Education	4.21	4.57	0.76	0.90	-0.14	-0.14
Tobacco & Alcohol	10.33	7.79	6.83	0.14	-0.16	-0.10
Gas & Electricity	15.32	20.57	10.21	-0.26	0.08	0.49
Fuel	25.30	32.07	19.04	-0.53	-0.31	0.21

Note: Reported are the standard deviations and persistence of annualized quarter-on-quarter sectoral inflation series over various subsamples. Persistence is calculated as the sum of the coefficients in a fitted autoregressive model of order 4.

Table 3: Expenditure Share of Sectoral Inflation Series

	Before 2000	2000-2010	After 2010
Raw Food	8.78	9.99	15.11
Food in Core	19.06	18.11	19.86
Clothing	3.83	3.52	2.90
Housing x Gas	25.85	22.30	19.17
Healthcare	7.05	6.91	6.24
Transport x Fuel	19.28	19.78	16.59
Recreation & Education	8.47	7.75	6.21
Tobacco & Alcohol	1.03	1.16	1.36
Gas & Electricity	3.95	4.48	3.92
Fuel	3.93	6.78	8.64

Note: Reported are the actual expenditure shares of sectoral inflation series in the consumer price index averaged over various subsamples.
Source: Thai Ministry of Commerce.

Finally, to estimate the model, we follow Stock and Watson (2016) and estimate the MUCSVO with Bayesian methods. As we are analyzing inflation ex-post, throughout this paper we report smoothed estimates of the unobserved components, defined as the date t posterior mean of the component given the full dataset. To estimate the posterior, we use the Markov Chain Monte Carlo (MCMC) approach and stochastic volatility is handled by following the method outlined in Kim et al. (1998), modified to use the Omori et al. (2007) 10-component Gaussian mixture approximation for the log-chi squared error. Readers are referred to the Appendix of Stock and Watson (2016) for details on estimation.

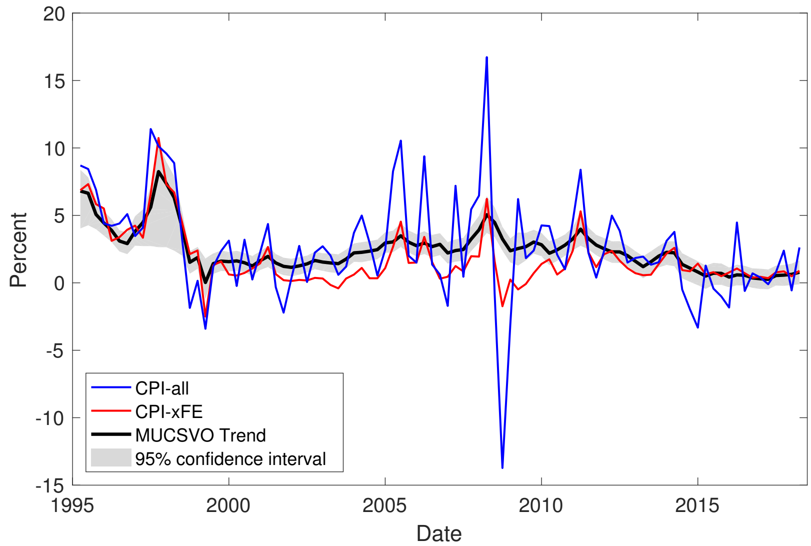
2.2.3 Empirical Results

The estimated MUCSVO trend is plotted alongside headline and core inflation in Figure 5. Similar to core, the multivariate trend tracks headline inflation closely in the pre 2000 period, but diverged in the period thereafter. In the latter period, the MUCSVO trend is more smooth when compared to core, and lies closer towards the midpoint of headline inflation which suggests that it may be a better representation of inflation levels in the long-run. Nevertheless, while the MUCSVO trend appears relatively stable in the post 2000 period, estimates of trend inflation still contains notable fluctuations within the 0.26 to 5.05 percent range, reaching its highest level in 2008Q2 and its lowest recently in 2017Q2. Trend inflation has been declining since 2010, in line with the persistent declines in headline inflation. In the most recent 2018Q2 quarter, the MUCSVO trend estimate is 0.79 while core is higher at 0.89 percent. Finally, note that the MUCSVO is estimated with some error as shown by the 95 percent confidence bands in gray. With a less volatile trend however, this band narrowed substantially after the year 2000.

Next, we analyze the nature of underlying shocks that drive CPI inflation more generally. Panels (a) and (b) of Figure 6 show the volatilities corresponding to total trend and cycle components[6]. Most noteworthy are their relative magnitudes. The cyclical component is substantially more volatile, peaking during the Asian Financial Crisis and the Great Recession. This is consistent with the notion that the trend is a slow moving component of inflation while the cycle reflects noisy fluctuations around that trend. Also, we observe a steep decline in the volatility of trend shocks after the year 2000. To further investigate this occurrence, we plot the posterior means of shock volatilities for only the common component of the trend in Panel (a) of Figure 7. As shown, the volatility of the common component has a similar shape to those of the overall trend, implying that the decline in 2000 must have stemmed from changes in common rather than sector-specific persistent

[6]The variability of shocks to the overall trend and cycle in contains both the influences of common and idiosyncratic shocks.

Figure 5: Estimated MUCSVO Trend Inflation



Note: Plotted are quarter-on-quarter headline (CPI-all) and core (CPI-xFE) inflation plotted alongside the posterior mean estimates of the MUCSVO trend with associated 95 percent confidence bands (shaded in gray).

shocks[7]. This is in line with the reasoning that the adoption of the inflation targeting framework, which delivers macroeconomic wide effects, has effectively helped lower and stabilized trend inflation through the anchoring of long-term expectations[8]. The effectiveness of the inflation targeting framework is highlighted by the observation that after the adoption of the inflation target, σ_τ remained exceptionally stable despite large and volatile transitory shocks as well as outliers occurring during the Great Recession (see Panels (b) and (c) of Figure 7).

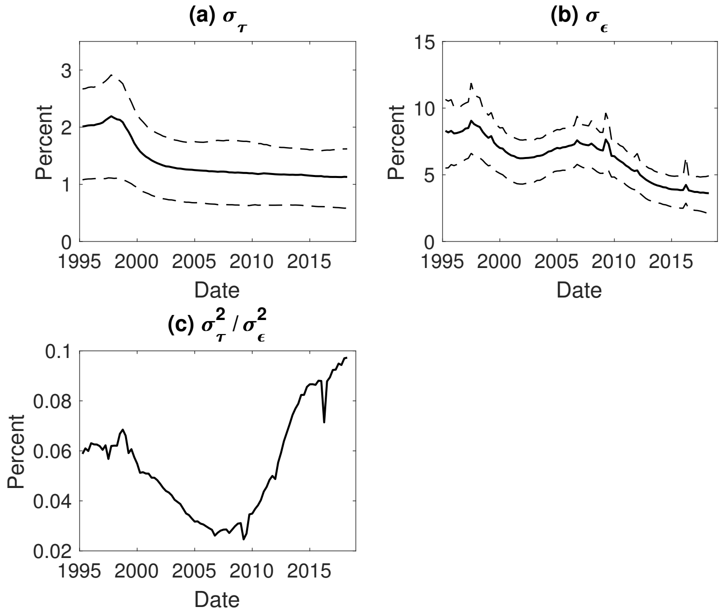
As explained by Stock and Watson (2007) and Cecchitti et al. (2007), the relative variances of trend to cycle variability, which is also known as the signal-to-noise ratio, is related to the visible persistence of inflation[9]. We plot the signal-to-noise ratio as implied by the MUCSVO model in Panel (c) of Figure 6, which has a shape that is consistent with our measure of persistence in Table 1 in the stylized facts section. More specifically, inflation persistence declined in the early 2000s, but increased significantly during recent years. In explaining why such is the case, our estimates of trend and cycle volatility shocks that are used to construct the signal-to-noise ratio provides important insights. More specifically, it illustrates

[7]To confirm this point, we plot the volatilities of idiosyncratic trend shocks in Panels (d) of Figures B1-B10 in Appendix B. As expected, they are all relatively stable

[8]By estimating a New Keynesian Phillips curve for Thailand, Manopimoke (2018) reports a similar finding.

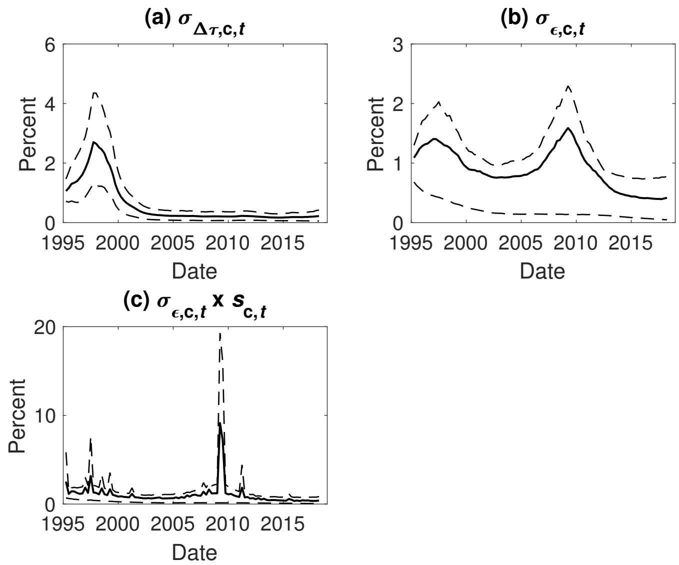
[9]The idea is that the unobserved components model can be mapped as an IMA(1,1) model $\Delta\pi_t = a_t - \theta a_{t-1}$ where θ is inversely related to the persistence of the inflation process and is a decreasing function in the signal-to-noise ratio.

Figure 6: Volatilities of Total Trend and Cycle Shocks and Signal to Noise Ratio



Note: Panels (a)-(b) display the standard deviation estimates of shocks to the total permanent and transitory components repsectively. Panel (c) displays the signal-to-noise ratio between the variability of trend and cycle shocks. All estimates are full-sample posterior mean estimates based on applying the MUCSVO to data on 10 disaggregated sectoral inflation series.

Figure 7: Volatilities of Common Trend and Cycle Shocks

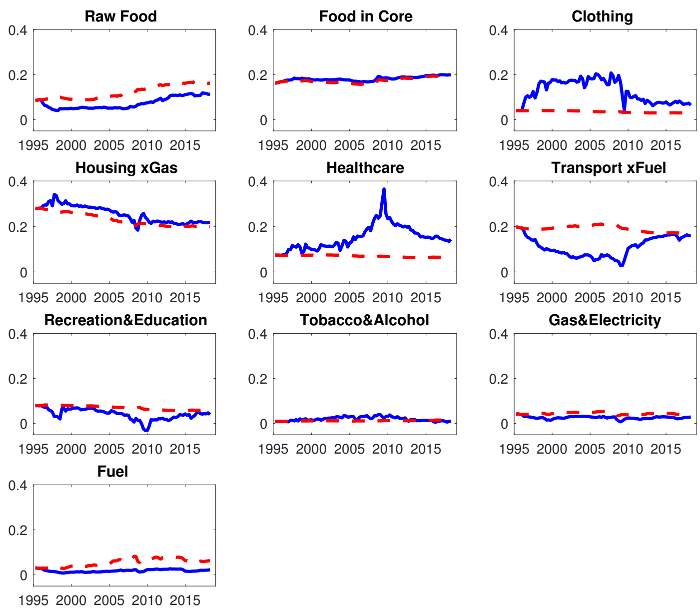


Note: Panels (a)-(b) display the standard deviation estimates of shocks to the permanent and transitory components that are common to all sectors respectively. Panel (c) displays the standard deviation estimates of outliers to the common transitory component of inflation. All estimates are full-sample posterior mean estimates based on applying the MUCSVO to data on 10 disaggregated sectoral inflation series.

that high persistence in the pre 2000 and post 2010 periods occurred for different reasons. In the pre 2000 period, persistence was high from volatile permanent shocks because of the lack of an explicit central bank inflation target. However, since 2010, persistence increased due to the substantial decline in noisy fluctuations around a stable target[10]. This is consistent with the findings of Stock and Watson (2007) for the US, except that the sharp decline in the variability of permanent shocks for the US occurred earlier during the Great Moderation in the mid 1980s.

Stock and Watson (2016) apply this same idea of persistence as related to the signal-to-noise ratio to determine the contribution of each sector to the overall estimate of the MUCSVO trend. More specifically, sectors with high persistence, or high signal-to-noise ratios, receive higher weight in the trend. We follow the approach of Stock and Watson (2016) compute these implied contributions and plot them against its actual expenditure share in Figure 8 (see Appendix C for a description of how these weights are calculated). When contrasted against its expenditure share, we can analyze whether each sector is getting more or less weight in the MUCSVO trend than it does in CPI-all.

Figure 8: Time-varying Weights for the Ten Component MUCSVO Trend and Expenditure Shares



Note: The solid line is the approximate weights on each of the ten inflation components in the MUCSVO trend estimate. The dashed line is its corresponding expenditure share.

[10]According to Panel (e) of Figures B1-B10 of Appendix B, the substantial decline in temporary shocks that occurred in 2010 were largely driven by the transportation excluding fuel, healthcare and raw food sectors.

A quick glance at Figure 8 reveals that the importance of allowing for time-variation in the sectoral weights of the MUCSVO model cannot be understated, as half of all sectoral weights show significant time-variation despite their expenditure shares being relatively constant. Upon closer inspection, the implied weights and actual expenditure share weights differ the most for clothing, healthcare and transportation excluding fuel sectors. Despite having a relatively low expenditure shares in CPI-all, Panel (e) of Figure B3 in Appendix B shows that the clothing sector receives more weight in the MUCSVO trend in the pre 2010 period because the volatility of its transitory shocks ($\sigma_{\varepsilon,i,t}$) were lower than the estimates of $\sigma_{\varepsilon,i,t}$ in other sectors. Next, while the estimated weight for the healthcare sector was comparable to its actual expenditure share in the pre 2005 period, it gained dominance in the period thereafter. According to Panel (e) of Figure B5, this can be explained by its substantial decline in $\sigma_{\varepsilon,i,t}$ coupled with the increase in magnitude of the factor loading on the transitory component which took place in the mid 2000s (see Panel (c)). Last, for the transportation excluding fuel sector, the sectoral weight was comparable to its expenditure share in the post 2010 period, but was lower during 1997-2010. Based on Panel (e) of Figure B6, this result is not surprising given the volatile transitory shocks affecting this sector during the pre 2010 period.

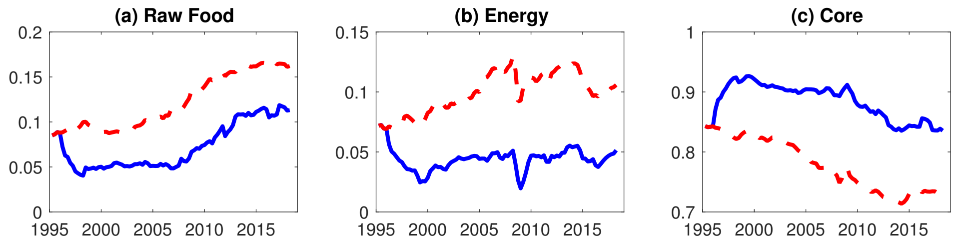
Three Sector Results

Traditional core inflation measures typically exclude raw food and energy sectors due to high volatility in these components. A quick glance at $\sigma_{\varepsilon,i,t}$ in Panel (c) of Figures B1, B9 and B10 in Appendix B makes this evident. The fuel sector exhibits the highest degree of volatility in the transitory component, while the gas and electricity sector contains many outliers. Transitory shocks to the raw food sector is also volatile to a considerable degree.

Interestingly, upon closer inspection of Figure 8, the filtered weights for these sectors are not exactly zero, implying that they should not be excluded from measures of trend inflation altogether. In other words, these sectors contain persistence that can serve as useful indicators for estimates of the overall trend, and this information should not be overlooked particularly because of the substantive roles that these sectors play in Thailand's consumer price basket.

To gain a better understanding about the role of food and energy prices in the MUCSVO trend, Figure 9 groups the results from Figure 8 into three broad sectors. Here, the raw food sector remains the same, both the gas and electricity and fuel components are combined as an energy component, and the remaining sectors make up the core component.

Figure 9: Time-Varying Weights for Food, Energy and Core Components and Expenditure Share



Note: The solid line is the approximate weights on each of the three components and the dashed line is its corresponding expenditure share.

First examining the approximate weight on the raw food sector, the filtered weight gradually increases from 5 percent in the post Great Recession period, reaching a level that exceed 10 percent by the end of the sample. While the rising expenditure share of actual raw food items could be part of this result, according to estimates of $\sigma_{\varepsilon,i,t}$ in Panel (e) of Figure B1, the food sector could have also become more important in the MUCSVO trend due to the fall in the volatility of its transitory sector-specific component since 2010. The finding that the raw food sector has become more persistent during the more recent period and should receive more weight in the overall trend inflation measure is similar to the findings for the US (Stock and Watson, 2016).

In contrast, the approximate weight on the energy component as shown in Figure 9 appears relatively stable, despite the gradual rise in its expenditure share. Only a slight dip in its weight occurred during 2008-2009, which according to Panels (f) of Figures B9 and B10, was due to large outliers in the transitory component. The approximate weight for the energy sector is lower than the food component, but is nonetheless non-zero, implying that persistent movements in these components contain useful information towards measurement of the overall CPI trend.

Finally, the last plot in Figure 9 shows the approximate weight for all remaining CPI sectors excluding food and energy components. The influence of core components on the estimated MUCSVO trend declines with its expenditure share but not as quickly. For the most recent period, the weight of core components in the filtered trend is around 85 percent, while food and energy takes up the remaining 15 percent share. In sum, the results in this section show that while traditional core inflation measures places no weight on food and energy price components, the MUCSVO recognizes that persistent movements from these sectors actually 'pass-through' to the overall trend with a non-negligible weight of 15 percent, which is approximately half of their expenditure shares.

2.2.4 Importance of Trend Inflation

One important finding in the previous section is that the variability of the permanent component in headline CPI inflation declined dramatically since the year 2000. Given the relative stability of the trend especially when compared to the cycle during the past decade, is the trend component still important towards explaining overall movements in headline inflation? How much of the fluctuations in headline inflation can be ascribed to movements in the trend versus the cycle?

We answer this question by calculating the proportion of variation in one-year-ahead inflation that is described by movements in the trend. We pick the one-year-ahead horizon because it is the time period in which the inflation target of the BOT is defined, and is computed as $\bar{\pi}_{t:t+3} = \frac{1}{T}(\pi_t + \pi_{t+1} + \pi_{t+2} + \pi_{t+3})$. Over the entire sample, the first row of Table 4 indicates that about half of the variation in headline inflation within the one-year-horizon can be explained simply by the trend, which is sizable. This proportion is slightly higher in the pre 2000 and post 2010 periods, which is not surprising given that the signal to noise ratio is higher during these periods. In the second row, we compute the percentage of forecast error explained by shocks to the trend. As shown, in any given period, news in the trend only accounts for a very small percentage of the overall forecast error from the model. Taken together, these calculations suggest that although it appears that in any given period most of the news in inflation relates to noisy innovations around the trend, over longer time horizons a sizable share of the variation in inflation is explained by movements in the low-frequency trend.

Table 4: Importance of Trend Inflation

	Full Sample	1995Q2-1999Q4	2000Q1-2009Q4	2010Q1-2018Q2
One-year Inflation Variation	0.49	0.69	0.19	0.53
Forecast Error Share	0.05	0.05	0.04	0.07

Note: The first row calculates the percent of one-year-ahead inflation variations explained by the trend: $\frac{\sum_{t=1}^{T}(\tau_t - \frac{1}{T}\sum_{t=1}^{T}\bar{\pi}_{t:t+3})^2}{\sum_{t=1}^{T}(\bar{\pi}_{t:t+3} - \frac{1}{T}\sum_{t=1}^{T}\bar{\pi}_{t:t+3})^2}$ where $\bar{\pi}_{t:t+3} = \frac{1}{T}\pi_t + \pi_{t+1} + \pi_{t+2} + \pi_{t+3}$, and the second row is the average percentage of forecast error explained by shocks to the trend: $\frac{1}{T}\sum_{t=1}^{T}\frac{\sigma^2_{\eta,t}}{\sigma^2_{\eta,t} + \sigma^2_{\epsilon,t}}$.

2.3 Pure and Relative Inflation

Theoretical models for inflation often assume a single consumption good in a world, which makes describing the price changes of consumption becomes a trivial manner. In reality however, there are many goods and prices, thus there is an important distinction between price changes that affect all goods in equal proportions (pure or absolute price changes), and price changes that only happen in some goods relative to others (relative price changes). In an economic model, pure and relative price changes stem from different fundamental shocks. An exogenous but anticipated increase in the money supply that leads all price-setters to raise their prices in the same proportion, for example, leads to pure inflation. An unanticipated increase in money to which some firms respond but others do not on the other hand, leads to relative price changes.

Strictly speaking, a pure disturbance to inflation stems from changes in supply and demand conditions that leaves the production possibilities frontier and real output unchanged. It is termed pure inflation because it measures a change in the unit of account, that is, it measures how much the cost of an arbitrary basket of goods would change, no matter how it is weighted. Since the pure inflation component are rid of relative price shocks, it is the component in which economists believe that monetary policy should have the most control over in the long run, since policymakers do not have control over the drivers of most relative price changes such as global commodity prices. Also, since relative price movements are often transitory, the pure component of inflation is often associated with the concept of core or trend inflation.

Relative price changes on the other hand, is not inflation. The classical argument is that, when the prices of some goods rise more than others as a result of a relative-price shock, this leaves consumers with less income to buy other goods, so their prices decline, and the aggregate price level is unchanged. However, this rests on the assumption that nominal prices are perfectly flexible. In modern models for inflation and monetary policy, relative price changes can affect the price level in the short-run. Relative price changes thus lie behind the real effects of inflation and are the reason why central banks need to tradeoff between stabilizing inflation versus stabilizing real activity. This short-run inflation-output tradeoff is typically captured by the famous Phillips curve relation.

In this section, we utilize the richness of price movements across hundreds of goods and services that underlie the CPI to help identify three components of inflation which are pure inflation, relative price inflation, and a residual term which captures remaining price changes at the idiosyncratic level. Note that the latter component also represent relative price changes but the distinction is the first two components are driven by aggregate shocks whereas the idiosyncratic component only captures the effects of shocks at the goods level. Doing so will not only help advance our understanding about the source of shocks driving overall inflation rate movements, but will also provide us with an alternative measure of the underlying trend.

2.3.1 Model Specification

Following the methodology of Reis and Watson (2010), the comovements of N price series can be modeled according to the following factor model[11]:

$$\pi_t = \Lambda F_t + u_t \tag{9}$$

where π_t is an $N \times 1$ vector of inflation series for N goods, of which their common sources of variations in prices are summarized by the k factors in F_t. The $N \times k$ vector Λ contains the factor loadings that determine how the price of each individual good responds to these shocks. Finally, the $N \times 1$ vector u_t is the residual that captures goods-specific relative price variability associated with idiosyncratic events.

Given that F_t captures information on the aggregate shocks that macroeconomists care about, it can be decomposed further:

$$\Lambda F_t = \mathbf{1} a_t + \Gamma R_t \tag{10}$$

where a_t is the absolute price component that captures price changes that are common and equiproportional to all goods. As such, a_t can be driven by, for example, monetary policy, aggregate productivity, or government spending. As absolute price changes affect all prices in the same proportion, $\mathbf{1}$ is a $N \times 1$ vector of ones. R_t on the other hand, are price changes that affect many but not necessarily all sectors which could stem from changes in energy prices, weather events, or exchange rate fluctuations. R_t can have more than one factor and has size denoted by $k-1$. Since relative price changes affect prices in different sectors disproportionately, their affects on price changes are captured by the $N \times (k-1)$ matrix Γ.

As highlighted by Reis and Watson (2010), one important issue in the decomposition is that a_t and R_t are not separately identified, making the decomposition in (10) not unique[12]. To overcome this problem, the authors focus on two independent components instead:

$$v_t = a_t - E[a_t|\{R_t\}_{t=1}^{T}] \tag{11}$$

$$\rho_t = E[F_t|\{R_t\}_{t=1}^{T}] \tag{12}$$

[11]Bryan and Cecchetti (1994) also estimate a dynamic factor model to separate absolute from relative price changes. Boivin et al. (2009) also develops a dynamic factor model for inflation but only tries to seperate the components of inflation that are driven by aggregate versus sector-specific shocks, with no distinction between the pure and relative price components.

[12]To see this, for any arbitrary $(k-1)\times 1$ vector α, we have $\mathbf{1}a_t + \Gamma R_t = \mathbf{1}(a_t + \alpha' R_t) + (\Gamma - \mathbf{1}\alpha')R_t$, so that (a_t, R_t) cannot be distinguished from $(a_t + \alpha' R_t)R_t$. Intuitively, it may not be possible to distinguish absolute change in prices from a change in 'average relative prices'.

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.

2.3.2 Data Description and Estimation Methodology

We use quarterly price series that are constructed from the average of the monthly chained price index of goods and services that are used to compute CPI inflation. Inflation at an annual rate for good i is computed according to $\pi_{it} = 400 \times ln(P_{it}/P_{it-1})$ where P_{it} is the price index for the quarter[13]. The sample spans 2002Q2-2018Q2 and is obtained from the Thai Ministry of Commerce. Figure 10 provides a glimpse of the percentage change in the price levels of selected goods and services in Thailand over the 2006-2017 period. Compared to the overall price level of the CPI which only increased by 26 percent, food at home increased by 84 percent while electronic products such as televisions, communication equipments and personal computers have seen continuous declines. Overall, the main takeaway is that the difference between the prices of various goods and services in an economy can be quite striking.

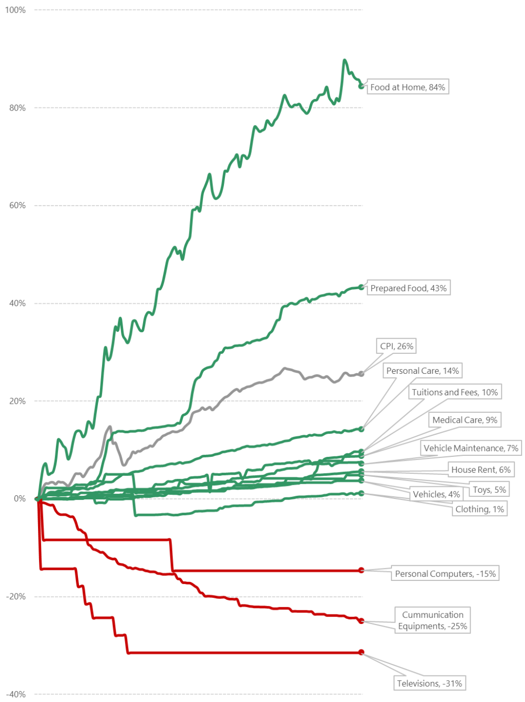
In our dataset, we have a total of 225 goods and services[14]. These are goods defined at the broad level and includes for example, rice, soy sauce, shampoo, leather belt, refrigerator, haircut services, airfare, diesel, and cigarettes. Several of these price series contain very few price changes making it problematic for estimation, thus we exclude 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[15]. Also, to remove collinearity, we remove series j if there was another series i that are highly correlated ($Cor(\pi_{it}, \pi_{jt})$ >0.99 and $Cor(\Delta\pi_{it}, \Delta\pi_{jt})$ >0.99), which ultimately leaves us with

[13] The use of quarterly data means that the relative price factors capture only those relative price changes that persist for at least one quarter. Most macroeconomic models analyze aggregate shocks based on quarterly data so we opt for quarterly instead of monthly data.

[14] 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 include in our sample both pre and post inflation targeting regimes.

[15] We also experimented with different criteria and our results appear robust to alternative reasonable specifications.

Figure 10: Percent Change in Price Levels by Categories of Goods and Services in the Consumer Price Index



Note: Figure 10 of Apaitan et al. (2018). Compiled by the authors using micro-level price series over 2006-2017.

179 price series. Finally, large outliers were evident in some of the series and thus we follow Reis and Watson (2010) and replace them with centered seven-quarter local medians.

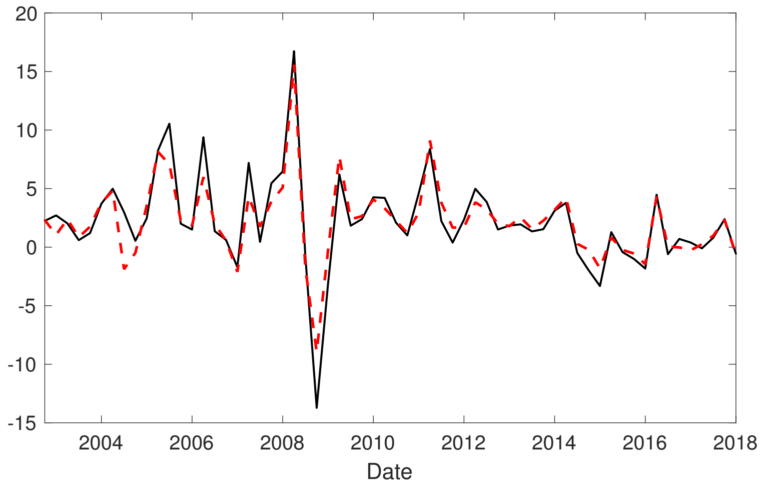
The first panel of Table 5 describes the sample coverage of our data grouped into 10 categories. Our sample covers approximately 65 percent of the CPI. Coverage is lacking in some categories but these typically have low weight in the CPI except for transportation excluding fuel. However, when viewed across economic sectors, our dataset provide decent coverage (see Table 6). To check that our dataset can broadly provide a good representation of CPI inflation, we plot the constructed inflation rate from our dataset and compare it to actual CPI inflation in Figure 11. With the exception of only a few periods, the constructed price index from our dataset tracks overall inflation well.

Table 5: 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 share and sample share (in percent) of the CPI for each group in percent, calculated using 2011 expenditure share weights obtained from the Ministry of Commerce. The number of goods and services that fall into each group are in parentheses.

Figure 11: Constructed and Actual CPI Inflation

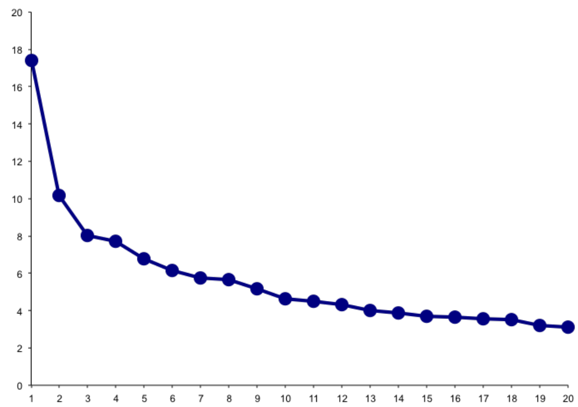


Note: Plotted is quarter-on-quarter actual CPI inflation (solid black line) compared to the constructed inflation series from our dataset with 179 goods and services (dashed red line) based on year 2011 expenditure share weights. Source: Thai Ministry of Commerce, authors' calculations.

Prior to estimation of the model, we need to determine the number of factors k that is suitable to the dataset. 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 the number of factors, 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 12, and while it is clear that there is one large eigenvalue, it is less clear whether 2 or 3 total factors should be employed. Last, we calculate the fraction of variance explained by unrestricted factor models with 1-4 factors for the 179 inflation series. In Figure 13, 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 (a_t and 2 relative price factors in R_t) to be on the cautious side.

Figure 12: Eigenvalues of the Correlation matrix



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

Once k is defined, we set up the empirical model for estimation. Equations (9)-(12) can be summarized by the following specification:

$$\pi_t = 1v_t + \Theta\rho_t + u_t, \tag{13}$$

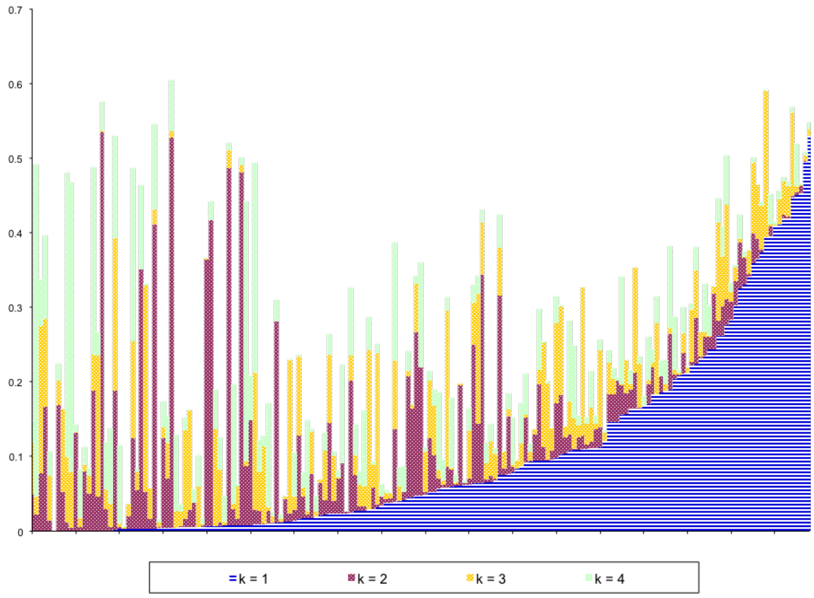
where estimation of the model follows three steps. First, it requires making parametric assumptions on the latent components (a_t, R_t, u_{it}), then estimating the parameters of the model via maximum likelihood, and finally computing estimates of the factors using signal extraction formulae.

For the first step, we specify the dynamics of the latent components as the following unobserved components model:

$$\pi_{it} = a_t + \gamma_i R_t + u_{it} \tag{14}$$

where the latent components (a_t, R_t) follow a vector autoregression and u_{it} follows an autoregressive process as follows:

Figure 13: 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 $i = 1, .., 197$ goods.

$$\phi(L) \begin{pmatrix} a_t \\ R_t \end{pmatrix} = \epsilon_t \tag{15}$$

$$\beta_i(L)u_{it} = c_i + e_{it}. \tag{16}$$

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

Next, 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 use an expectation-maximization (EM) algorithm computed by Kalman smoothing in the E-step and linear regression for the M-step. Once we obtain the parameters of the model, the final step is to compute factors using signal extraction. This involves imposing certain restrictions such as those defined by Eqs. (11)-(12). In order to do so, we calculate the expectation of absolute price changes conditional on relative price changes by jointly modeling the dynamics of a_t and R_t as a VAR as specified by Eqs. (7)-(9) which is estimated by Gaussian MLE. Once $\phi(L)$ is obtained, we compute the implied projection in Eqs. (11)-(12) to obtain the pure and relative price indices. Readers are referred to the Web Appendix of Reis and Watson (2010) for more details on estimation.

2.3.3 Empirical Results

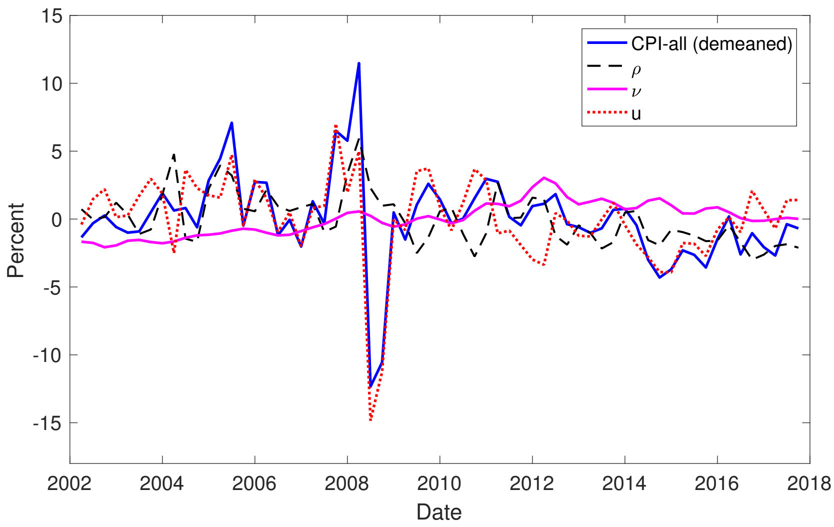
Figure 14 shows the decomposition of historical CPI inflation into pure, relative and idiosyncratic components using the price series of 179 individual goods and services. Overall, the trajectory of the pure inflation component (v_t) is smooth and more or less tracks the sample mean of headline CPI inflation. Pure inflation was slightly lower than the sample mean of headline inflation in the pre 2010 period but rose slightly higher since then. Currently, it remains roughly at the sample mean of headline CPI inflation. Compared to Figure 5, estimated pure inflation moves in line with trend inflation from the MUCSVO model, with some minor differences. While both measures increased slightly during the year 2012 and persistently declined since then, the MUCSVO trend also increased during the Great Recession, whereas pure inflation remained relatively stable. These differences come from the way the underlying long-run rate is defined but also from the pure inflation component being extracted from the cross-sectional movements of a wider variety of goods and services.

According to Figure 14, the relative price components (ρ_t and u_t) play a substantial role in explaining within-quarter inflation fluctuations. The large swings in inflation during the Great Recession can be attributed almost entirely to relative price fluctuations, although the idiosyncratic component appears to play a larger role. In the pre 2010 period, the relative price components seem to put upward pressure on headline inflation while the pure inflation component was low, while in recent periods, favorable relative price shocks seemed to be accounting for what is now seen as surprisingly persistent and low inflation in spite of loose monetary policy conditions.

Next, we formally investigate the degree of variability in inflation as explained by the three factors. Table 6 reports both simple standard deviation measures as well as the fraction of the canonical R^2 measures that are averaged over all frequencies and just business-cycle frequencies[16]. According to the R^2 measures, we find that 11 percent of movements in aggregate headline inflation are accounted for by pure inflation, 57 percent is accounted for by the relative price index and the remainder is accounted for by the idiosyncratic shocks. This implies that fluctuations of macroeconomic wide aggregate shocks explains roughly 68 percent of all fluctuation in headline inflation at all frequencies which is substantial. This proportion

[16] We follow the approach of Reis and Watson (2010) to compute these frequency domain versions of variance decompositions or R^2's (squared coherences). As described in more detail in their paper, it allows us to 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 such as business cycle frequencies.

Figure 14: Headline CPI Inflation (Demeaned) Decomposition



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

is similar at business cycle frequencies[17].

Table 6: 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	ρ_t	v_t
Aggregate Inflation Rates								
CPI Inflation	3.91	1.15	2.97	3.10	0.57	0.11	0.56	0.09
Disaggregated Series								
25th Percentile	1.57	1.15	0.88	2.02	0.15	0.07	0.10	0.02
Median	2.98	1.15	1.47	4.13	0.21	0.10	0.23	0.04
75th Percentile	7.71	1.15	3.64	9.85	0.30	0.15	0.46	0.08
Average	13.04	1.15	6.34	12.59	0.23	0.12	0.29	0.06

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.

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 role of the aggregate component is around 70 percent of overall inflation fluctuations at all frequencies and 90 percent at business cycle frequencies. By estimating common components of five UK inflation series with principal components, Forbes et al. (2017) finds that up to 72 percent of the variation in the five inflation series can be explained by just one shared factor, highlighting the importance of aggregate shocks

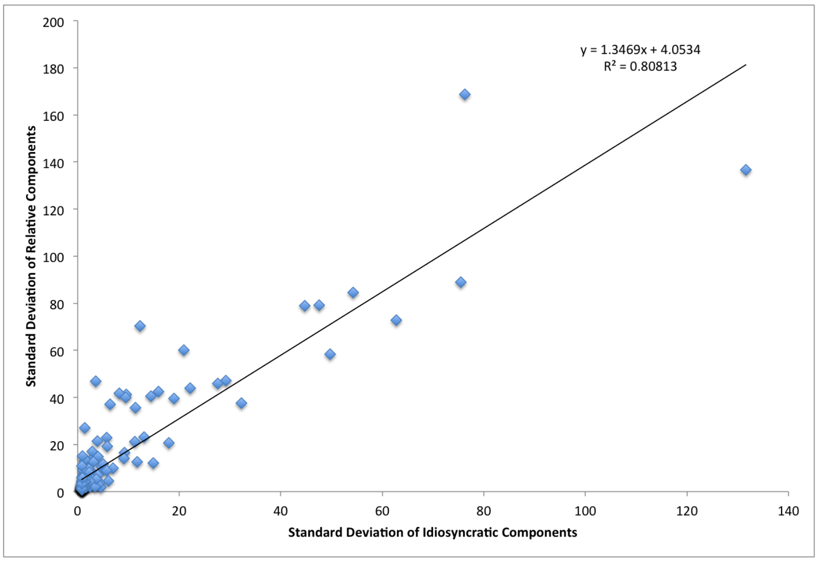
[17] We expected the portion of variation explained to increase at business cycle frequencies given that the relative price component plays a large role. However, note that these R^2 estimates are not exact and are estimated with some error.

in explaining overall inflation dynamics. 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). Last, we emphasize that the relative price index contributes to a larger proportion of the aggregate shocks that drive inflation fluctuations. The 5-1 ratio in the relative variances of relative price index and pure inflation may be suggesting that a weighted average of the variance of anticipated shocks is significantly less volatile than an average of the unanticipated shocks.

In the second panel of Table 6, we report the distribution of variance and variance decompositions for the 179 inflation rates. The picture is quite different from the aggregate analysis. First, we note that the disaggregated inflation rates are much more volatile than aggregate series with a standard deviation that is on average (across sectors) almost three times as large as the aggregate headline inflation. There is also considerable heterogeneity across goods in terms of inflation volatility, where much of this volatility is driven by goods in food and energy sectors. Examining the R^2 measures, much of the volatility at the disaggregated level is driven by idiosyncratic disturbances. Looking at the twenty-fifth and seventy-fifth quartiles, the relative price index accounts for between 10 to 46 percent of the business cycle variability of individual inflation rates, with pure inflation accounting for only 2 to 8 percent. On average, these aggregate components together only explain 35 percent of all inflation rate fluctuations, which is only half of what was reported for headline inflation. For the US, the results are similar. For example, based on a factor-augmented vector autoregression (FAVAR) which utilizes large macroeconomic series to help disentangle the aggregate and idiosyncratic shocks, Boivin et al. (2009) finds that idiosyncratic price movements drive a sizable share of 85 percent in inflation rate fluctuations at the goods level. Finally, since we found that aggregate shocks are the key drivers of headline CPI inflation, this suggests that noise at the individual goods level eventually cancels each other out, which is why inflation at the aggregate level ends up being less volatile than disaggregated inflation series at the goods level.

Since most of the fluctuation in prices at the goods level are driven by the idiosyncratic component, we investigate further what can explain fluctuations in u_{it}. An interesting observation that emerges is that relative price fluctuations at the idiosyncratic level is strongly positively correlated with those at the aggregate level (see Figure 15). This suggests that goods with volatile idiosyncratic shocks also respond strongly to macroeconomic shocks, which could be the case if frequent price adjustments associated with idiosyncratic volatility are also used as an opportunity to adjust to changes in the macroeconomic environment. However, we are aware that besides capturing structural disturbances in the individual good, by construction measurement error in the disaggregated price series may end up being captured by the idiosyncratic component u_{it}[18]. While it is difficult to rid this sampling error from overall movements in u_{it}, we have some indirect evidence that volatile movements in u_{it} are reflecting actual price changes to a considerable degree. According to Figure 16, there is a strong positive correlation between fluctuations in the idiosyncratic component for a particular good against its corresponding frequency of price change measure as constructed from micro-level data by Apaitan et al. (2018). Also coupled with evidence that the variability in the idiosyncratic component follows those of the aggregate relative price component, we believe that fluctuations in u_{it} is merely not the result of measurement error.

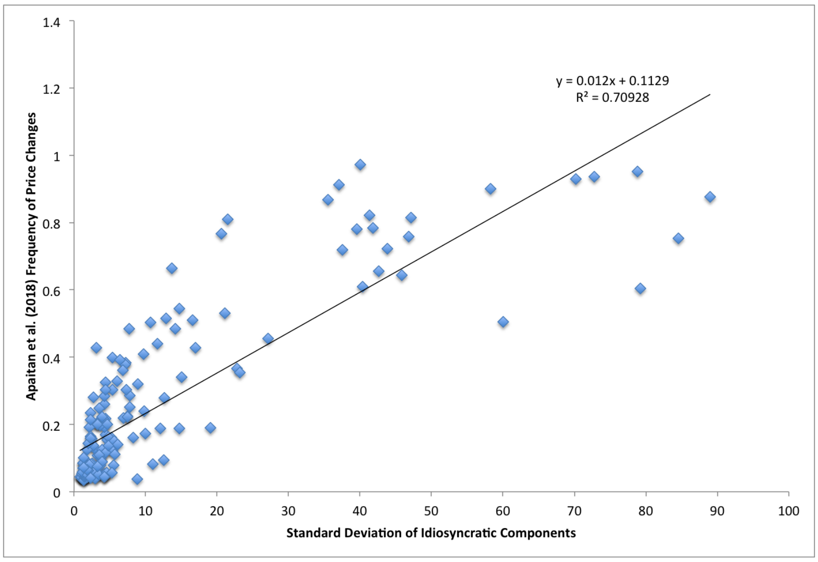
Figure 15: Volatility of Aggregate and Idiosyncratic Components at the Disaggregated Level



Note: Standard deviations (in percent) are shown for relative and idiosyncratic components of disaggregated inflation rates. Solid line represents the linear regression line.

[18] Measurement error can arise because in each month, the Ministry of Commerce collects prices from only a subsample of all retail prices, and not from all retail prices.

Figure 16: Frequency of Price Changes and Volatility of Idiosyncratic Components at the Disaggregated Level



Note: Plotted above are the standard deviations (in percent) of the idiosyncratic components and their corresponding frequency of price changes as calculated by Apaitan et al. (2018). Solid line represents the linear regression line. Two outliers for the idiosyncratic component that had standard deviations greater than 100 percent were removed.

Finally, we use the estimated inflation components to provide insights on inflation persistence. Table 7 computes the degree of inflation persistence for both headline CPI inflation and its components at aggregate and disaggregated levels. On average, inflation at the disaggregated level displays notably less persistence than the aggregated series, although there is some degree of heterogeneity. This is consistent with the findings of Clark (2006), Altissimo et al. (2007) and Boivin et al. (2009) who find that individual rates of inflation are on average more volatile and less persistent than the aggregate inflation rate for the US and Europe, and display widespread heterogeneity across categories. By disentangling and estimating the response of disaggregated prices to common and idiosyncratic shocks, Boivin et al. (2009) argue that the finding of high persistence at the aggregate level but flexible price changes at the disaggregate level is because disaggregated prices respond sluggishly to common macroeconomic shocks (especially monetary policy shocks) but quickly to sector-specific ones. As supporting evidence to their argument, we find that the component of the individual price series that are driven by the aggregate factors (v_t and ρ_t) are highly persistent, whereas the idiosyncratic component is fairly flexible.

Last, we ask what is the relation between persistence and inflation variability? Bils and Klenow (2004) argue that goods that display relatively low volatility should

Table 7: Persistence of Inflation and its Components

	Persistence			
	π_t	v_t	ρ_t	u_t
Aggregate Inflation Rates				
CPI Inflation	0.30	0.96	0.64	0.15
Disaggregated Series				
25th Percentile	0.07	0.96	0.43	-0.02
Median	0.28	0.96	0.57	0.23
75th Percentile	0.42	0.96	0.63	0.44
Average	0.12	0.96	0.49	0.11

Note: Inflation persistence is calculated as the sum of coefficients on all lags of an autoregressive process of order 4.

have high persistence. This is because a good with higher price stickiness reduces the impact of exogenous shocks on current inflation, increasing inflation persistence. For the US, Bils and Klenow (2004) and Boivin et al. (2009) find only a mild negative correlation between inflation volatility and persistence, although the latter study reports a higher negative correlation of about 0.45 if only the common component of inflation (compared to our study, this is the pure and relative components combined) is taken into consideration. For our study, we find that the correlation between volatility and persistence for disaggregated price series is strong, whether considered for the total inflation series or when decomposed into relative and idiosyncratic components. The correlation is -0.70, -0.65 and -0.63 respectively.

Components of Inflation and Other Observables

A key input to monetary policy is to understand the source of changes in aggregate price movements. Table 8 examines the canonical R^2 correlation between the relative price index with several conventional measures. In the first two rows, it appears that food and energy prices can explain about 40 percent of relative price movements at all frequencies. This figure is high, but still falls short of capturing all of the variability in relative prices. This share increases at business cycle frequencies for food, but surprisingly declines for energy, which may suggest that a sizable component of relative price changes in energy are being passed through to the trend. Similar to Reis and Watson (2010) whom find that prices in energy only account for about one third of all relative price shocks hitting the economy at business cycle frequencies, we find that for Thailand, this proportion is even lower at one fifth[19]. Even when combining food and energy, together these sectors can only explain about 60 to 70 percent of all relatively price shocks, leaving about a third of the movements to be explained by other relative price factors. These could

[19] We also examine the split sample in 2010 to investigate whether the influence of energy price shocks increased during the recent period, but we found that the full sample results are relatively robust.

be the relative prices of services, durables and imports, and as expected, we find that they can explain for a decent share of movements in ρ_t. Together, the five dimensional index of relative prices (food, energy, services, durables, imports) can account for almost all movements in relative price movements in Thailand. Finally, given that Thailand is a small open economy, we also examine the role of the nominal exchange rate towards driving relative price changes. We find that its role is quite small compared to other relative prices considered.

Table 8: 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)
USDTHB	0.16 (0.07)	0.21 (0.15)
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 overall 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. Observed relative price series are defined as relative to headline CPI inflation. The term spread is calculated as the difference between 10 year and 3 month nominal bonds.

In the bottom panel, we investigate the correlation of pure inflation with measures of monetary policy, the policy rate, and the term spread. Theoretically, money growth and inflation are known to be tightly linked in the long-run (Friedman and Schwartz, 1963). Fisher (1930) also established that there is a strong link between nominal interest rates and inflation. The term spread or the difference between long and short term nominal rates is often viewed as an indicator of the stance of monetary policy (Estrella and Mishkin, 1997) and is often used for forecasting future inflation (Fama, 1990; Day and Lange, 2997; Kozicki, 1998). Empirically, we find that the link between inflation and all these measures are quite low but non-zero at all frequencies. The smaller magnitude is not surprising since links between money growth and inflation are typically unstable and low (Stock and Watson, 1999) as well as for interest rates (Mishkin, 1992). As discussed in Blough (1994) the link between the term spread and inflation is also indirect, thus information content in the term spread for inflation may be confounded with market expectations about future term short rates and variation in liquidity or term premiums. At business cycle frequencies, the relationship between these measures and pure inflation decline to zero, confirming the notion of pure inflation as a long-term construct.

2.3.4 The Phillips Correlation

In the stylized facts section of this paper, we established that for Thailand, the slope of the Phillips curve which captures the short-run relationship between inflation and output has become muted in recent years. This finding is consistent with evidences for other countries, and have led researchers to question the validity of the Phillips curve relation in modern economies with low inflation. 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).

Based on a new line of research, some authors suggest 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. In this section, we build on this line of research and examine whether it is necessary to decompose inflation into its components to appropriately search for the Phillips curve relation.

We examine the Phillips correlation using measures of squared coherence. As shown in Panel A of Table 9, at business cycle frequencies the R^2 measure between inflation and real GDP is 0.23 but is only marginally significant at the 10 percent level. Considering the correlation of inflation with other components of real GDP, the relationship is stronger for investment and strongest for exports and imports, but is weak and not statistically significant for consumption and domestic demand. The finding that inflation comoves strongly with the global component of real economic activity and less 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 finds that since the year 2000, the global output gap has replaced the role of the domestic output gap in driving short-run inflation rate movements in Thailand.

Next, we examine the Phillips curve relation with the estimated pure, relative, and idiosyncratic components from the dynamic factor model. In Panel B, we only examine the correlation between real variables and the aggregate components of inflation (v_t and ρ_t). Interestingly, the R^2 measure more than doubles for real GDP at business cycle frequencies. The correlation for other real components also increase although to a lesser extent. Nevertheless, this finding shows that excluding idiosyncratic price fluctuations makes the inflation-output relation much more pronounced, implying that noise in inflation can indeed be masking key economic relationships.

Table 9: Fraction of Variability of Real Variables Associated with CPI Inflation

	Frequencies	
Real Variable	All	B-Cycle
Panel A. Headline CPI Inflation		
GDP	0.21 (0.10)	0.23 (0.13)
Consumption	0.06 (0.03)	0.11 (0.09)
Investment	0.31 (0.11)	0.38 (0.15)
Domestic Demand	0.16 (0.10)	0.23 (0.13)
Exports	0.26 (0.09)	0.46 (0.12)
Imports	0.44 (0.10)	0.44 (0.14)
Panel B. 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 C. 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)
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)

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.

To examine which aggregate components are responsible for driving the Phillips correlation, Panel C only examines the Phillips relation with the pure inflation component. Overall, the correlation is negligible and not statistically significant. This finding implies that when there are changes in pure inflation due to all prices increasing in the same proportion independent of relative price changes, nothing happens to quantities which is consistent with the notion of money neutrality. On the other hand, Panel D shows that when we control for the relative price index, the correlation between CPI inflation and the real activity variables in large part disappears, implying that the relative price component is responsible for the short-run inflation-output tradeoff. This is consistent with the theory of sticky-price models that explains how monetary policy affects inflation in the short-run. An intervention by monetary policy will cause some firms to change prices while others do not, given that prices are not fully flexible. These changes in relative prices in turn affect consumption and production plans, causing a change in real output. In sum, our findings in this section imply that the Phillips curve has not completely disappeared during recent periods, but has been hiding in the component of inflation that reflects only the common relative changes in prices.

3 Decoding Inflation with Online Data

E-commerce is a rapidly growing segment of the retail market in many countries including Thailand. Currently, Internet retail in Thailand is still in its nascent stages. In 2017, the National Statistics Office of Thailand reported that only 10.9% of Thai users purchase goods online. However, according to the latest report of the Electronic Transactions Development Agency (ETDA), the market value of e-commerce in Thailand ranked the highest in Southeast Asia at US$23 billion with an 8.6% year on year growth rate. Therefore, although the presence of Internet retail may not have a significant impact on aggregate inflation dynamics in Thailand as of yet, the e-commerce market is only bound to grow and it is important that policymakers attempt to understand how the pricing behavior of online goods will evolve to prepare them for the not-so-distant future when e-commerce becomes a major force of retail in Thailand.

The general consensus among economists is that the power of e-commerce has the potential to deliver long-lasting effects on inflation. E-commerce markets provides efficiency unparalleled to traditional markets and has the ability to profoundly affect both the shopping behavior of consumers as well as the price-setting behavior of firms. On the consumer side, it lowers search costs as finding the best prices on the Internet becomes a costless and simple task which can be done within a matter of clicks. On the supplier side, firms can by-pass intermediaries and operate more efficiently due to lowered cost from the reduction or elimination of sales force and physical storefronts. As a result, many economists conjecture that the e-commerce market will have characteristics associated with those of perfect competition. This should then lead to lower overall level of prices due to profit margins that are slim, as well as lower price dispersion since homogenous goods on the Internet should approach the law of one price. Furthermore, as the physical cost of changing prices such as menu costs become more irrelevant in online markets, Internet retail should also make prices more flexible (see Gates, 1995; Brynjolfsson and Smith, 2000; Bakos, 2001; Goldfarb and Tucker, 2017).

We are interested in carrying out an empirical analysis to assess whether the characteristics of goods sold online in Thailand are consistent with what has been conjectured above. Closest in spirit to our analysis are studies by Lünnemann and Wintr (2011), Gorodnichenko and Talavera (2017), Gorodnichenko et al. (2018) and Cavallo (2018). These studies also use micro-level online prices to analyze the price-setting behavior of goods sold on the Internet[20]. However, they only focus on the experience of advanced economies. To our knowledge, this paper will be the first to study the price-setting characteristics of online goods for an emerging country.

Our analysis on the micro-level behavior of prices is also related to a longstanding literature that studies the price-setting characteristics of goods and services collected from brick-and-mortar stores that are used to construct national price indices such as the CPI. This includes Bils and Klenow (2004), Dhyne et al. (2005), Nakamura and Steinsson (2008) for advanced economies and Gouvea (2007), Medina et al. (2007) and Apaitan et al. (2018) for emerging countries. While these studies show that important micro-level price characteristics such as price rigidity can be quite different from their aggregate counterpart, one shortcoming to this literature is the lack of analysis on the genuine underlying determinants of price adjustments. Therefore, to the extent that the structural environment of Internet retailing is different from conventional retail outlets, we view that providing an analysis of online goods can also provide further insights on how the role of retail structures (eg. competition), price frictions (eg. menu costs), search costs for consumers (Benabou 1988, 1992) and costs of updating information (Mankiw and Reis 2002) may play a key role in explaining the price-setting behavior of firms.

3.1 Data Description

The dataset consists of a list of prices, time-stamped by their time and date of price change for millions of online products sold through multiple retail outlets in Thailand during July 2015 - June 2018 (35 months). This data is collected by Priceza, a leading price comparison site in Thailand[21]. Price comparison sites such as Priceza have become popular recently, as it is a convenient way for consumers to shop and secure the 'best' price on the Internet. This is because for any given product search, Priceza returns a listing of prices that different merchants charge for an identical product, all summarized onto one webpage. Each product on Priceza is

[20] Alternative issues related to inflation have been assessed using online prices range from attempting to quantify the degree of measurement bias in national inflation rates (Boivin et al., 2012; Cavallo and Rigobon, 2016; Goolsbee and Klenow, 2018); international relative prices and real exchange rate dynamics (see Cavallo et al., 2014; Simonovska, 2015 and Gorodnichenko and Talavera 2017); measurement of consumer search costs (Brynjolfsson et al., 2003), and whether the implementation of state and sales tax benefits can explain the success of e-retail (Ellison and Ellison, 2009).

[21] Founded in 2010, Priceza currently secures a 85% market share of price comparison sites in Thailand with 3.3 million visitors per month. Priceza also currently operates in Malaysia, the Philippines and Singapore. Other price comparison websites in Thailand include PricePrice and PricePanda.

identified at a highly detailed level which contains a unique specification of a brand, detailed product characteristic or model number. Priceza also gives information on the store which carries the product. In our analysis, we will refer to a specific product-store pair as an 'item'.

Figure 17 contains a plot of price trajectories for 12 items, which correspond to 4 selected products that are sold across 3 identical retail stores. The 4 selected products are listed in the database as Sony Headset MDR-ZX310AP, Samsung Galaxy J7 Pro (Gold), Mitsubishu Electric MS-GN18VF 18084BTU, and Casio Baby-G Women's White Resin Strap Watch BA-110-7A. We create the price trajectory for each item by converting the dates of price changes in our database into a time series[22]. First, looking across each row, we point out that each product may be listed at different times during the sample depending on when the merchant chooses to list the product for sale. Second, there is significant heterogeneity in the movement of prices for each item. While it is not surprising that the same store may choose to price the different products that they sell in different ways, what is striking is that for the same identical product, characteristics such as its price level, frequency of price change, as well as size of price changes can differ significantly across stores. Finally, the price plots make evident that price changes of online goods can in fact be quite frequent. Since we have high-frequency data on the timing of price changes, we find that as much as 25.3 percent of all price changes in the sample occur intraday.

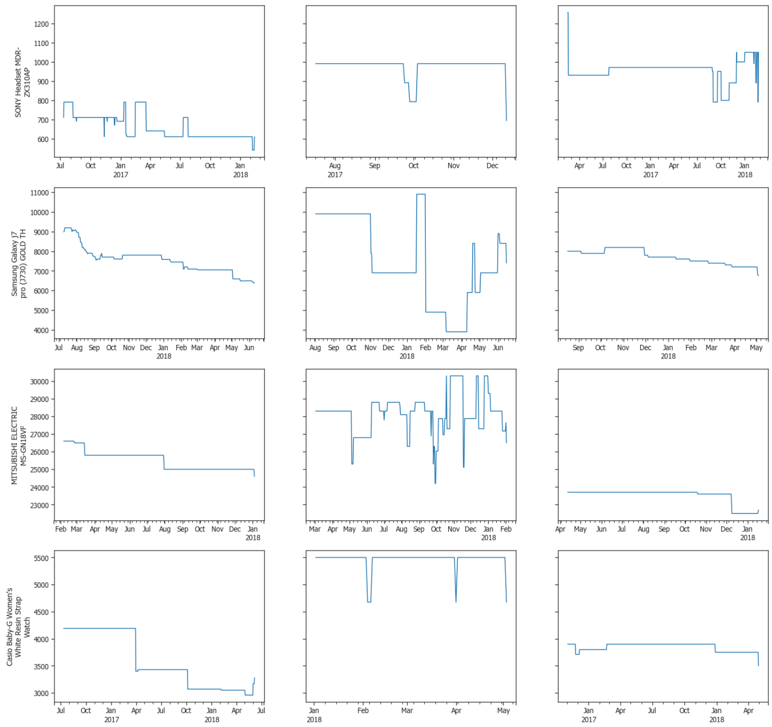
Priceza groups online products into 9 categories. To get a sense of the size of each category, we scraped the Priceza website on 17 July 2018 and counted the number of products that belong to each category. Among 6,995,816 goods, clothing and jewelry covers the largest share of the website, followed by health and beauty, and electronic goods such as cameras and phones (see Figure 18)[23]. Unfortunately for the first two categories, we cannot classify items into homogenous product groups because different merchants assign very different names to otherwise identical products. An exception is the watch subcategory in clothing and jewelry,

[22] The first price change for each item in the database marks the date of entry, but we do not have information on the date of exit. We therefore treat the date of last price change as the date in which the item leaves the market. Although this is not ideal, it is similar to the use of uncensored price spells in the literature to calculate statistics such as duration of price changes (see Dhyne et al., 2005; Nakamura and Steinsson, 2008).

[23] The dataset does not contain weights on expenditure share for each product, thus we must rely on taking simple averages for the aggregation of statistics. However, this is acceptable if we view the number of products being listed on Priceza as a reflection of consumer demand. There is some evidence that this may be the case. The size of each category on Priceza is more or less in line with a survey by ETDA in 2017 which reports that 44% of online shoppers use the Internet to purchase goods in the clothing category, 33.7% in the health and beauty products category, followed by 26.5% in IT equipment and 19.5% for household electronics.

since the item name often contains the brand and model number of the watch. Not being able to characterize items into homogenous product groups makes it impossible to analyze important online price characteristics that we are interested in such as the degree of price dispersion and price synchronization across stores.

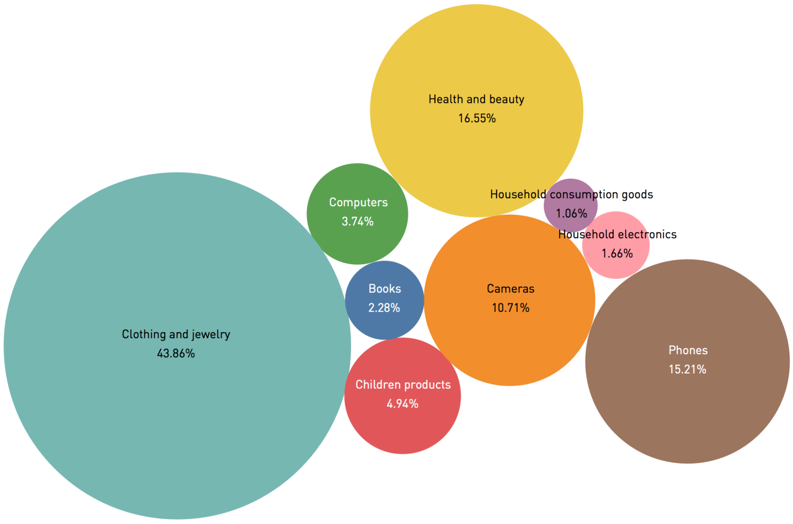
Figure 17: Selected Price Trajectories for Four Identical Products



For the abovementioned reason, our analysis only focuses on analyzing the price characteristics of watches and four other categories in which we find it possible to group the majority of items into homogenous product groups via their brand and model numbers. Including watches, which we henceforth treat as its own category for ease of reference, the five categories that we study are computers, phones, camera, household electronics, and watches, which altogether account for 32.4% of all items on Priceza[24]. Lünnemann and Wintr (2006) also limit their analysis to a very similar group of products for the US and some countries in the Euro area, thus we find it useful to compare our findings against theirs. Also, since the subset of products that we choose to analyze represents a very small fraction of total consumer expenditures, we stress that our results about the price-setting behavior of online goods should not be directly compared to nor generalized to findings about the CPI as a whole.

[24]For these five categories, there still remains a number of items to be sorted into product groups which is an ongoing effort by the team. We are currently looking into the use of more sophisticated text mining and machine learning techniques to help identify items that can be classified as the same product.

Figure 18: Categories of Products on Priceza



Note: As shown are the percentage shares of 9 broad categories according to the number of products listed on Priceza on 17 July 2018.

After grouping as many items as we can into homogenous product groups, we clean the data according to a process outlined in Appendix D. Table 10 offers some summary statistics of the cleaned dataset. Note that when viewing these statistics, readers should be aware that within each category, there are a wide range of products being offered for sale in terms of size and price point. For example, goods belonging to the computers category ranges from computer mouses to computer CPUs. Household electronics contains everything from lightbulbs to sewing machines to larger and more durable items such as refrigerators (see Appendix E for a complete list of subcategories).

According to column (1) of Panel A, we have 53,929 individual items or 11,920 homogenous products in our dataset. There are comparable number of items in the computers, phones and household electronic categories, and approximately half the amount for phones and watches. Column (2) shows that the lifespan of an average product is approximately 253 days or 8 months, with the lifespan of an average product in each category being comparable. However, as evident by large standard deviation measures, the lifespan can vary substantially across products.

In our study, we have information on the retail outlet that is listing the specific product. We characterize the retail outlets into three groups. The first are larger retail stores that have more than one brick component and have long operated offline, but now also have an online presence. In the literature, these stores are

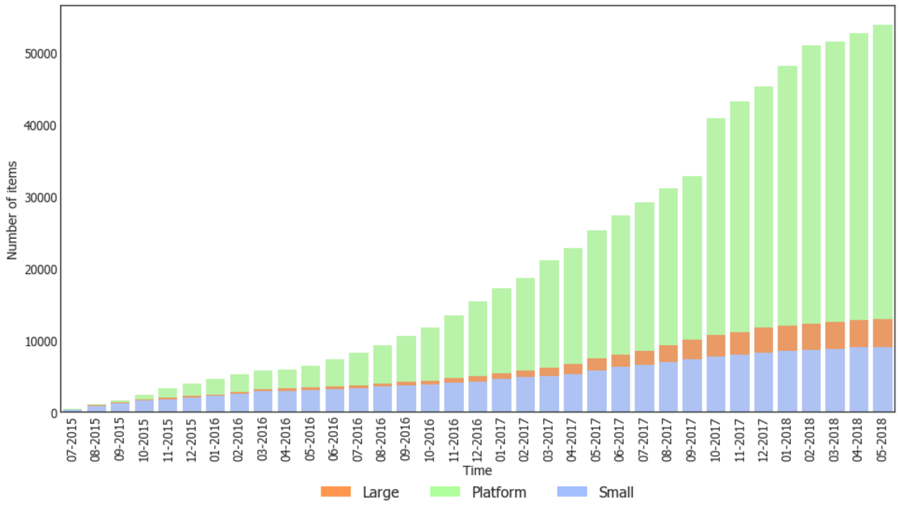
Table 10: Description of Dataset

	Items (products)	Lifespan (SD)	Items per product (max)	Sales ratio	Mean (median) sale size
Panel A. Category					
Computers	12536 (3820)	251.31 (165.11)	4.43 (36)	0.22	6.79 (4.70)
Phones	6438 (903)	214.25 (148.23)	27.49 (183)	0.23	8.86 (7.10)
Camera	11065 (1071)	246.01 (147.17)	455.87 (2209)	0.18	7.28 (5.00)
Household electronics	17023 (4211)	237.19 (150.55)	15.41 (172)	0.27	9.60 (8.00)
Watches	6867 (1915)	312.89 (187.20)	4.92 (41)	0.27	6.83 (5.00)
Panel B. Outlet type					
Large	3921 (2765)	265.48 (204.85)	4.69 (183)	0.45	7.34 (5.46)
Platform	40973 (9006)	244.22 (158.70)	99.26 (2209)	0.23	8.24 (5.38)
Small	9003 (5543)	281.34 (210.21)	3.77 (183)	0.15	6.34 (4.26)
All	53929 (11920)	252.93 (163.58)	72.15 (2209)	0.24	7.76 (5.22)

sometimes referred to as multi-retailers (Cavallo and Rigobon, 2016), and in our study we simply refer to them as 'large' merchants. The second type of retail outlets are 'small' stores, which consists of pure online retailers or retailers which may only have a small offline component (perhaps a small showroom) but operate predominantly online. Finally, 'platforms' are electronic marketplaces such as Amazon, Lazada or Shoppee, which act as intermediaries between buyers and sellers. We conjecture that these three different outlets have quite distinct characteristics, and may explain the differences in the price-setting behavior of identical products across stores. For example, as consumers can easily compare prices of comparable goods that are being offered by different stores on a marketplace platform, the average price level or degree of price dispersion may be lower due to heightened competition. Column (1) of Panel B shows that the majority of items sold online are listed through platforms. Of the 40,793 items that belong to online marketplaces, Lazada is responsible for 19,979 of the items. As shown in Figure 19, growth in marketplace platforms as measured by the number of unique items listed have been astounding.

One drawback to our dataset is that we cannot differentiate between the different vendors that list their items through the online marketplace. While we have the store name for large and small retailers, all vendors that list their items through Lazada for example, will have store name labeled as 'Lazada'. Therefore, it becomes impossible to count the number of unique stores per product as a small merchant may also be listing their product through the online marketplace. Therefore, the best we can do to get a sense of the number of stores that offer an identical product for sale at any one point in time is by counting the number of items associated with a particular product, which is to be treated as the upper bound number of sellers per product. As reported in column (3) of Table 10, the average number of items per product is 72 although there is significant heterogeneity (4 items per product for computers to 455 items per products for cameras). As expected, the retail outlet type that has the highest number of items per product is the marketplace platform.

Figure 19: Number of Unique Items Listed by Different Retail Outlets on Priceza



Given that we have high frequency data for the timing of price changes, we can separately analyze the characteristics of prices with sales (posted prices) and prices excluding sales (regular prices)[25]. The existing literature emphasizes the importance of doing so particularly when studying the degree of price rigidity. For the US, Nakamura and Steinsson (2008) show that regular prices in brick and mortar stores change on average once every 8-11 months, while posted prices remain unchanged for only 3-5 months. To make a distinction between posted and regular prices, we follow Nakamura and Steinsson (2008) and identify sales by applying a symmetric V-shaped filter to look for sale patterns. More specifically, we identify a sale period as a part of the price trajectory where there is a price decrease from P_1 to P_2, followed immediately by a price increase back to P_1. Note that this only finds temporary sales and not clearance sales[26].

According to column (4) of Table 10, sales occur fairly frequently. Almost one forth of all price changes in our dataset can be characterized as a temporary sale. Sales may occur frequently since there are no menu costs associated with changing prices on the Internet, but frequent sales may also be an inherent characteristic of electronic products that undergo a faster rate of obsolesce. Interestingly, we observe that products listed by large retailers go on sale most frequently, whereas sales occur least frequently for small stores. This may be due to the more frequent and effective marketing campaigns launched by large retailers. Last, column (5)

[25] For the offline dataset that Apaitan et al. (2018) analyze for Thailand, the identification of sales is not possible for sales that occur intra-month since data collected from the Ministry of Commerce is at a monthly frequency.

[26] As noted in the literature, one drawback to this filter is that in some items with highly volatile prices, sale filters may identify sales even when there are none simply because prices change by equal discrete amounts.

shows that while sales are prevalent in our dataset, their average size which is on the scale of 5-7 percent is considered to be somewhat small.

3.2 Stylized Facts

In this section, we summarize the patterns of price changes for online products into 5 stylized facts. All statistics in this section are calculated by first computing statistics at the item level, then aggregating up to the product level by taking the simple mean (median). Then, we finally aggregate to the category level by taking the mean (median) across products. This approach ensures that all information at the granular level of our dataset is preserved when calculating aggregate statistical measures[27].

Stylized Fact 1: Prices of online goods are flexible, but are far from being completely flexible. On average, prices change as often as once every 1-3 months.

The frequency of price changes can be computed as the ratio of observed price changes to all observed price records and is often used to assess the degree of price rigidity. This measure can then be converted into the implied duration of price spells (i.e. the time span a price is unchanged) but requires making assumptions about whether price changes are discrete or continuous. To avoid making specific assumptions about the distribution of price changes over time, many studies report the duration of price changes that are computed directly from the dataset. We opt for this approach and calculate the mean (median) duration as the average (median) length of price spells that are associated with each item's price trajectory. As discussed previously, since we treat the last date of an observed price change as the date in which the item exits the market, our price spells are uncensored (price spells start and end with a change). As discussed by Baudry et al. (2004), uncensored price spells could introduce some downward bias in duration measures because goods being sold in brick and mortar stores change infrequently. However, prices are more flexible for goods that are sold online thus empirical duration measures in this study could show some upward bias.

According to the prediction of the menu cost hypothesis, prices of goods sold on the Internet should be flexible given the lower cost associated with making a price change. However, we do not observe that posted prices on the Internet change everyday. Based on Table 11, posted prices do not change for approximately 2.5

[27] It would be ideal to also compute weighted statistics based on the market share of merchants or the number of clicks the item receives. However, we do not have this information. For the US and UK, Gorodnichenko et al. (2017) shows that there are only some minor differences between statistics that are based on taking the simple average versus those that are click-weighted.

months, although the median statistic implies that half of all Internet price spells have a duration of less than one month. Given that the median duration is shorter than the mean by about one month for all of the five categories, this implies that the distribution of price changes for the products in our dataset is skewed towards fairly frequent price changes[28]. Also, as expected, the duration of price changes are longer for regular prices, although we find that filtering out sales only lengthens the duration of price changes by about 1 month.

Table 11: Duration of Price Spells by Category and Retail Outlet Type

	Posted Prices		Regular Prices	
	Mean	Median	Mean	Median
Panel A. Category				
Computers and Accessories	78.22	38.99	110.02	64.34
Phones and Accessories	59.24	27.58	85.75	47.00
Camera and Accessories	88.02	37.37	117.94	73.00
Household electronics	65.34	28.42	100.25	58.15
Watches	88.65	31.27	124.47	68.33
Panel B. Outlet type				
Large	37.03	14.27	88.07	45.62
Platform	68.95	30.52	102.38	60.37
Small	104.24	51.01	130.04	79.01
Total	74.79	31.27	107.76	62.84

Note: Reported are the mean and median duration of price spells for regular and posted prices in days.

Overall, our results suggest that although online prices are on the flexible side, they are far from being completely flexible. This finding is more or less in line with Gorodnichenko et al. (2018), whom for a much broader range of consumer products find that the duration of price spells in the US and UK online markets are between 2-5 months, depending on the treatment of sales. Lünnemann and Wintr (2006) analyze the behavior of Internet prices for a similar set of consumer electronics in France, Germany, Italy, the US and the UK. They find that the median duration of price spells lies between 17 days (LCD TVs in the UK) and slightly more than half a year (microwave ovens in the US). In our dataset, there is also significant dispersion between duration of price spells at the subcategory level. We find that it ranges from 6 days for CDs/DVDs to 349 days for Virtual Reality headsets.

Finally, we analyze the duration of price changes by retail outlet type. In Panel B, we report that the average duration of price spells are shortest for large stores (37 days) and longest for small retailers (104 days). This may be due to the existence of sales, especially because we found that sales occurred more frequently in large retail stores. However, even with sales removed, the duration of price spells for large

[28]Although not directly comparable, we point out that Apaitan et al. (2018) find that the empirical duration of offline prices that make up the CPI ranges from 4-7 months and price changes are skewed towards being more infrequent rather than is the case here. However, note that our analysis is for electronic products which are known to be characterized by more frequent price changes.

retailers are still shorter by about one month. This result is interesting insofar as large retail stores are those that operate mainly through a brick component whereas small retailers are those with dominant online presence. Assuming that large retail stores have the desire to maintain consistency of online and offline prices[29], this finding implies that online goods in Thailand may not be necessarily more flexible than goods sold offline.

Our findings on duration by retail outlet type stands in sharp contrast with those of developed countries. Cavallo (2018) for example, shows that the duration of price spells for large brick and mortar stores with online operations like Walmart tends to be longer than the duration of purely online retailers sold through Amazon. Gorodnichenko et al. (2018) note that the frequency of price adjustment in their dataset is higher than that of multichannel stores in Cavallo (2017), due to the adjustment of online prices for multi-retailers are likely slowed down by the stickiness of offline prices. We conjecture that the difference in results stems from the e-commerce market in Thailand still being in its nascent stages, especially those of small retailers which may not yet have large volumes in sales. On average, small retailers in our dataset lists 67 products while large retailers list 145. As the market matures, the duration of price spells may decrease for online retailers, as has been found to be the case for the US (see Cavallo, 2018). The author finds that the duration of price spells for the US decreased from 6.7 months in 2008-2010 (comparable to brick-and-mortar stores) to 3.65 months in 2014-2017.

Stylized Fact 2: Price decreases are as common as price increases with equal size of price changes when sales are excluded. The average size of price changes is within the range of 5-13 percent depending on the treatment of sales.

Another measure used to assess the degree of price rigidity is the size of price changes. For conventional retail price changes, the general finding is that the frequency of price changes is often inversely related to its size. Another common feature for offline prices is that price decreases are common, in contrast to standard macroeconomic analysis that generally assume downward price rigidity. For the Euro area, approximately four out of ten price changes are price reductions (Dhyne et al., 2005), which are consistent with the findings for Thailand using micro-level price data (Apaitan et al., 2018). For the US, Nakamura and Steinsson (2008) report that one-third of all non-sale price changes are price decreases. Implications of the lack of downward price rigidity for the optimal inflation target is that

[29] Based on a large scale comparison of online and offline items from websites and physical stores in 10 countries, Cavallo (2017) reports that prices of multi-channel retailers are identical 72 percent of the time, with the share as high as 83 percent for electronics. When there is a difference, the online markup tends to be small, with a magnitude of -9% for electronics.

a higher inflation objective may not be needed in order to facilitate relative price adjustments.

For the subset of online goods that we study, we find that price decreases also occur as frequently as price increases. We also find that the average size of price changes in both directions are not particularly large. Table 12 summarizes these findings. As shown, while the average size of price increases for posted prices are slightly higher than price decreases, they are more or less comparable once sales are filtered out. The average size of price changes in both directions range from 5-13 percent, and the median size is lower than the mean implying that price changes are on the small side with some larger outliers. We also observe that the average size of price changes in both directions tend to be larger for phones, camera and household electronics,while being somewhat lower for computers and watches.

Table 12: Size of Price Increase and Decrease by Category and Retail Outlet Type

	Posted Prices					Regular Prices				
	Price Increase		Price Decrease		Fraction	Price Increase		Price Decrease		Fraction
	Mean	Median	Mean	Median	Decrease	Mean	Median	Mean	Median	Decrease
Panel A. Category										
Computers	7.22	4.92	7.28	5.03	0.55	7.91	5.26	8.31	5.84	0.42
Phones	9.32	6.39	9.17	6.46	0.61	9.78	6.70	10.32	6.90	0.35
Camera	9.34	6.46	9.57	7.16	0.56	9.90	6.76	11.91	7.85	0.41
Household electronics	10.21	8.34	9.99	7.96	0.53	11.09	8.80	11.34	8.38	0.46
Watches	8.38	6.90	9.16	7.30	0.38	8.36	7.03	9.26	6.41	0.65
Panel B. Outlet type										
Big	11.55	9.23	11.33	8.91	0.54	11.76	8.90	12.49	9.42	0.43
Platform	8.74	6.44	8.97	6.70	0.53	9.62	7.17	10.49	7.32	0.46
Small	7.54	5.41	7.39	5.35	0.51	7.88	5.54	7.84	5.61	0.48
All	8.78	6.45	8.85	6.56	0.52	9.40	6.86	10.00	6.94	0.54

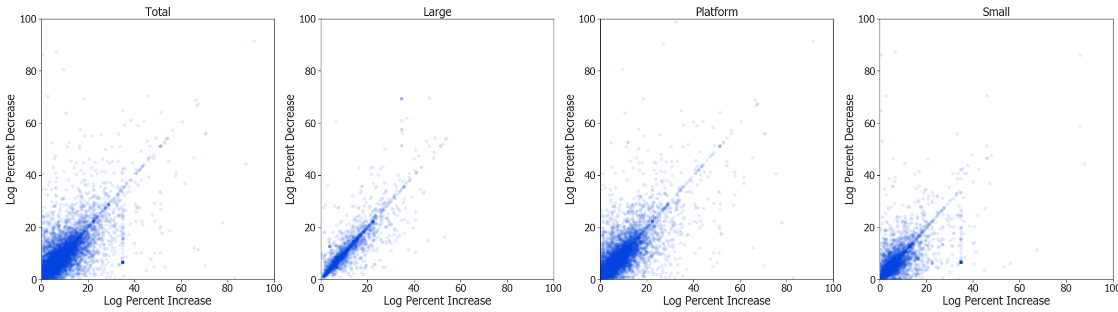
Note: Reported are the mean and median size of price increases and decreases in percent for posted and regular prices. The fraction of price decreases is calculated as the average fraction of price changes that are decreases over the sum of all price changes.

Comparing our results to the literature, the size of price changes are consistent with those reported by Gorodnichenko et al. (2018). For a broad range of online goods sold in the US and UK, they find that the average size of price changes are in the range of 5-12 precent, while Lünnemann and Wintr (2006) report that price changes are within the range of 5-7 percent for consumer electronics sold in the US and Euro area. The authors note that these magnitudes are surprisingly similar to those of offline markets. For Thailand, while not directly comparable because Apaitan et al. (2018) compute the size of price changes for a broad range of consumer goods and services that underlie the CPI, the average size of price changes for offline goods in Thailand were found to be in the range of 5-10 percent.

Next, Panel B of Table 12 reports the average size of price changes for each retail outlet type. We find that price increases are approximately 5% larger and price declines are approximately 3% larger at large retail stores when compared to products being sold through the marketplace and small retail stores. Combined with our earlier findings on duration, large retailers tend to change their prices more frequently and when they do so, the size is also larger. This finding runs counter to the usual finding that frequency is often inversely related to size. Here it may be merely reflecting the market power that large retail stores still have over online retailers given that the e-commerce market in Thailand is still in its nascent stages.

Last, we examine the degree of heterogeneity in the size of price changes across products and retail outlets. In doing so, we plot the average size of price increases and decreases associated with a particular product in Figure 20. We also plot a 45 degree line for reference, so if a product lies on the 45 degree line it means that the size of price increases and decreases are equal for that particular product. For the entire dataset, we observe that large price increases are more common, and can sometimes be larger than 100%. We also observe large heterogeneity in the average size of price changes across products due to the high degree of dispersion around the 45 degree line. Separating the analysis by retail outlet types, this heterogeneity is mostly inherited from the marketplace platform, as well as small retailers albeit to a lesser degree. By contrast, products listed by large retailers lie closer to the 45 degree line, implying that there is less dispersion in the average size of price changes and that large outliers are rare. These findings reflect that differences in retail structures may play an important role in explaining the observed differences in the average size of price changes.

Figure 20: Average Size of Price Increases and Decreases



Note: Plotted are the average size of price increases and decreases in percent for a particular product. The line through the origin is a 45 degree line.

Stylized Fact 3: Price synchronization across sellers is considered to be extremely low for identical products being sold online. The average daily synchronization rate is around 2 percent while the monthly synchronization rate only increases to 20-30 percent.

The degree of price synchronization can help provide information about the nature of price changes. Typically, we tend to think of low synchronization as reflecting price changes that are driven by seller specific factors while high synchronization being consistent with similar adjustment of prices in response to aggregate shocks. The degree of price synchronization may also be a reflection of existing frictions in the market environment as well as costs associated with changing prices. In an online market where physical menu costs are negligible and the costs of monitoring competitor prices are low, we may expect the degree of price synchronization to be substantial.

We follow Gorodnichenko et al. (2018) and calculate synchronization of price changes across sellers for an identical product i as the mean share of sellers that change the price for product i when another seller of the same product changes its price. With A as the number of sellers of product i that changes their prices at time t and B as the number of all sellers for product i at time t, the synchronization rate is $(A-1)/(B-1)$, provided that $A > 0$, $B > 1$. Note that accordingly, the synchronization rate will range between zero and one, where zero reflects no synchronization of prices while one means that there is perfect synchronization.

Panel A of Table 13 shows the degree of price synchronization for all goods in the dataset. The first set of columns reports the daily rate of price synchronization which is extremely low. While the standard deviation measure reflects large heterogeneity across products, the median figure of price synchronization confirms that price synchronization is low in the dataset as half of all products in the sample have zero price synchronization.

This finding of exceptionally low synchronization may be due to the time horizon that is used to compute synchronization. Therefore, we repeat our analysis by extending the horizon window to one month which allows a longer period for sellers to monitor and adjust to competitors' prices. While the degree of synchronization increases to around 30 percent for posted prices and 20 percent for regular prices, the median figure is still zero.

Table 13: Price Synchronization

	Daily			Monthly		
	Mean	SD	Median	Mean	SD	Median
Panel A. All						
Posted	2.79	13.63	0.00	30.98	39.63	0.00
Regular	2.39	12.79	0.00	20.73	33.70	0.00
Panel B. Platform only						
Posted	17.04	31.55	0.00	42.17	41.15	33.33
Regular	11.58	26.24	0.00	27.66	36.14	0.00

Note: Reported are the mean, standard deviation and median of the daily and monthly synchronization rates (in percent) for an identical good across sellers.

We conjecture that the degree of price synchronization may be larger for marketplace platforms because sellers can easily monitor the prices of its competitors. Therefore, we recompute synchronization statistics for products that are only sold through marketplace platforms. We find that the daily synchronization rate increases substantially to 17 percent for posted prices and 11 percent for regular prices, although there is still large differences in price synchronization across products and the median rate of synchronization is still zero. Expanding the window to the monthly horizon, the synchronization rate increases to around 40 percent depending on the treatment of sales. Half of the items now have a synchronization rate of 33 percent but we find that this non-zero synchronization rate is due entirely to sales.

In sum, our findings are similar to those of Gorodnichenko et al. (2018) whom also report extremely low levels of price synchronization across sellers for homogenous goods sold online in the US and UK. An interpretation of this finding is that there is a large degree of heterogeneity in price responses across sellers. In other words, low price synchronization reflects that some sellers are rather active while some never react to changes in competitor prices. However, we find that sellers become slightly more active when selling their goods through online marketplace platforms.

Stylized Fact 4: The dispersion of prices for a homogenous product across sellers can be quite substantial in online markets. We find that this high degree of price dispersion is a spatial rather than a temporal phenomenon.

Apart from being a central determinant of welfare, price dispersion is a key metric that helps explain the sources of price stickiness and the nature of price competition. It is often speculated that for online goods, the degree of price dispersion should be small, since it is easier to monitor competitor prices. Also, store characteristics such as geographical differences and shopping experiences should no longer be causing large price differentials between otherwise identical products across stores.

In this paper, we gauge the degree of price dispersion for product i using its relative range, calculated as $(P_{i,max} - P_{i,min})/P_{i,min} \times 100$ (see Geistfeld and Key, 1991; Brynjolfsson and Smith, 2000) and the percentage gap between the two lowest prices $(P_{i,min2} - P_{i,min1})/P_{i,min1} \times 100$ (see Baye et al., 2001). According to these two statistics, a higher measure corresponds to a higher degree of price dispersion. Price dispersion as measured by the latter statistic is motivated by the Bertrand model, as the gap between the two lowest prices in theory should be zero in any competitive equilibrium. Note that in measuring price dispersion, we do not use other conventional measures such as the coefficient of variation and standard deviation of log prices. This is because in our dataset, the number of sellers for many products can be quite small (the median number of items per product in any given day is 4).

Table 14 summarizes our findings on price dispersion. On average, the degree of price dispersion for goods sold online can be quite high. For all categories, the average price difference between the lowest and highest priced item is as high as 40 percent, while the gap between the two lowest prices is still substantial at 18 percent. These findings are robust to the exclusion of sales, as well as only considering products that are sold on marketplace platforms.

Table 14: Price dispersion of Posted and Regular Prices across Sellers

	All		Platform	
	Range	Gap	Range	Gap
Posted	41.98	17.98	47.07	20.57
Regular	41.96	17.83	46.96	20.28

Note: Reported are price dispersion measures according to relative range and gap measures expressed in percent. Price dispersion is computed for an identical product across all sellers and for an identical product across only sellers in marketplace platforms.

The finding of considerable price dispersion among Internet retailers is a common one. For the US and the UK, Gorodnichenko et al. (2018) report significant degrees of price dispersion for a set of narrowly defined goods. They find that the degree of price dispersion for online goods is on the scale of 20 percent, which is similar, if not larger than brick and mortar stores (see Kalplan and Menzio, 2014; Sheremirov, 2015). For other narrowly defined product markets such as books, CDs and electronics sold online, other authors have also found the degree of price dispersion to be within the range of 20-30 percent (Brynjolfsson and Smith, 2000; Baye et al. 2001; Clay et al., 2002)[30]. All in all, these findings seem to refute the classic argument that the law of one price should hold for homogenous goods being sold on the Internet.

Price dispersion could be caused by many reasons. Many studies investigate whether observed price dispersion is spatial, caused by differences in consumers' preferences for certain stores. For example, some stores may choose to cater to a premium segment of customers, charging prices that are permanently higher than their competitors. This could be due to differences in shopping experiences and terms of sale such as shipping costs, return policies and store reputation. Note

[30] Using supermarket scanner data, Kaplan and Menzio (2015); Sheremirov (2015) also find price dispersion to be substantial for brick-and-mortar stores.

that in this case, sellers would be able to let prices for the same product differ in a persistent way because differences in prices reflect that the same product is not perceived as exactly identical by customers when bought in different stores. In other words, products that are otherwise homogenous are in fact 'differentiated products' due to the heterogeneity of the different sellers.

Since differentiated store characteristics should matter less for online stores, we expect that this type of price dispersion should not be prevalent. In such a case, price dispersion should be temporal. According to Varian (1980), price dispersion for homogenous goods should disappear over time because consumers will learn which store is selling at the lowest price. For price dispersion to exist then, firms must be changing the prices of their products over time to make it difficult for consumers to learn which store offers the best price.

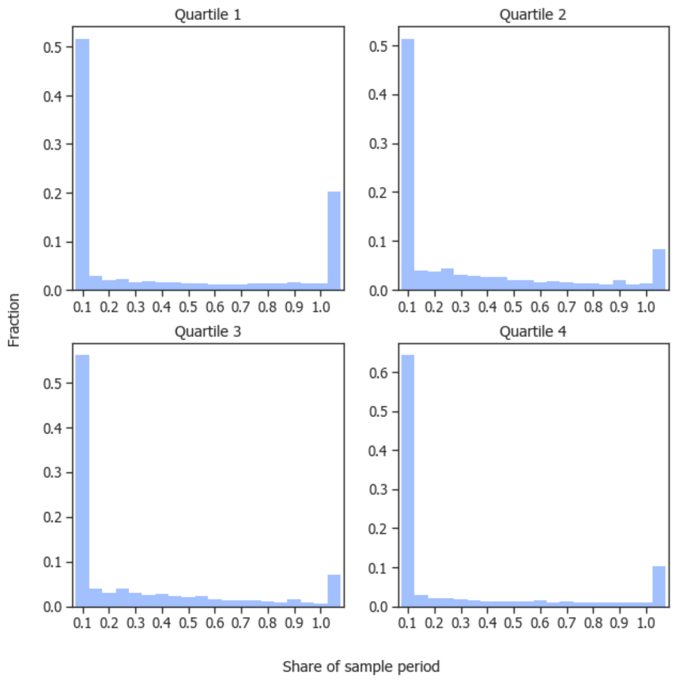
To investigate whether price dispersion is spatial or temporal, we sort products with 4 or more items into 4 quartiles depending on how their price compares with their competitors at each time t. If a particular item belongs to the first quartile at time t, this means that the item is relatively cheap compared to other sellers. Then, if the ranking remains the same over the item's life cycle, this suggests that the source of price variability is spatial rather than temporal. On the other hand, if the ranking of the item changes randomly over the time, the source of price dispersion is to be characterized as temporal[31].

Figure 21 shows the distribution of the fractions of time that each items spends in each of the four quartiles. We find strong evidence of spatial price dispersion, particularly for items that fall into the first quartile (cheapest), followed by the fourth quartile (most expensive). To better illustrate why Figure 21 shows evidence of spatial price dispersion, we calculate the height of the first ($< 5\%$) and last bars ($> 95\%$) for each panel and display them in Table 15. As shown, 20 percent of all items always remain in the 1st quartile while 10 percent always remain in the 4th quartile. In total, about 45 percent of all items spend more than 95% of the time in one quartile of the cross-seller distribution. This implies that price dispersion can be explained by the fact that sellers, especially those that charge high and low prices, hardly move along the cross-seller distribution.

[31] Spatial price dispersion does not mean that stores will consistently set low or high prices for all goods. A given store may charge high price for some, low for others so that the price of a purchase bundle is similar to other stores. We cannot test this in our dataset since we do not have information on purchased basket of goods but this line of argument may not be particularly relevant to online shopping because while offline shoppers buy multiple goods upon visiting a store, customers choose a store and then choose what to buy. For online shopping, customers choose an item then choose the store conditional on receiving the best price. Therefore, online sellers should have less incentive to price specific goods high or low to keep the prices of a basket constant.

Another way to see why price dispersion is spatial is to examine the fraction of items that appear in the lowest 5% of the distribution. We find that around 50-60% of all items spend almost no time in a particular quartile. For example, 52% of items never appear in the first quartile while 64% never appear in the fourth. This finding that price dispersion of online products are spatial rather than temporal is similar to Gorodnichenko et al. (2018) for online goods in the US and UK, and Berardi and Sevestre (2018) for goods sold in brick and mortar stores in France. Lach (2002) on the other hand, reports evidence of temporal price dispersion for offline goods in Israel[32].

Figure 21: Distribution of Spatial vs Temporal Price Dispersion



Note: For each item, we compute the share of the time period spent in each quartile of the cross-seller distribution. The above plots the distribution of fraction of time spent in each quartile.

[32]We also investigate other sources of price dispersion but did not find any to be significant. For example, we investigate whether price dispersion stems from a product being in different stages of their life cycle. In particular, high dispersion may reflect the prevalence of recently introduced goods rather than the inability of online markets to eliminate arbitrage opportunities. As consumers learn through search and firms collect information about their competitors' prices, price dispersion should decline. Similar to Gorodnichenko et al. (2018), we find no evidence of price convergence over the course of the product life cycle, thus heterogeneity in product lives cannot explain cross-sectional dispersion of prices. In fact, we find that price dispersion seems to widen somewhat with the life cycle similar to Haynes and Thompson (2008) who analyzed prices of digital cameras from a price comparison website. They argue that this is the case because it is unlikely that individual consumers will make multiple purchases of electronic products like a camera and therefore learning is expected to be lower than that for goods with repeated purchases. Results are available upon request.

Table 15: Spatial vs Temporal Price Dispersion

	$< 5\%$	$> 95\%$
1st quartile	51.67	20.27
2nd quartile	51.34	8.32
3rd quartile	56.10	7.11
4th quartile	64.27	10.39

Note: For each item, we compute the share of the time period spent in each quartile of the cross-seller distribution. The table reports the share of items that almost never (less than 5% of the time) or almost always (more that 95% of the time) fall into a given quartile.

Stylized Fact 5: Across broad product groups that can be matched online and offline, online inflation rates are generally lower and more volatile. Price changes are also substantially smaller and more frequent.

While our dataset only covers a small proportion of the national CPI basket, there are 9 broad product groups in our dataset that overlap with those collected offline. Although the items that fall within each of the broad product groups are not exactly identical, we still find it useful to compare the overall characteristics of the two to get a sense of how the pricing behavior of goods sold online may be different from those of brick-and-mortar stores.

Table 16 reports the following statistics calculated for the 9 broad product groups that are sampled online and offline: (1) the average annualized monthly inflation rates calculated as the mean of $(P_t - P_{t-1})/P_{t-1} \times 1200$. Note that for online items, we convert daily to monthly prices by taking the monthly average; (2) the standard deviation of annualized monthly inflation rates; (3) duration of price changes in days (4) monthly average size of price increases in percent and (5) monthly average size of price decreases in percent. As shown, there are substantial differences between the five measures for online versus offline product groups. Strikingly, the average inflation rates of phones and televisions online are much lower than those sampled from brick and mortar stores. The monthly standard deviation of inflation rates for online goods are also much larger, indicating more noise. Finally, duration of price spells are much shorter and size changes are substantially much smaller online compared to offline. In fact, the size of price increases offline appear quite substantial.

In general, for the subset of products that we study, changes in online prices tend to be lower and more flexible. Similar efforts by previous studies reach the same conclusion. For books and CDs in the US, Brynjolfsson and Smiith (2000) find that the mean prices were lower, and Internet retailers change prices in smaller increments than do conventional retailers. Focusing on standardized DVD brands,

Table 16: Comparison Between Online and Offline Prices

	Online Prices					Offline Prices				
Product Group	Mean	SD	Duration	Size Inc	Size Dec	Mean	SD	Duration	Size Inc	Size Dec
Refrigerator	-0.18	-0.18	86.24	6.78	6.66	-1.01	2.70	204.62	4.80	9.40
Fans	0.38	10.19	57.58	9.17	9.50	-0.28	1.85	274.09	8.35	13.81
Microwave	2.69	9.32	66.13	9.45	9.44	0.01	3.73	191.91	14.39	13.28
Air conditioner	-3.70	15.36	64.45	7.55	8.63	-0.32	2.19	166.82	16.36	24.43
Phones	-13.90	11.21	46.52	6.57	6.73	-1.08	2.29	212.40	14.19	9.88
Television	-13.51	11.10	48.81	8.51	8.43	-0.51	1.78	230.80	21.96	17.70
Washing machine	0.47	8.20	70.74	8.69	8.12	-0.55	3.29	226.23	8.86	8.34
Irons	1.93	17.47	55.31	11.29	10.94	-0.77	2.25	177.57	9.90	9.41
Watches	1.80	7.69	80.46	8.56	9.23	-0.91	5.83	269.67	14.61	19.69

Note: Reported are the mean annualized month-on-month inflation rates (in percent), standard deviation of the inflation rates, duration of price spells (in days) and average size of price increases and decreases in percent for 9 broad product groups sampled online and offline.

Tang and Xing (2001) find that prices by pure Internet retailers are significantly lower than prices by online multichannel retailers by an average of 14%. With a coverage of more categories, Goolsbee and Klenow (2018) use Adobe Analytics data in the US to show that online prices scraped from the Internet is 1.3 percent lower than those reported by official CPI statistics. A large-scale effort by Cavallo and Rigobon in the Billion Price Project also show that prices collected online exhibit very different characteristics compared to prices collected for the official CPI. For example, the difference between average inflation rates computed from online and offline sources for Argentina during 2008-2011 was a staggering 8 percent (see Cavallo and Rigobon, 2016). While we draw no conclusions from our findings regarding measurement of national price statistics given that our sample is small and products are not matched carefully, our findings can at least illustrate the potentially very different characteristics of online and offline price behavior.

3.3 Determinants of Online Price Characteristics

In this section, we aim to identify the determinants of key online price characteristics. We run a regression with the average duration, absolute size of price changes, and price dispersion for each product against certain market and good characteristics. These are (1) the average number of items per product (2) the median price of the product (3) the share of prices that end with 99 (4) the absolute size of price changes (5) the average lifespan of the product (5) a dummy variable that is 1 if the average price of the product is higher than the median price of all products in the sample and (6) the degree of price synchronization. For all measures, we first compute relevant statistics at the item level, then aggregate up to the product level by taking the simple average.

Due to the time dimension of our sample being relatively short, we run regressions that exploit the cross-sectional variation in product characteristics rather than a panel regression. We control for fixed effects in categories and run the set of regressions for the entire dataset. To examine whether any of the relationships matter more or less for online marketplace platforms, we repeat the analysis again for the subset of items that are listed only on Lazada, the largest marketplace platform in our sample.

Table 17 contains the regression results. Overall, we find that most market and good characteristics show some explanatory power, and the findings are generally intuitive. First we examine the results for the entire dataset (Regression (1)-(6)). As expected, as the number of items grows, the duration of price spells decrease indicating that prices become more flexible. The size of price changes also decline as well as the degree of dispersion. Since the number of items here is proxying for the number of stores, our findings indicate that with more competition in online markets, prices become more flexible and less dispersed.

Table 17: Predictors of Posted-Price Stickiness and Price Dispersion

	All Retail Outlets (1)-(6)						Lazada only (7)-(12)					
	(1) Duration	(2) Duration	(3) Size	(4) Size	(5) Dispersion	(6) Dispersion	(7) Duration	(8) duration	(9) Size	(10) Size	(11) Dispersion	(12) Dispersion
Log number of items	-5.00***	-4.98***	-0.89***	-0.89***	-5.67***	-5.85***	2.24	2.49	-1.30***	-1.39***	-6.98***	-7.08***
	(-4.84)	(-4.81)	(-7.80)	(-7.83)	(-8.77)	(-9.04)	(1.69)	(1.88)	(-6.41)	(-6.83)	(-4.37)	(-4.43)
Log median price	3.77***	5.92***	-1.05***	-1.29***	-3.12***	-4.95***	1.57*	3.68*	-0.87***	-1.83***	-1.13	-2.37
	(8.46)	(6.84)	(-21.63)	(-13.53)	(-10.69)	(-9.40)	(2.49)	(2.53)	(-8.94)	(-8.19)	(-1.30)	(-1.26)
Share of price points	-0.27***	-0.25***	0.03***	0.03***	0.03	-0.01	0.07	0.09	0.02*	0.01	-0.05	-0.05
	(-4.17)	(-3.84)	(4.76)	(4.39)	(0.53)	(-0.17)	(1.24)	(1.65)	(2.28)	(1.51)	(-0.47)	(-0.47)
Size	0.74***	0.75***			0.83***	0.83***	0.88***	0.896***			1.12***	1.11***
	(8.92)	(9.02)			(10.79)	(10.77)	(10.21)	(10.34)			(6.11)	(6.01)
Lifespan	0.14***	0.14***	0.00	0.00	-0.01*	-0.01*	0.03***	0.03***	0.00	0.00	0.0101	0.01
	(36.55)	(36.39)	(-0.62)	(-0.58)	(-2.34)	(-2.37)	(8.64)	(8.54)	(-0.87)	(-0.61)	(1.45)	(1.50)
High-priced		-8.16		-0.09		-26.41**		55.42**		-12.50***		-0.83
		(-0.54)		(-0.05)		(-2.61)		(3.05)		(-4.45)		(-0.03)
High-priced × Log median price		0.008		0.097		3.31**		-6.56**		1.64***		0.511
		(0.00)		(0.53)		(3.03)		(-2.94)		(4.76)		(0.16)
Duration			0.01 ***	0.01***	-0.01*	-0.01			0.02***	0.02***	-0.03	-0.02
			(8.92)	(9.02)	(-2.03)	(-1.94)			(10.21)	(10.34)	(-1.06)	(-1.04)
Syncrhonization					-0.09*	-0.0812*					0.05	0.05
					(-2.15)	(-2.04)					(1.06)	(1.06)
N	11920	11920	11920	11920	5995	5995	5488	5488	5488	5488	1816	1816

Note: The table presents estimates of the regression of the duration (in days), absolute size of price changes (in percent), and price dispersion (in percent). We report t-statistics in parenthesis and *,**,*** denote statsitical significance at the 5, 1, and 0.01 percent level.

Next, we find that more expensive goods (higher median price) tend to change prices infrequently and there appears to be no non-linearity in this relationship due to the statistical insignificance of the coefficient on the interaction term. The size of price changes are also smaller for more expensive products as well as the degree of price dispersion, consistent with the traditional view that the prices of larger and more expensive products are stickier. We also find that with the larger share of price points, the more flexible price changes become, perhaps reflecting that sellers that price their goods ending in 99 are more active. We also observe a positive relationship between lifespan and duration, implying that products that are short-lived change prices more often. This is intuitive because technological products that may become obsolete quickly may have higher incentive to change prices frequently. Finally, size and duration have a mildly positive relationship, consistent with the traditional view that the size of price changes for sticker goods are often larger. Also, enhanced degrees of synchronization reduces price dispersion. This is consistent with the understanding that if firms synchornize their prices, cross sectional dispersion should disappear. The findings are more or less similar for the Lazada set of regressions but some coefficients are not statistically significant, perhaps due to the smaller sample size.

4 Conclusion and Policy Implications

Many countries including Thailand are currently facing an environment of persistently low inflation. With central banks consistently undershooting their inflation targets, the question of what is actually the true underlying rate of inflation that policymakers should target has been brought to the forefront. At the same time, the past decade has also witnessed large and volatile relative price shocks which makes understanding important price characteristics such as persistence, and analyzing key economic relationships such as the inflation-output tradeoff as captured by the Phillips curve, more difficult. In the meantime, ongoing structural changes from the information technology revolution highlights the urgency that policymakers understand how price-setting behavior is evolving in online markets, as these fundamental forces can potentially affect aggregate inflation dynamics in Thailand in years to come.

We address the abovementioned challenges in this paper, to also bring with it a deeper understanding of Thai inflation dynamics more generally. Utilizing the richness of cross-sectional information in disaggregated online and offline price data, we employ several econometric frameworks to disentangle and understand the underlying sources of generalized price fluctuations. We are able to show that the behavior of inflation at the disaggregated level is highly heterogenous, and is comprised of various components that behave differently in the face of different types of shocks. The key results that we draw from our analysis have important policy implications that deserve further research and are relevant towards ongoing discussions about i) the determination of the appropriate inflation target and frameworks and ii) monetary control.

A general consensus long reached by academics and policymakers is that central banks should try to target a price index that overweighs the persistent component of inflation because they contain more information about future inflation. Also, the main cost of business cycles in New Keynesian models stem largely from the sticky sector, thus central banks can improve welfare by stabilizing sticky prices (Aoki, 2001). As a result, central banks often target core inflation, which excludes volatile food and energy sectors. However, our results show that the underlying true rate of inflation that correspond to the 'sticky' component of inflation is not the same as core inflation, as food and energy components play a 15% role in explaining this long-run trend. Similarly, we find that food and energy sectors are not responsible for all volatile price fluctuations as it only explains 70% of the relative price changes at the business cycle frequency. This finding implies that in an era where the dynamics of the sticky component of inflation is changing, central banks may have to recalibrate their targeted measures of inflation. However, the issue of how to redefine this inflation target may become all the more challenging in the near future as e-commerce plays a larger role in Thailand's retail landscape. In a world where search for the best prices is easy and menu costs become irrelevant, what constitutes as the sticky component of inflation will become a complex question for policymakers as the prices of many online goods become more flexible.

Given that the structure of online marketplaces can make consumer prices more flexible, one may start to question the central bank's ability to control inflation. Inflation may become increasingly dominated by volatile transitory shocks, which begs the question of what frameworks are appropriate to control inflation in this flexible-price environment. On the one hand, strict adherence to inflation targets, despite output being reasonably close to trend, may imply overly accommodative monetary policy with potential financial stability risks down the road. The communication challenges of potentially widening the target band to accommodate more volatile shocks can be especially daunting, as it may may undermine public confidence in the central bank's inflation anchor with the associated risk of more volatile inflation outcomes.

Increasing flexible prices also have implications towards the ability of monetary policy to achieve desired economic outcomes in the short-run. Sticky prices for example, can help avoid deflationary spirals. If there is a negative shock that pushes prices down, because prices are rigid, deflationary pressures are attenuated. With increasingly flexible prices, monetary policy may need to become more aggressive in combatting recessions. In addition, we have shown through our decomposition that the Phillips curve relation which is the key channel in which nominal interest rates affects the economy can become weaker when clouded by noisy price fluctuations.

Currently, this component which reflects the relative price responses to aggregate shocks can explain almost up to 60% of all inflation rate fluctuations. However, in an increasingly flexible-price world, monetary policy may have a weaker grip on inflation through this channel, implying that a larger interest rate change is required to achieve a given affect on prices.

The bottomline message of this paper is that the dynamics of inflation is ever evolving and thus its behavior will always remain a puzzle to policymakers. We have shown that in the pre 2000 period, observed persistence in Thailand can be largely attributed to permanent shocks due to the lack of a well-defined inflation target. Since 2010, sustained deviation from inflation targets are instead largely driven by the inherited persistence of external shocks such as those coming from the raw food sector. Looking forward, we have illustrated that if prices become more flexible due to a growing e-commerce sector, the underlying drivers of persistence in prices may continue to change again. We agree with authors such as Gorodnichenko et al. (2018) among others, that to understand inflation of the future, the development of theoretical models with alternative mechanisms that generate price stickiness, dispersion and other online-pricing frictions are crucial. We leave this important agenda as an avenue for future research.

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6 Appendix A

The reduced form Phillips curve based on the time varying parameter model with GARCH(1,1) disturbances of Harvey et al. (1992) can be written as:

$$Y_t = X_{t-1}\beta_t' + \epsilon_t^*$$

$$\beta_t = \beta_{t-1} + v_t$$

$$\epsilon_t^* | \psi_{t-1} \sim N(0, h_t)$$

$$h_t = \alpha_0 + \alpha_1 {\epsilon_{t-1}^*}^2 + \alpha_2 h_{t-1}$$

$$v_t \sim N(0, Q)$$

where Y_t is current time t inflation and X_{t-1} is a $t \times 6$ vector of explanatory variables comprised of an intercept term, four lags of inflation and the first lag of the output gap. β_t is a 6×1 vector of time-varying parameters modeled as a random walk. The scalar shock ϵ_t^* is subject to GARCH(1,1) to capture stochastic volatility in the inflation process.

The model can be estimated with the Kalman filter once cast into the following state-space form:

$$Y_t = \begin{bmatrix} X_{t-1} & 1 \end{bmatrix} \begin{bmatrix} \beta_t \\ \epsilon_t^* \end{bmatrix}$$

$$(Y_t = X_{t-1}^* \beta_t^*)$$

$$\begin{bmatrix} \beta_t \\ \epsilon_t^* \end{bmatrix} = \begin{bmatrix} I_5 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \beta_{t-1} \\ \epsilon_{t-1}^* \end{bmatrix} + \begin{bmatrix} v_t \\ \epsilon_t^* \end{bmatrix}$$

$$(\beta_t^* = F^* \beta_{t-1}^* + v_t^*)$$

where

$$E(v_t^* v_t^{*\prime}) = \begin{bmatrix} Q & 0 \\ 0 & h_t \end{bmatrix} = Q_t^*,$$

and is estimated with quarterly data spanning 1995Q2-2018Q2. For the burn-in period of the Kalman filter, we use 8 quarters of data.

7 Appendix B

Table B1: Raw Food Idiosyncratic Trend, Volatility of Idiosyncratic Trend and Cycle Shocks and Factor Loadings

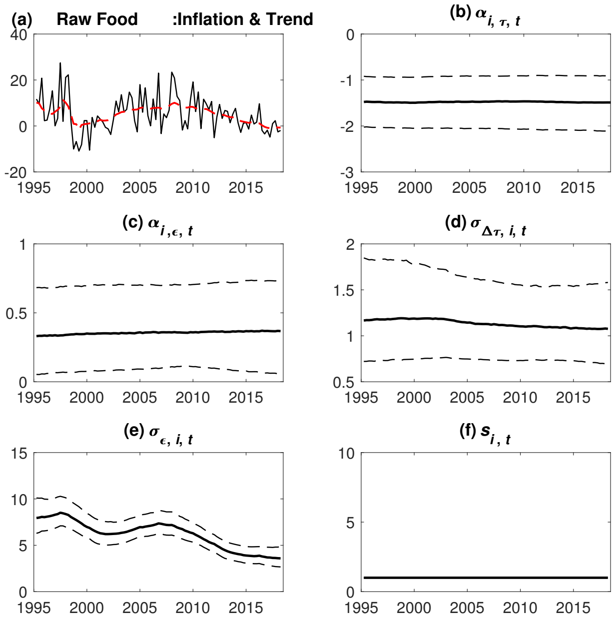


Table B2: Food in Core Idiosyncratic Trend, Volatility of Idiosyncratic Trend and Cycle Shocks and Factor Loadings

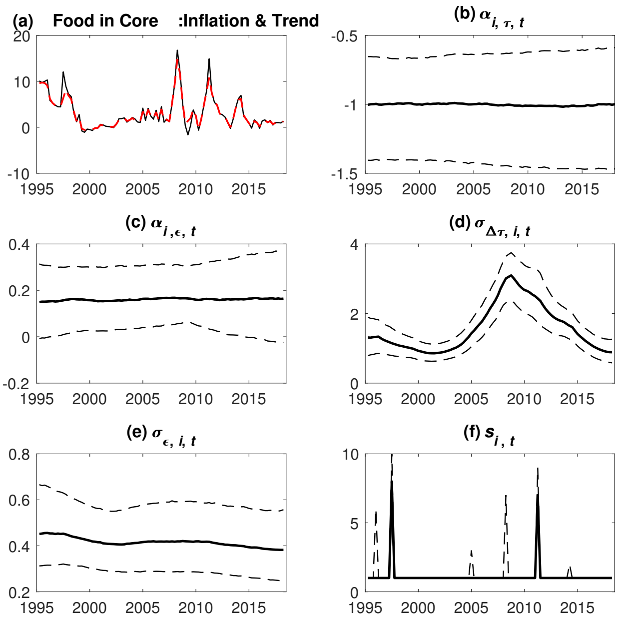


Table B3: Clothing Idiosyncratic Trend, Volatility of Idiosyncratic Trend and Cycle Shocks and Factor Loadings

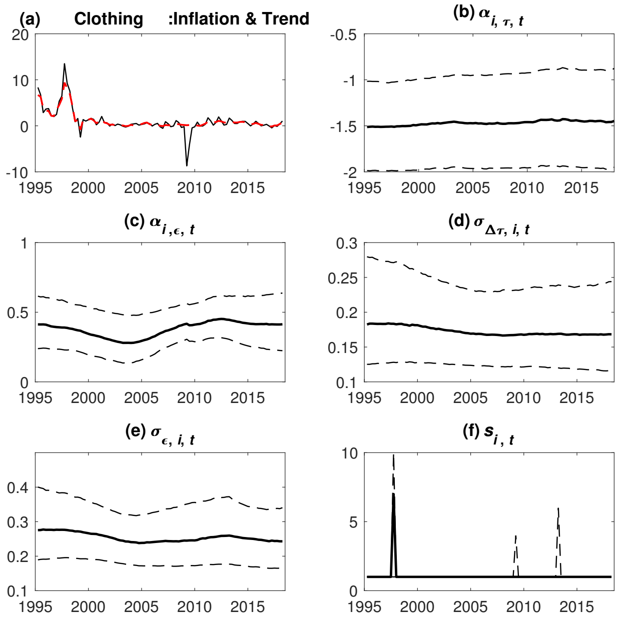


Table B4: Housing Excluding Gas Idiosyncratic Trend, Volatility of Idiosyncratic Trend and Cycle Shocks and Factor Loadings

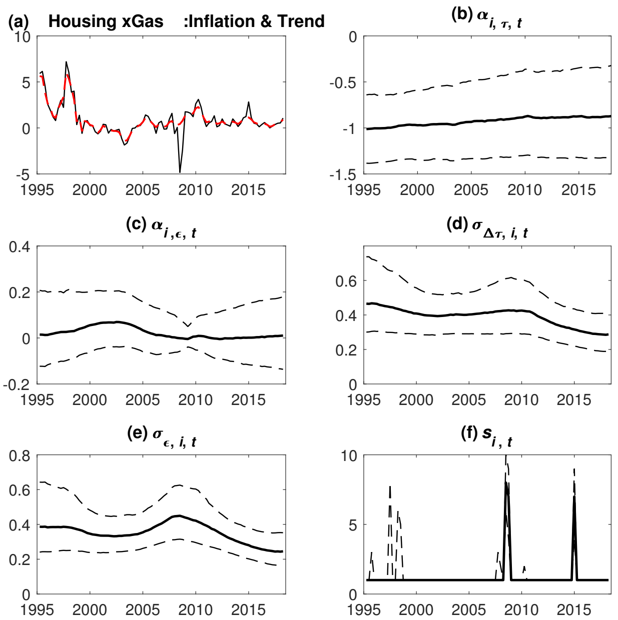


Table B5: Healthcare Idiosyncratic Trend, Volatility of Idiosyncratic Trend and Cycle Shocks and Factor Loadings

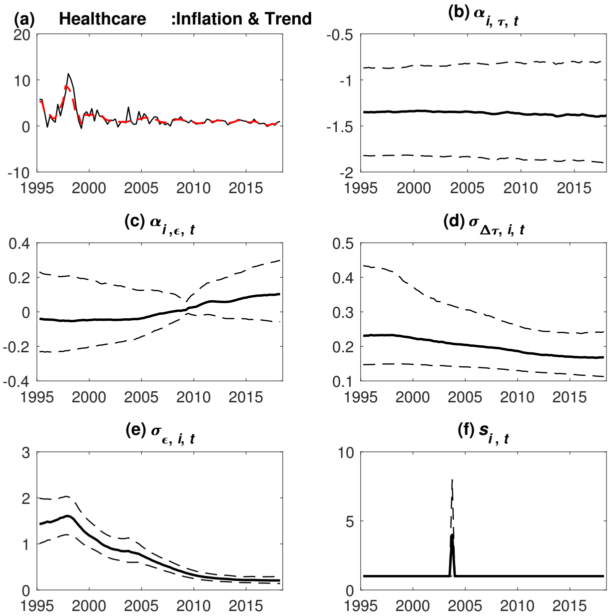


Table B6: Transportation Excluding Fuel Idiosyncratic Trend, Volatility of Idiosyncratic Trend and Cycle Shocks and Factor Loadings

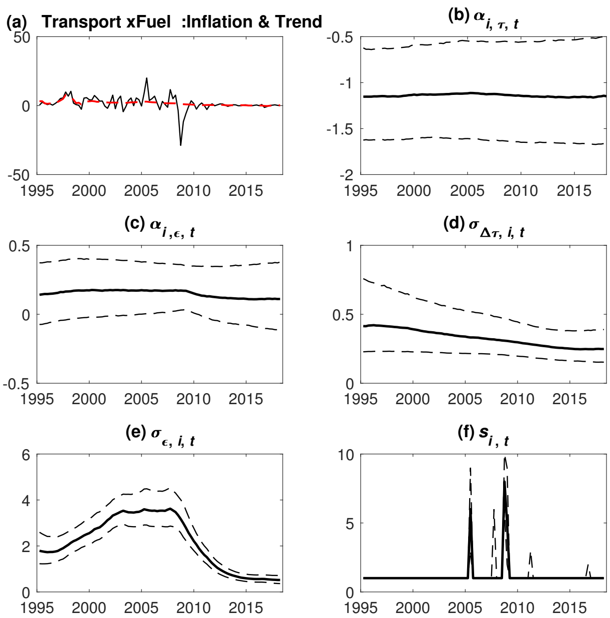


Table B7: Recreation Idiosyncratic Trend, Volatility of Idiosyncratic Trend and Cycle Shocks and Factor Loadings

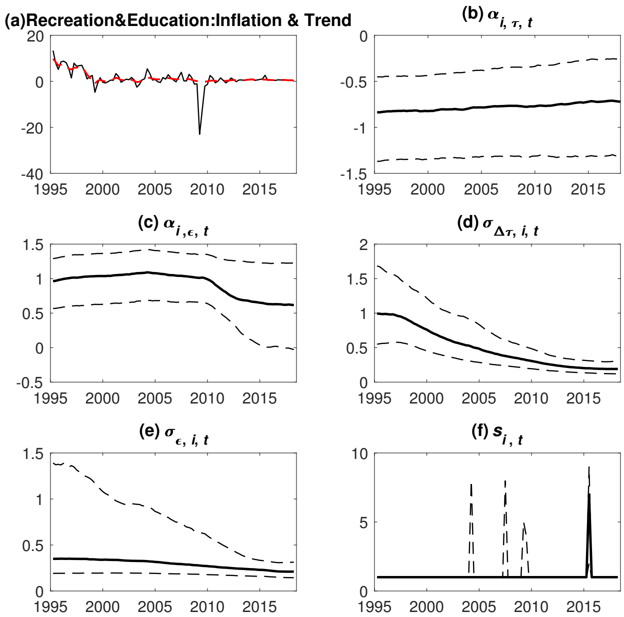


Table B8: Tobacco Excluding Alcohol Idiosyncratic Trend, Volatility of Idiosyncratic Trend and Cycle Shocks and Factor Loadings

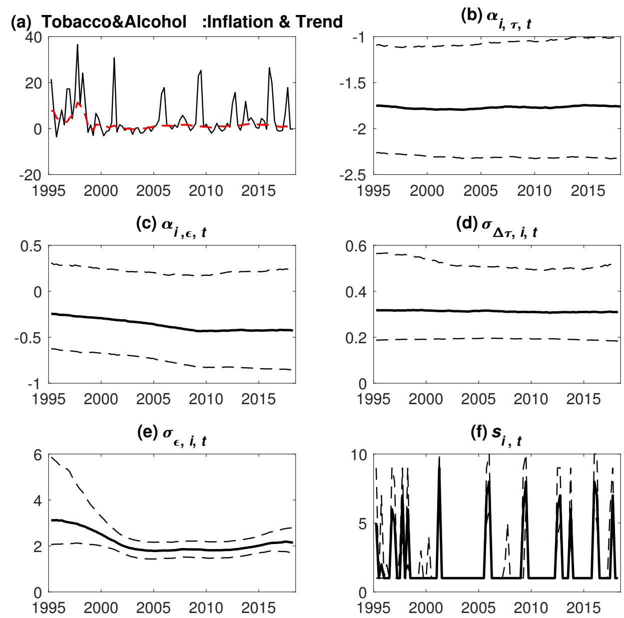


Table B9: Gas and Electricity Idiosyncratic Trend, Volatility of Idiosyncratic Trend and Cycle Shocks and Factor Loadings

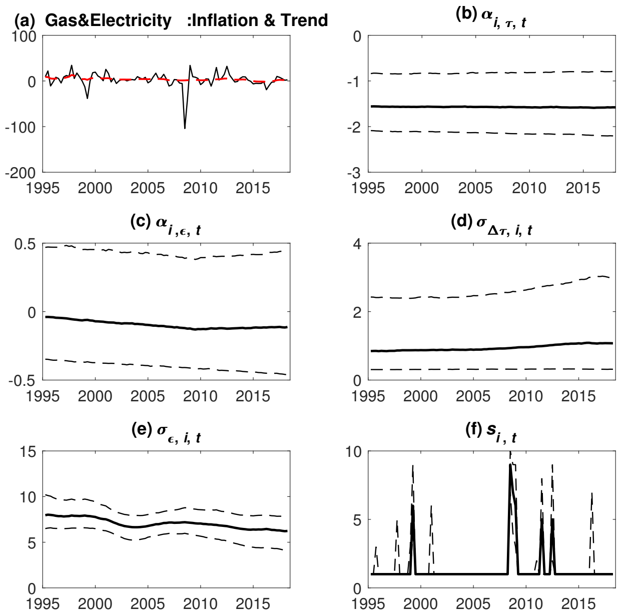
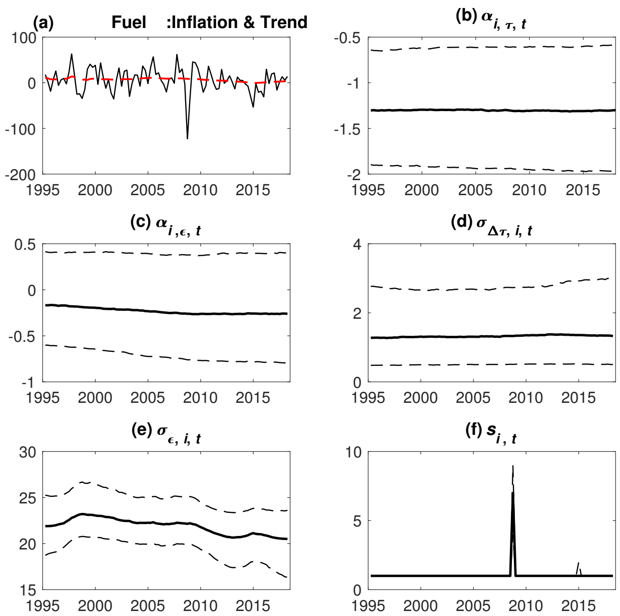


Table B10: Fuel Idiosyncratic Trend, Volatility of Idiosyncratic Trend and Cycle Shocks and Factor Loadings



8 Appendix C

To compute the implied-time varying weights that captures the contribution of each sectoral inflation series towards explaining the overall MUCSVO trend, we need to estimate $\omega_{ij,t}$ which are the implied time-varying weights for each sector. Given the filtered MUCSVO trend for each sector, this can be done according to the following relation:

$$\tau_{i,t|t} = \sum_{j=0}^{t-1} \omega_{ij,t} \pi_{i,t-j} \tag{C1}$$

However, at any given point in time, the one-sided estimates of the MUCSVO trend is a nonlinear function of current and past values of the 10 sectoral series, making the weights a complicated time-varying function of the volatilities, persistence, and correlations across sectors. Due to the existence of outliers however, obtaining an exact representation for the time-varying weights in terms of a linear weighted average is not feasible. Therefore, we resort to an approximation by computing the one-sided trend from applying a Kalman filter to Eqs. (1)-(7). In doing so, we ignore outliers by setting $s_{c,t} = s_{i,t} = 1$ and hold the time-varying factor loadings and volatilities $(\alpha_{i,\tau,t}, \alpha_{i,\varepsilon,t}, \sigma_{\Delta\tau,c,t}, \sigma_{\varepsilon,c,t}, \sigma_{\Delta\tau,i,t}, \sigma_{\varepsilon,i,t})$ fixed at their full-sample posterior means.

Then, we compute the weights according to Eq. (C1) based on the one-sided estimate of the trend. The approximate linear weights are then defined as sum of the weights on the current and first three lagged values of the component inflation series over the sum of all component weights across the 10 sectors, i.e. $\bar{\omega}_{i,t} = \sum_{j=0}^{3} \omega_{ij,t} / \sum_{i=1}^{10} \sum_{j=0}^{3} \omega_{ij,t}$. Note that the sum of all approximated linear weights in Figure 8 sum to one and that when we compare the approximate linear weights $\bar{\omega}_{i,t}$ to its expenditure share, the linear weight for each sector shows whether the sector is getting more or less weight in the MUCSVO trend than it does in CPI-all.

9 Appendix D

Our data cleansing procedure entails five steps:

- Remove items with only one price change, as it is not possible to compute statistics such as duration of price spells.
- Remove inactive sellers by removing items with duration of price spells more than 500 days (top 0.05 percentile of the duration distribution).
- Remove fringe sellers by removing items with total life span of less than 30 days (based on judgment as there was no clear cut-off point based on the distribution of life span.)
- Remove large outliers by removing items with percentage change in prices of less than -70% and more than 500% (bottom 0.01 percentile and top 0.05 percentile of the distribution of price changes).

Note that to determine the cut-off percentiles, we used judgment according to whether cut-off values were reasonable as well as took into consideration the amount of data we would lose after cleaning.

10 Appendix E

Table 18: Categories and Their Subcomponents

1. Computers	Mouse, other in computer category, ink cartridge, Keyboard, Printer, other in printer category, UPS, Flash Drive, Webcams, Switches-Hubs, Other Network Component, Routers, External Hardisk, computer Display, Scanner, PC, CPUs, Notebook, Access Point, Ram, Power supply, Internal HDD, Other computer equipment, Mainboard, Cable, PC Case, Heatsink, Software, Card Reader, Other memory storage equipment, Graphic Card, Mouse Pad, CD DVD, USB Hub, TV Tuner
2. Phones	Other phone accessory and communication equipment, mobile phone, charger, home phone, fax, tablet, battery for telecommunication equipment, smart watch, power bank, phone screen protector, VR headsets
3. Household Electronics	Plugs, transformers, speakers, headphones, water heaters, electric kettle, rice cookers, other kitchen utensils, washing machines, game accessories, fans, battery, microwaves, electric cookers and pans, vacuum cleaners, pumps, refrigerators, air purifiers, stoves, food preparation equipment, toasters, irons, water filter, sewing machine, sound system, high pressure cleaner, air conditioner, amplifier, other in audio category, television, freezer, VCD-DVD-Blue Ray player, coffee maker, cooker hood, grill, lamp, streaming media player, game, mosquito trap, game console, portable music players, other products in video player category, other in the lighting category, other in cleaning category, light bulbs, heater, switches, other bathroom appliances, other in washing machine category, flashlight
4. Camera	Memory-related products, memory card, CCTV, lens, grip, camera battery, case bag, filter, digital camera, tripod, hood, camera battery charger, flashlight, camcorder, vehicle camera, camera accessories, remote control, camera strap, CCTV recorder, film camera, lighting system, studio equipment, film, lens adapter
5. Watches	