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Inflation at risk in Thailand

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Abstract

Using monthly Thai data from 2003-2020, we examine the determinants of the future distribution of inflation. We evaluate how different risk factors predict 1-year-ahead future distributions of CPI inflation and its components. Risk factors come from 5 different groups of variables: inflation expectations, domestic economic activity, global economic activity, financial conditions, and component-specific factors. We obtain points on the future distributions of inflation through quantile regressions and fitting those points with skewed-t distributions. Our focus is on the outlook in the tails of the distribution, which recent literature referred to as 'inflation-at-risk.' We find, as expected, that the whole inflation distribution has shifted lower, and thus the probability of negative inflation has increased markedly in recent years. There is a structural break around 2015 that affects both the distributions of inflation and their determinants. This structural break makes it challenging to make out-of-sample forecasts, thus, we focus on in-sample evaluation and explanations. For risk factors, we observe that the tightening of financial conditions and the decreasing world production are prominent sources of downside risks to inflation. Inflation expectations also play a smaller role in the lower quantiles, signaling its lower effectiveness in anchoring actual inflation during disinflationary periods. Finally, high global and domestic economic activity can be effective in decreasing downside risks in the lower tail, providing policy makers a way to counter these risks by stimulating the economy.

Keywords: Inflation determinants, Central bank policies
JEL Codes: E31, E52
Topics: Macroeconomics, Monetary policy

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1 Introduction

Taking into account many different scenarios and evaluating the entire future distribution of the factors of interest are keys to risk management. In a world with high risks and uncertainties, a risk management approach to decision-making is becoming essential. Price stability or inflation is a key macroeconomic variable that policy-makers should monitor continuously; its future distribution something to be approximated and used in making decisions. This is especially relevant for a central bank with an inflation targeting framework like the Bank of Thailand. With the recent episodes of low inflation, the downside risks in the left tail of the future inflation distribution, referred to as 'inflation-at-risk' by some, is a key indicator to track and study.

There have been two previous studies on 'inflation-at-risk' using similar methodologies by López-Salido & Loria (2020) and Banerjee et al. (2020). These studies are either carried out using very long historical samples from the US and Europe or are conducted using a cross-country panel data. By using quantile regression approach with conventional inflation determinants, Banerjee et al. (2020) show nonlinear relationships between economic factors and future inflation. Domestic slack and exchange rate in emerging markets have significant nonlinear effects on future inflation. Also, in developed countries, financial conditions are found to be essential in explaining future inflation dynamics (López-Salido & Loria 2020). However, only few studies have looked at the future inflation distribution with a focus on Thailand.

In this paper, we aim to specifically study the inflation drivers, inflation distribution, and inflation risks in Thailand. With a shorter sample and only one country, we use monthly data, as oppose to quarterly data, to obtain more data points for our quantile regressions. The quantile regression method allows us to account for differences at the tails of the distribution which could reveal more complex and different relationships between variables as oppose to the mean. We document some key findings. Focusing on the left tail, inflation expectations play a smaller role in anchoring future inflation when compared to the right tail. However, the central bank can leverage monetary policy to alleviate downside risks at the left tail of the distribution since the Phillips curve relationship becomes stronger in the lower quantiles. Lastly, tight financial conditions are a drag to future inflation in all quantiles.

The paper is organized as follows. Section 2 contains a review of literature. Section 3 describes the data used in the models. Section 4 is the methodology section that contains the econometric specification, variable selection, and the steps leading to the creation of a future distribution. Next, we visit the topic of model robustness. Finally, we end with a conclusion of key findings and policy recommendations.

2 Literature Review

The literature review is divided into 2 parts: the literature on the determinants of inflation in general, and the literature on determinants of the future distribution of inflation.

2.1 Inflation determinants

The empirical literature on inflation dynamics is well developed; particularly over the past few decades. In this section, we provide an overview of key developments in inflation dynamics based on recent findings. This helps us scope the variables to use as predictors to future inflation in Thailand.

The underlying idea that prices in the economy can be explained by the real economy through unemployment can be traced back to Philips (1958). This strong relationship, which could almost single-handedly determine the price level prior to the US stagflation episode of the 1970s, was found to have flattened down and became close to zero in many economies. In a widely cited study, Blanchard et al. (2015) noted that the slope of the Phillips curve in advanced economies has decreased, but remained roughly stable since the early 1990s and did not appear to fall during the financial crisis. The specific case for Thailand has also been studied by Manopimoke (2018) and Dany-Knedlik & Garcia (2018). The resulting estimates show that Phillips curve relationship is consistently positive but is declining since early 2000. With this declining relationship between the real economy and prices, using solely output to explain inflation is no longer adequate. Recent literature have introduced three groups of factors that help augment the understanding of inflation dynamics.

First, global factors play a prominent role in inflation dynamics with the growing importance of globalization. Auer et al. (2017) suggested that the increase in the impact of global slack on domestic inflation reflects international integration. The intensive use of global supply chains and the practices of mobilizing manufacturing to cheaper locations can reduce the bargaining power of domestic workers. This expansion weakens the effects of national resource constraints on local inflation. Also, Forbes (2019) showed that global economic forces have been tightly linked to domestic inflation rates. She strongly suggested extending inflation models to include global factors such as global slack, non-fuel commodity prices, exchange rates, and global price competition. These global factors can significantly improve the ability of models to explain inflation dynamics. However, it is important to mention that the empirical results of globalization's role on inflation are still ambiguous. While the two cited works earlier documented a positive impact of a global output gap on inflation, Mikolajun & Lodge (2016) provided evidence to the contrary, confirming that global economic slack has minimal effect on domestic inflation, especially with the more recent data which inflation has become more stable.

A comprehensive analysis of the Thai economy by Manopimoke (2018) modeled the linkage between global determinants and domestic inflation movements in open-economy macroeconomic models. The conclusion is more in line with those of Auer et al. (2017) and Forbes (2019). The short-run inflation dynamics in Thailand is affected by global factors, namely, the global output gap and oil prices.

A second group of factors that helps explain inflation dynamics comprises of the various measures of inflation expectations. The anchored inflation expectations hypothesis, suggested by Bernanke (2007) and Mishkin (2007), proposes that inflation did not move with economic slack due to the fact that monetary policy is very effective. More specifically, when prices and wages are set in line with the long-term inflation expectations, on condition that these expectations respond less to variations in economic activity, then inflation itself will become relatively more insensitive to demand and supply shocks. A more recent study, domestic forward-looking inflation expectations appear to perform well in explaining local inflation compare to other factors such as global inflation (Mikolajun & Lodge 2016). Consistent with international experience, Manopimoke (2018) suggested that inflation expectations became well-anchored after the Bank of Thailand adopted the inflation targeting framework. Albeit, Thai inflation expectations' contribution to actual inflation have been lower recently, as is documented by Dany-Knedlik & Garcia (2018).

Financial conditions are included as the last group of factors that influences inflation dynamics. While many studies show that the Phillips curve relationship seemed to have broken down during crisis, Del Negro et al. (2015) argued that the sharp decline in inflation in 2008 can be captured by adding financial frictions to a standard DSGE model. Similarly, Gilchrist et al. (2017) suggested that financial shocks are responsible for firms' price-setting behaviors. The main hypothesis the authors made is that the firms set prices based on their ability or inability to finance. To be specific, when external financing is expensive (tighter credit conditions), a liquidity constrained firm may need to accumulate liquid assets and cannot lower prices, while firms without these constraints may cut prices substantially. More recently, López-Salido & Loria (2020) suggested that tight financial conditions, approximated by credit spreads, carry substantial downside inflation risks.

2.2 Inflation distribution and inflation at risk

While the determinants of the conditional mean, which dominated past literature, is sufficient to produce a good representation of the inflation model, those estimates do not adequately represent the inflation outlook during extreme events such as the 2009 financial crisis. Nevertheless, the concept of studying the distribution of inflation is not novel. Tillmann & Wolters (2015) used quantile regression to study inflation persistence across quantiles. In addition, Ghysels et al. (2018) developed a quantile autoregressive distributed lag model with mixed frequency sampling to develop a risk measure to assess and monitor possible extreme inflation realizations.

More recent research incorporates a variety of inflation determinants and the idea of predicting the full future inflation distribution (López-Salido & Loria 2020, Banerjee et al. 2020). These studies investigated the shape of the entire inflation distribution, including tail risks which are referred to as 'Inflation at Risk.' They augmented a Philips curve model where the future inflation distribution is affected by four different risk factors - domestic activity, global activity, financial conditions, and inflation persistence. It is worth noting that inflation expectations is an additional variable in López-Salido & Loria (2020)'s model.

Economic factors - domestic activity, global activity, inflation expectations, and inflation persistence were found to have been major drivers of inflation dynamics in both studies. Additionally, López-Salido & Loria (2020) found that tighter financial conditions are associated with greater downside inflation risks. They also highlighted that risk factors related to financial conditions are essential; the quantile regressions without financial variables can be a misleading model of downside inflation risk if there are significant changes in credit spreads.

While López-Salido & Loria (2020) studied advanced countries, the United states and the European union, Banerjee et al. (2020) examined inflation distribution for a large panel of advanced and emerging market economies, including Thailand. The result in the role of the financial conditions is consistent with the previous study, tightening financial conditions increase both inflation tail risks. One of the striking results of Banerjee et al. (2020) is a nonlinear relationship between economic factors and future inflation. They showed that domestic slack and exchange rate in emerging markets has significant nonlinear effects on future inflation; that the effects vary at different quantiles. Downside inflation risks increase significantly when output is weak, but the effects of domestic output is relatively muted at the higher quantiles. An exchange rate appreciation leads to lower inflation, but its effects are more pronounced at the higher tails. The possible documented explanation is that price rigidities tend to be present in normal conditions, but firms' steep discounting only occur when demand is sufficiently low. For the effect of the exchange rate on upside risks, the explanation is that firms adjust price more frequently at a higher inflation rates than at low inflation.

3 Data

The main monthly dataset covers the time period between January 2003 and June 2020. However, alternative periods are also considered for robustness checks. The time period for the main dataset is roughly consistent with the adoption of the inflation targeting framework by the Bank of Thailand, which started in May 2000. While the majority of the variables are available on a monthly basis, some are available on a less frequent quarterly or semi-annually basis; their values are kept constant over those months.

The principal focus of this paper is to look at the predictors of future inflation rates, thus the dependent variables in the regressions are one-year percentage changes in Thailand's consumer price indices, both the overall headline inflation, as well as its components: core, raw food price, and energy price inflation.

The set of potential explanatory variables includes variables that influence inflation rates. We consider a wide variety of factors which can be classified into 5 groups.

- **(1) Inflation expectations:** in line with the theory behind the expectations-augmented Phillips curve, inflation expectations can help anchor actual inflation as agents in the economy may plan for the future by making economic decisions based on their expectations and some of these decisions, such as wage and price setting, can make it self-fulfilling. With regards to measures of inflation expectations, we consider two alternatives: consensus inflation forecasts from surveys of economists and the term structure model of inflation expectations derived from nominal government bond yield curves[1].

- **(2) Domestic economic activities** and **(3) foreign factors:** demand and supply pressures can command changes in consumer prices. Additionally, the fact that Thailand has become integrated in the global trading system suggests that Thai inflation is prone not only to the influences of domestic activities, but also to foreign ones.

- **(4) Financial conditions:** in line with López-Salido & Loria (2020), we include financial factors that represent risks to the economy.

- **(5) Component-specific factors:** additional specific determinants can help capture key events and information in each disaggregation. For example, in addition to fundamental factors, food prices are often determined by seasonal factors such as weather and world agricultural prices, while global oil conditions drive local energy prices.

Where applicable, most explanatory variables are seasonally adjusted and transformed to the previous three months' growth rate. This is a balancing act to capture the most

[1]see Apaitan (2015)

recent development without using the single data point from the latest month, which can be noisy. On the other hand, the policy rate, minimum lending rate (MLR), and financial conditions are used in the regressions as levels. The rationale being that we think these variables have long memories and the levels are more indicative of the current conditions than recent changes.

Table 1 shows some example variables for each of the 5 groups.

Table 1: Example of used variables. Full list and description can be found in Appendix A.

Factors	**Example Variables**
1. Inflation Expectations	1Y-ahead survey-based expectations 5Y-ahead market based expectations from term structure models
2. Domestic economic activity	Leading Economic Index Coincident Economic Index Business Sentiment Index
3. Foreign factors	World Manufactured Product (PPI) Nominal Effective Exchange Rate (NEER) Thai Import price World Trade Volume
4. Financial conditions	Credit spreads (corporates vs Thai government) The Chicago Fed's National Financial Conditions Index (NFCI) Policy rate
5a. Energy specific factors	World oil supply Energy retail price Oil futures spread (4-month vs 1-month)
5b. Raw food specific factors	World food price Agricultural production Oceanic Nino Index (ONI)

4 Methodology

This section contains three subsections. The first subsection describes the general form of the econometric specification used to find linkages between various variables and future inflation. The second subsection details the methodology used to select and narrow down the explanatory variables. The final subsection explains the methodology to map results from the quantile regressions into future conditional distribution of inflation.

4.1 Econometric specification

To understand the main drivers of future inflation distribution, we perform quantile regressions using the following general specification:

$$\hat{Q}_\tau(\pi_{t+12}|x_t) = \hat{\alpha_\tau} + \hat{\beta}_\tau x_t \tag{1}$$

where the dependent variable is the specific quantile $\hat{Q}_\tau$ of the twelve-month-ahead year-on-year CPI inflation, raw-food price inflation, energy price inflation, and core inflation. $\hat{\alpha_\tau}$ represents the intercept at different quantiles and β_τ represents a vector of coefficients for the quantiles of interest, for us, these quantiles are 10^{th}, 30^{th}, 50^{th}, 70^{th}, and 90^{th}. The x_t variables on the right-hand side consist of the five groups of variables as specified in the previous section. Each dependent variable has a different set of explanatory variables; the selection methodology for each set is explained in the next subsection. The estimation methods is performed using exterior point methods as described by Koenker & d'Orey (1987).

4.2 Variable selection

We use a combination of two methods to sub-select variables to use as explanatory variables for each of the dependent variable. Castle et al. (2009) described and tested multiple model selection algorithms. One of the methods described is the stepwise AIC regression. We perform backward stepwise AIC quantile regression on the whole range of explanatory variables. Starting with the all the variables, we remove the one variable that result in the best improvement of the Akaike Information Criterion. We repeat this step until no further improvement can be made by removing a variable.

Quantile LASSO is used as a complementary method of variable selection as there are some biases and shortcomings in performing the stepwise regression as described by Whittingham et al. (2006). Varian (2014) reviewed recent developments in econometric modeling that leveraged new techniques accompanying big data. One method that can be used to select a subset of variables is the LASSO regression. Least Absolute Shrinkage and Selection Operator (LASSO) is a regression that minimizes the following:

$$\sum_i (y_i - \sum_j X_{i,j} B_j)^2 + \lambda \sum_j |B_j| \tag{2}$$

where the first summation is minimizing function for ordinary least squares regression and the second term is the LASSO penalty function. This is type of regularization that places a constraint on the size of the coefficients. For a sufficiently large λ, the coefficients of some of the variables will be exactly zero. This equation can be extended to accommodate quantile regressions by adding the quantile function as follows:

$$\sum_i \rho_\tau (y_i - \sum_j X_{i,j} B_j) + \lambda \sum_j |B_j| \tag{3}$$

where ρ_τ is the tilted absolute value function

$$\rho_\tau = \begin{cases} \tau x & \text{if } y_i > \sum_j X_{i,j} B_j \\ (\tau - 1)x & \text{if } y_i \leq \sum_j X_{i,j} B_j \end{cases}$$

The weight on the penalty function, in other words, the value of λ, can be found using cross-validation.

We then combine the results from both variable selection methods. By using a union of variables selected by the two models and removing some irrelevant and highly correlated variables, we arrive at the set of variables used in the main regressions. We observe that, for each dependent variable, the factors that result from stepwise AIC regression and quantile LASSO at different quantiles are not too different. That is, factors that play a role at the 10^{th} percentile are also factors that also play a role at 50^{th} percentile, although to a lesser (or higher) degree. Thus, for ease of comparison across quantiles, we only have one set of explanatory variables for each dependent variable. There is one specific thing to note regarding our methodology to select the explanatory variables. Typically, we start with all the variables and narrow down using the scheme described earlier. The variable in the component specific factors, however, are not always included at the start, as we eliminate some unrelated variables out. One example is the elimination of local agricultural prices from the regression predicting energy price inflation.

4.3 Creating a conditional distribution

In order to generate a full distributional forecast of inflation, we need to use results from multiple quantile regressions. One way to do this is to perform quantile regressions on a large number of quantiles and map them into distributions, this is possible since the conditional prediction using the result of each quantile regression is a point on the inverse cumulative distribution function. However, due to estimation noise and the possibility of quantile curves crossing (the results of the 10^{th} percentile conditional prediction may be lower than the 9^{th} percentile), we follow Adrian et al. (2019) in fitting the skewed t distribution to five conditional quantile predictions (10^{th}, 30^{th}, 50^{th}, 70^{th}, and 90^{th} percentiles).

5 Results

We inspect the results for each of the components of headline CPI inflation; starting with core inflation, continuing to food price inflation, and ending with energy price inflation. In the last subsection, we examine the results for the aggregate headline CPI inflation.

5.1 Core Inflation

First, we start with results for core inflation. After the variable selection phase, we are left with 7 explanatory variables. With high correlation within the many inflation expectations variables, only the 10-year implied inflation expectations from the government yield curve are selected for use in the regression. We have two domestic variables in the regression including the leading economic index (LEI) and the change in wage rate. Two foreign variables also are included: world production and NEER. The lone financial variable in the regression is the credit spread between Thai corporate bonds and government bonds. Notably, we include one component specific variable, the world food price, at the start of the variable selection process and it is included in the final regression specification. We decide to include this variable at the start as there are food components such as prepared food and condiments in core inflation (28% of core inflation in 2015).

Figure 1 shows the coefficients of the quantile regression. The x-axis represents the quantiles, ranging from 0.1 (10^{th} percentile) to 0.9 (90^{th} percentile). The y-axis represents the value of the coefficients and the shaded area represents the 90% confidence bands, estimated using bootstrapping methods.

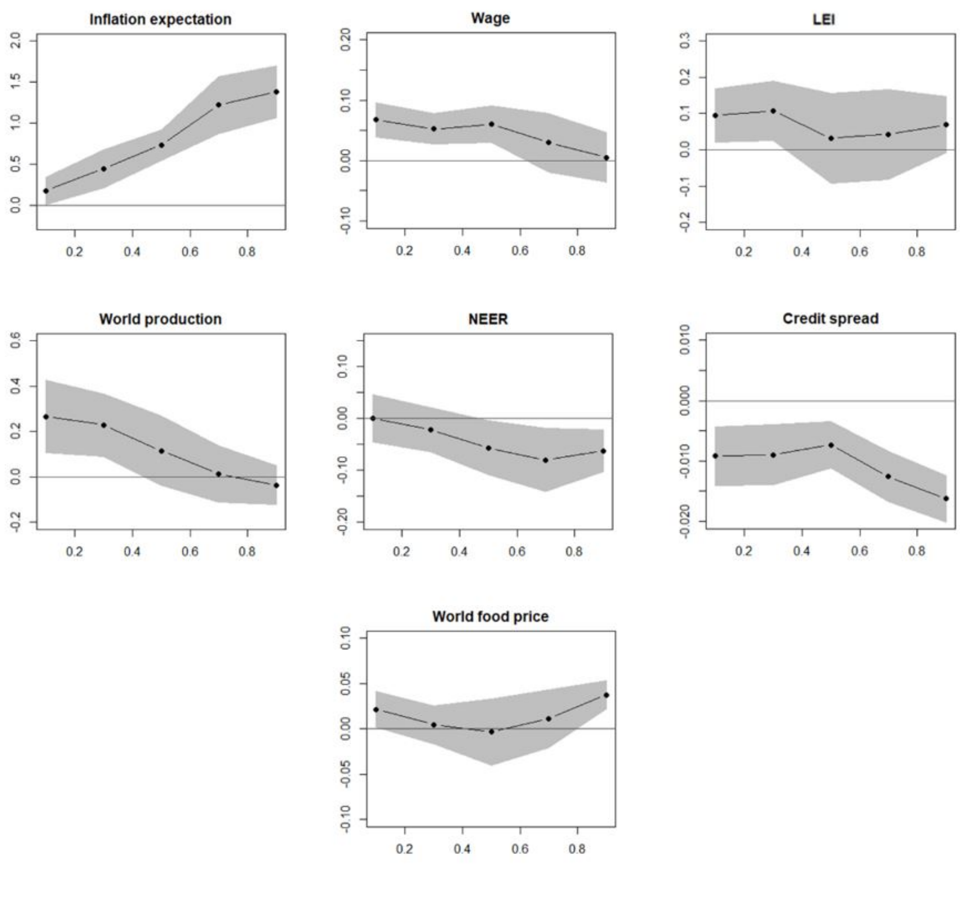


Figure 1: Core inflation

Inflation expectations matters a lot in predicting future core inflation. The coefficients for all quantiles are positive, as expected. They point to the anchoring effect of inflation expectations on realized inflation. However, there is a clear difference amongst the quantiles as we see a positive linear trend as we move from lower to higher quantiles. This points to the conclusion that inflation expectations provide a good anchor for core inflation in the middle and higher quantiles, but the anchoring effect is weaker when core inflation is low.

For domestic variables, a strong economy and increasing wages have a positive impact on future core inflation. Wage is straightforward, as it is a cost factor to production. In economic models, wage growth may have persistence and thus higher wages today can lead to a higher future inflation. LEI is a good proxy for output, and this result show the Phillips curve relationship for Thailand over this time period. The overall relationship between output and inflation seems slightly positive, however, they are not statistically significant at the median and the higher quantiles. This is consistent with the flattening of the Phillips curve, observed in many countries after the 1990s (Blanchard et al. 2015). However, the Phillips curve relationship is significant and positive at the lower quantiles, pointing to specific scenarios where output can have an effect on core inflation. These results are in line with Banerjee et al. (2020).

The general results for the two foreign factors are as expected. World production is often correlated with demand and foreign demand can lead to higher prices; the mostly positive coefficients reflect this. Similar to domestic output, this result is more pronounced in the lower quantiles of inflation. The nominal effective exchange rate (NEER – a higher value translates to currency appreciation) has negative coefficients, reflecting lower future inflation when the currency is strong. The channel for this could be via lower import prices and lower demand due to a decline in price competitiveness. With a negative sloping line in Figure 1, this result is more pronounced when inflation is higher.

Financial conditions are likely to be a drag on inflation. We see that the credit spread between corporate bonds and government bonds have negative coefficients. Credit spreads can be considered to be the measure of risks and uncertainty. Uncertainty can lead to consumers being more conservative and more likely to save rather than consume.

The last remaining variable in the regression is world food price, which we separately categorize as a component-specific variable. Although we expect world food price and future core inflation to be positively correlated, this is only statistically significant at the highest quantiles. One extreme episode of high core inflation occurred in 2008, where food components in core inflation accounted for a 2.3 percent increase in core inflation. During the previous year, there was a world food crisis originating from world population growth and United States' biofuel subsidy policy. This event led to a spike in cost of Thai food production such as cooking oil in the seasonings component of core inflation.

Next, we look at the drivers of the left tail of the inflation distribution, or 'inflation at risk.' Figure 2 shows the historical contribution of the prediction for future 10$^{\text{th}}$ percentile core inflation through time. The 10th percentile here can represent the risks to lower inflation, or 'inflation-at-risk.' There are a few things to note here. First, the predicted drop during the global financial crisis in 2009-2010 were driven by a drop in global production, an increase in credit spreads, and, to a lesser extent, a decrease in local wages. Second, the NEER has almost no effect at this particular percentile as the coefficient is very close to zero. Finally, despite having less of an effect at the left tail, inflation expectations still matter; and its downward trend is contributing to a lower 10$^{\text{th}}$ percentile prediction in the past few years.

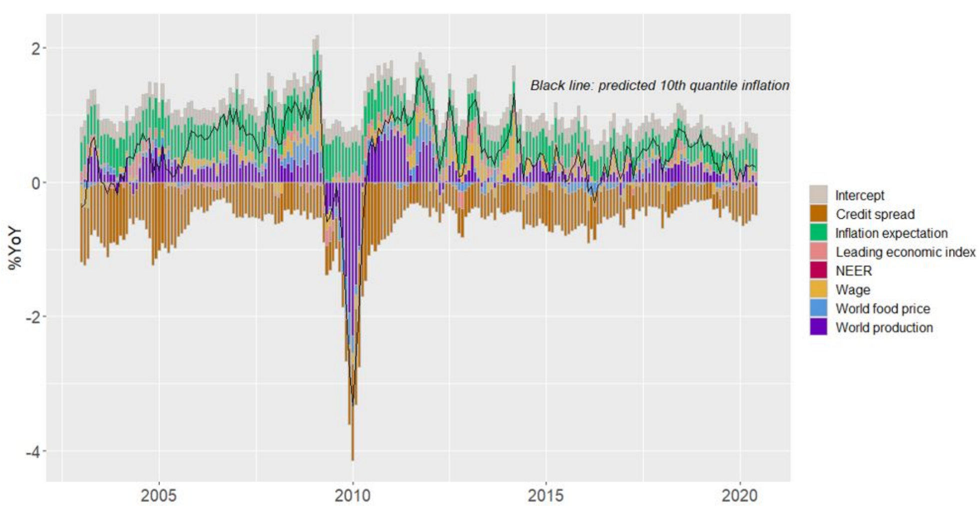


Figure 2: Historical contribution of core inflation (10$^{\text{th}}$ percentile)

5.2 Raw food price inflation

Next, we look at the drivers of future raw food price inflation. For these regressions, we use the alternative starting date of 2006 due to the fact that many of the raw food component-specific variables start later. Five variables remain after the variable selection process. Just as with core inflation, LEI is again an important factor and is the only domestic factor in this regression. The VIX index, a financial conditions indicator, also gets selected. Three component specific factors are included: world food price, retail oil price, and the oceanic niño index (ONI).

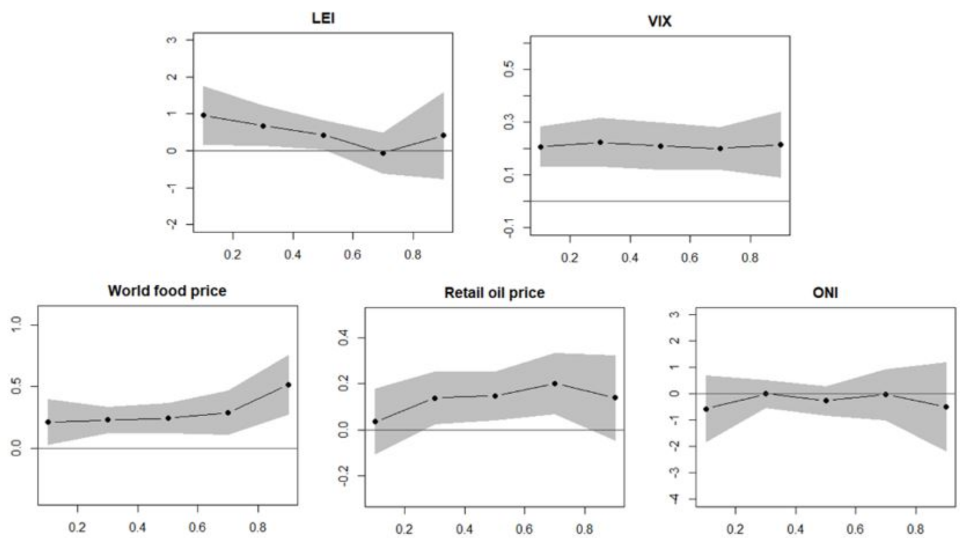


Figure 3: Results for raw food price inflation

Figure 3 shows the results for the quantile regressions when the dependent variable is raw food price inflation. LEI has a similar effect on raw food price inflation as it does on core inflation. The coefficients are positive and are more important at the lower quantiles. We are puzzled by the positive coefficients on the VIX across all quantiles. One possible explanation is that raw food demand might be higher as it is something people might hoard when uncertainty is high. In addition, investors might reallocate their portfolios to safer assets when uncertainty is high, moving from stocks and bonds into commodities such as gold and food (see Gozgor & Kablamaci 2014, Gilbert 2010). The world food price is positively correlated with the future local raw food price. The pass-through of prices is expected food price components are commodities and prices of commodities should converge. As with core inflation, the world food episode in 2007 -2008 was also responsible for domestic agricultural prices increase, notably rice products. Retail oil price is a cost factor in raw food price, thus has positive coefficients, although only significant in the middle quantiles. The oceanic niño index is included as a term in the regressions but all of the coefficients are not statistically significant.

5.3 Energy price inflation

We examine the third piece of the CPI component: energy price inflation. Five variables are included in this set of regressions. Since this factor is almost entirely driven by foreign oil prices, none of the domestic variables appear in the regressions. Component specific factors dominate this set of regressions with oil spread (difference between 4 month-ahead futures price and 1-month-ahead futures price), world supply of oil (production of oil and related products), and world demand of oil (using actual consumption as a proxy). NEER and the US's national financial condition index (NFCI) are the other two variables included in the regressions.

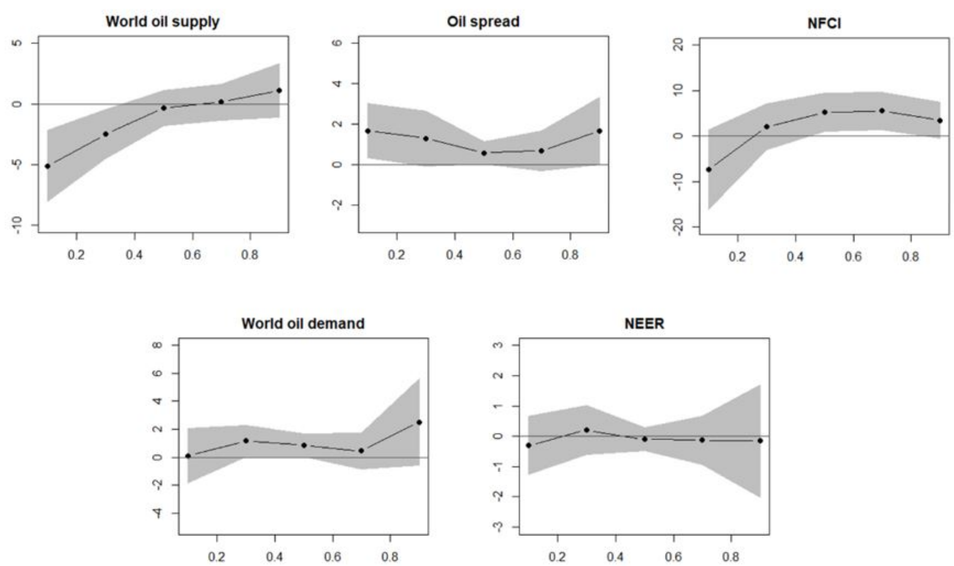


Figure 4: Results for energy price inflation

The coefficients of the regressions can be visualized in Figure 4. It is hard to predict future energy price inflation. This is reflected by the fact that, even after the narrowing down of variables, most of the coefficients are still statistically insignificant. However, a few trends can be observed. First, higher world oil supply has a negative effect on the lower quantiles of future inflation. This is interesting as this variable seems to have no prediction value at the median and higher quantiles. The negative effect of world oil supply to future energy price inflation is only observed in the lower tails. Between 2014 to 2016, oil prices were driven up by an oversupply caused by the productivity gains in US shale oil and the failure of OPEC to implement production cuts. High oil inventories depressed retail prices in the following years.

Next, when the oil price futures curve is in contango, the future energy price inflation is predicted to be higher, although only statistically significant at the lower tails. Lastly, the financial conditions, here represented by NFCI, seems to have a positive effect on inflation in the middle quantiles.

5.4 Headline inflation

Since the aggregate CPI index is composed of the three components whose results are described in detailed in the preceding sections, it is no surprise to see that results for headline inflation are, overall, in line with the previous results. The variables in this regression is almost just a combination of the all the variables used in the components. There are nine variables in this set of regressions: one inflation expectations variable, two domestic variables, two global variables, one financial conditions variable, and three component-specific variables. The full list is included in the appendix.

The partial results of the set of regressions for the aggregate headline inflation are displayed in Figure 5. Since there are a lot of variables, we only highlight some of them here. Driven by results from core inflation, inflation expectations play a bigger role in the higher quantiles of inflation. LEI and world production, on the other hand, are more important in the lower quantiles, suggesting that the Phillips curve relationship remains strong there. Higher credit spreads lead to lower inflation in the future, but only statistically significant at the higher quantiles for CPI. World oil supply brings down future inflation in the lower quantiles. Finally, current world food price provides a lift to future inflation in the middle quantiles.

With the determinants of future inflation previously mentioned, we want to compare how the predicted full inflation distribution look over time. In Figure 6, we show the conditional CPI forecasts for three time periods: January 2007 (forecasted using January

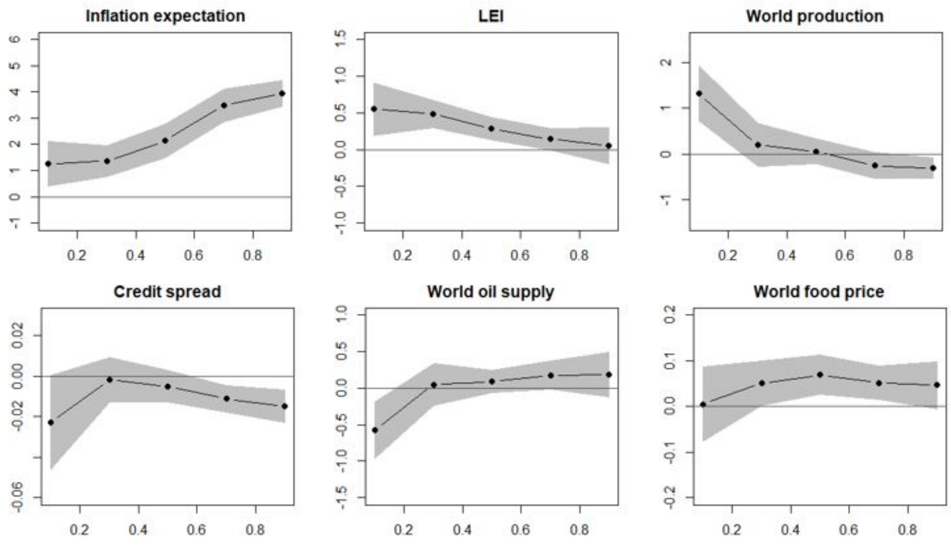


Figure 5: Results (partial) from headline inflation quantile regressions

2006) before the financial crisis, January 2015 when inflation is stable and low, and February 2021 (using data from February 2020, the normal period just before the large local outbreak of COVID-19).

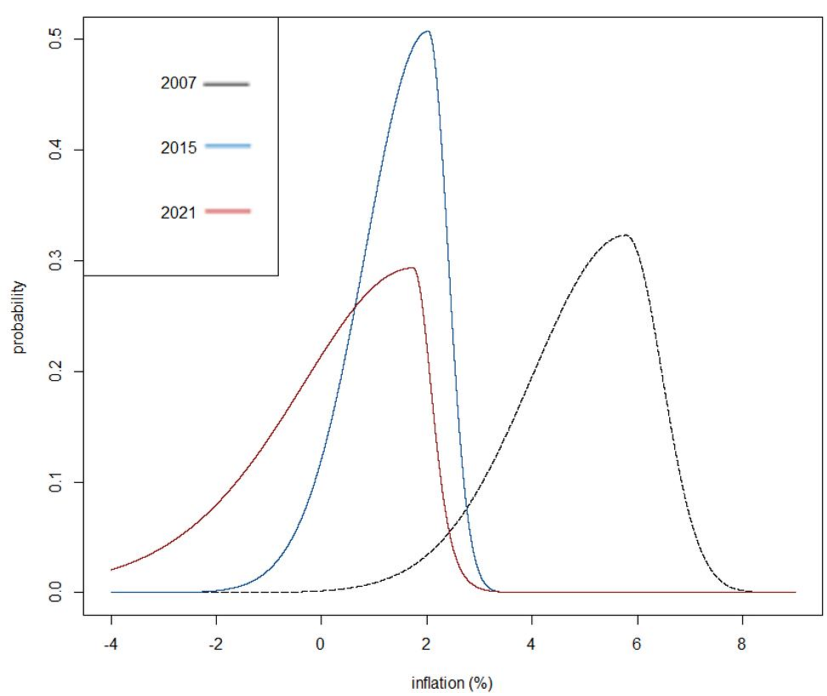


Figure 6: Conditional CPI forecasts at different time periods

These three time periods are very different from each other. There is a leftward shift in the distribution of inflation over time. Our regression results point to lower inflation expectations as the main culprit. The forecast for 2007 happened in an environment of higher inflation and the inflation of the years 2005 and 2006 are both higher than 4 percent. The distribution forecast for 2015 does contain negative inflation rates in the lower tail, and 2015 ended up being a year when the Thai inflation was negative. The 2021 distribution has more negative skew than the rest, and with little chance of inflation exceeding 2%.

Figure 7 illustrates the factors that drive 'inflation at risk' for the 3 time periods; the constant intercept is not shown. The factor that contributes to the biggest change is world production. Inflation expectations' and LEI's decline between 2006 and 2014 and world oil demand's drop between 2014 and 2020 can also help explain the lower tail kept moving left in this time period.

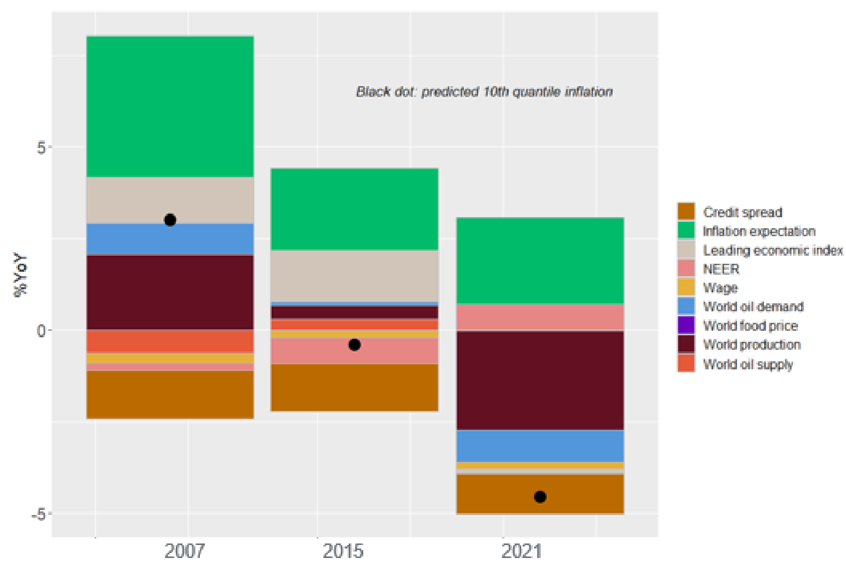


Figure 7: Factors driving conditional CPI forecasts at 10^{th} percentile

6 Robustness

In this section, we check the model for robustness. We divide the section into 3 subsections. For the first subsection, for some variables, we substitute another similar variable into the set of CPI quantile regressions and examine whether the coefficients deviate from the original regressions. In the second subsection, we perform the CPI quantile regressions using different timeframes. The last subsection scrutinizes past forecasting accuracy.

6.1 Alternative variables

For this section, the results are pretty robust to changes in the regression specifications. We substitute the variable used in the regression with another similar one. For example, in Figure 8, we substitute the different measures of inflation expectations into the equation. The original variable used is in the leftmost panel: the 10-year inflation expectations derived from the government yield curve. We separately substitute the variable with the 5-year inflation expectations, also derived from the yield curve, and the 1-year inflation expectations from a survey of economists. The results are shown in panels 2 and 3, respectively. We can still observe the same general trend across all the measures of inflation expectations. The coefficients are all positive and , generally, increasing as we move from lower to higher quantiles.

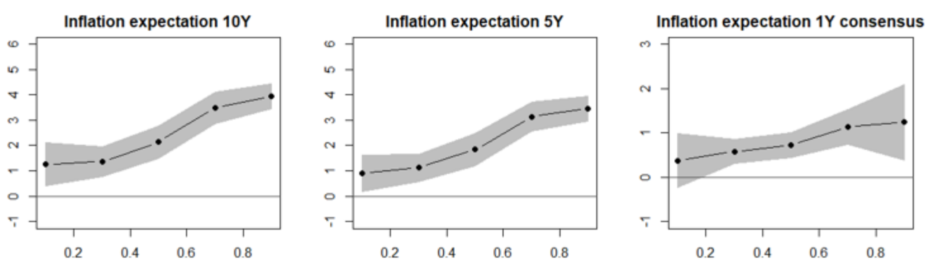


Figure 8: Alternative variables – inflation expectations variables

Next, we look at the group of variables representing the financial conditions. In the final specification, we include one variable, the credit spreads between 3-year AA Thai corporate bonds and 3-year government bonds. In Figure 9, we display the regression results if we instead substitute in the Chicago FED's National Financial Conditions Index (NFCI) in panel 2 and the VIX index in panel 3. For these three financial conditions variables, we can observe a similar trend, although the level of statistical significance vary from variable to variable.

We include two variables in the quantile regression from the domestic variables group:

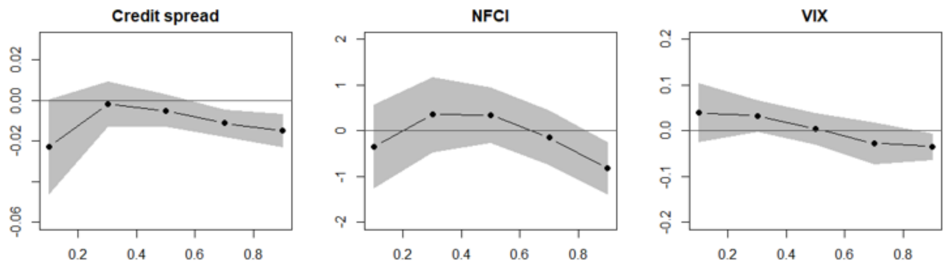


Figure 9: Alternative variables – financial conditions variables

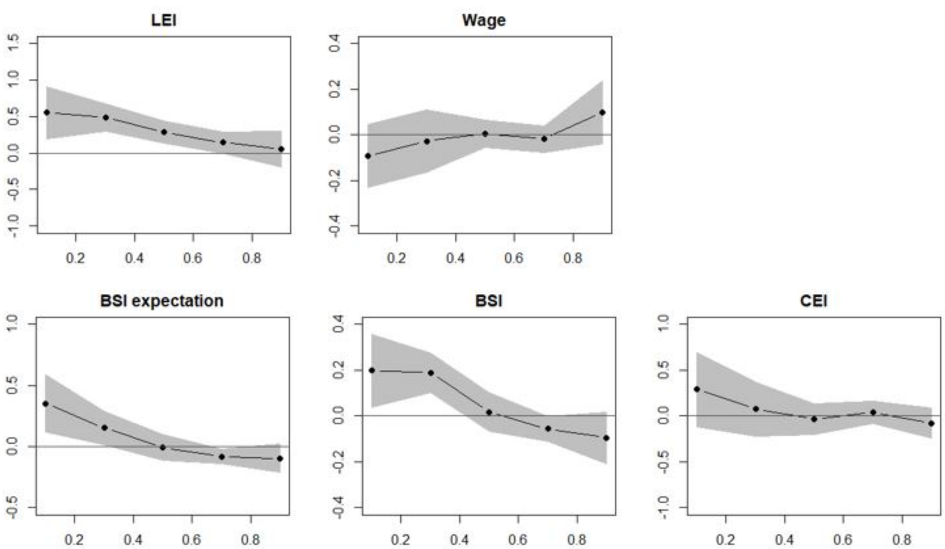


Figure 10: Alternative variables – domestic variables

Leading Economic Indicator (LEI) and the change in average wage. In this exercise, we replace them with one of Coincident Economic Indicator (CEI), Business Sentiment Index (BSI), and the 3-month-in-the-future expectation of BSI. By design, LEI is supposed to predict where the economy is headed through variables that take into account future expectations such as the value of the stock market and the number of new company registrations. On the other hand, CEI is supposed to measure the current state of the economy through variables such as the most recent sales of new automobiles. Since we are predicting ahead, a forward-looking indicator is more useful. The state of the current economy has little prediction power over future inflation; the coefficients for current domestic-economic variables such as wages and CEI are not statistically significant from 0. On the other hand, BSI and the expectations of future BSI also has a downward slope similar to LEI. Being surveyed together, it is likely that the future is somewhat taken into account in current BSI. From these variables, the results seem robust to forward-looking domestic variables.

6.2 Alternative timeframes

In this subsection, we perform quantile regressions on alternative timeframes. We find that data in the earlier periods are driving the trends we observe in the results section, as there seem to be a structural break during the period of lower inflation since 2015. In the two top panels in Figure 11, we show the coefficients from our main starting date, 2003, and an alternative date in 2007. Most of the results are in alignment. However, when we divide the full sample into two time periods, shown in the bottom two panels in Figure 11, we can see that the results are radically different. Most of the coefficients change drastically or become statistically insignificant; the only constant seems to be credit spreads, which act as negative factors in both samples.

Oka & Qu (2011) developed testing procedures to determine structural changes in any given regression quantile. We followed their testing procedures to determine structural breaks for each decile starting from the 10^{th} percentile to the 90^{th} percentile. We find that there is a structural break in 3 of the regressions: 20^{th} percentile, 30^{th} percentile, and 90^{th} percentile. The breaks for the lower quantiles lies in the 2^{nd} half of 2014 and the break for the 90^{th} percentile is in 2008. The breaks observed in the lower quantiles in the area of interest for 'inflation-at-risk' are consistent with our earlier claim that there is a structural break associated with the period of low inflation starting in 2015.

6.3 Forecasting accuracy

We find that the forecasting accuracy is reasonable in-sample, but is quite unreliable out-of-sample. Here, we follow Diebold et al. (1998) by using the probability integral transform (PIT) as a tool to evaluate the consistency between predictive forecasts (from our regression model) and actual observations. Theoretically, the resulting histogram should be flat and all bars should be the same height. We note where each actual observation falls within each part (for example in the 0^{th} to the 10^{th} decile) of the predicted distribution, and combine

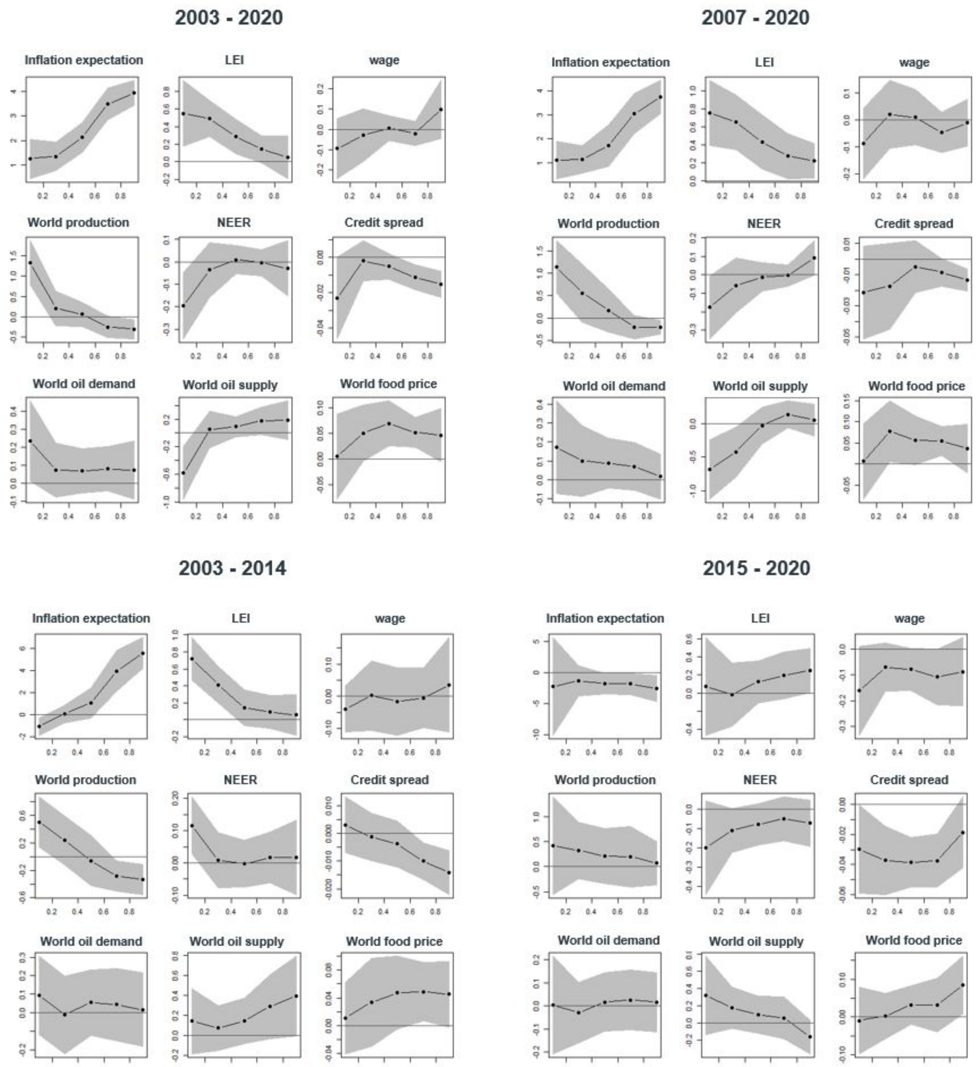
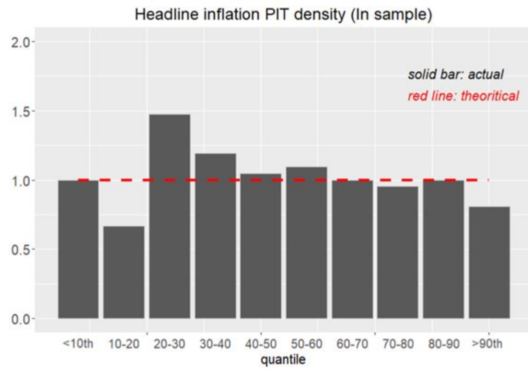
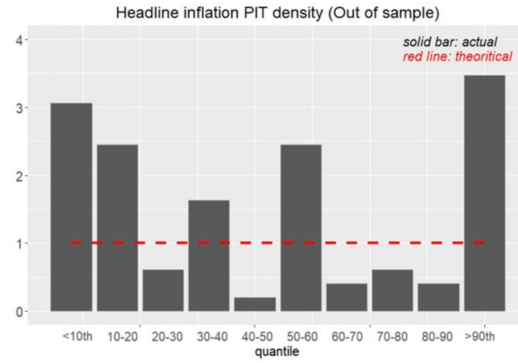


Figure 11: Alternative Timeframes

all observations to see whether there are similar numbers of actual observations falling in the 0th to 10th decile as there are number of observations falling in the 10th to 20th decile. In the left panel of Figure 12, we show the in-sample results. Other than the two deciles between the 10^{th} and 30^{th} percentiles, the distribution is quite uniform. We also perform out-of-sample tests using coefficients up to the current point in time to predict future distributions from 2016 onwards. Since we have a times series data, we can only test the more recent data after the presumed structural break. The result is in the right panel of Figure 12, and it is not close to being uniform; with way too many observations in two extreme deciles, and too few in the middle deciles. We suspect that this is driven by the same structural break observed in the previous section. It is hard to predict out-of-sample when we leverage so many observations from prior to the structural break in order to build our model.



(a) In-sample (2003-2016)



(b) Out-of-sample (2016-2020)

Figure 12: Forecasting accuracy (using PIT) in-sample vs out-of-sample

7 Conclusion

This paper analyzes the determinants of future inflation specifically for Thailand using monthly data on a wide range of variables. The key findings are as follows. First, inflation expectations play an important role in anchoring future inflation, but that role becomes less important in the lower quantiles. Second, tight financial conditions are a drag to future inflation in all quantiles. Third, component-specific factors, have the expected effects on future inflation. High world food prices today can lead to higher future inflation and today's oil supply can adversely affect 'inflation-at-risk.' Lastly, there is some evidence to show that in the middle quantiles, the relationship between output (using LEI as a proxy) and inflation is weak, however, this Phillips curve relationship becomes stronger in the lower quantiles.

The results can provide some guidance to policy makers. The central bank has the tools to change the future distribution of inflation. With a solid reputation and a sound communication strategy, the central bank can sway inflation expectations. Keeping financial conditions loose can push up inflation. Finally, the central bank, along with the ministry of finance through fiscal policies, can help boost output and help decrease the risks on the left tail of the distribution. Future research is needed to evaluate the specific effects of structural changes on forecasted inflation distribution since we found signs of a structural break around 2015. We believe that the ongoing COVID pandemic could create another structural change in inflation dynamics. Thus, once the world enters some sort of normalcy post pandemic, a deep dive into these possible fundamental changes in inflation dynamics will be useful for policymakers to manage future inflation risks.

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A Variables

Table A1: Inflation variables

Variables	Description	Data Availability	Source
Headline Inflation Core Inflation Raw Food Price Inflation Energy Price Inflation	The weighted average prices of consumer goods and services purchased by households	1995	Thailand's Ministry of Commerce

Table A2: Inflation expectations variables

Variables	Description	Data Availability	Source
1-Y Ahead consensus	Survey-based inflation expectations from economists	2001	Consensus Economics
5-Y Term Structure Models 5-Y Term Structure Models	Model-based inflation expectations derived from nominal government bond yield curves	2001	The Bank of Thailand

Table A3: Domestic factor variables

Variables	Description	Data Availability	Source
Leading Economic Index	Leading economic condition indicator constructed from newly registered companies, new construction area permitted, export volume index, business sentiment index, SET index, real broad Money, and oil price inverse index	2000	The Bank of Thailand
Coincident economic index	Economic condition indicator constructed from import volume index, manufacturing production index, real gross value added tax, volume sales of automobiles and real debit to demand deposit	2000	The Bank of Thailand
Business sentiment index	Survey-based economic expectations	1999	The Bank of Thailand
Unemployment rate	The percentage of unemployed workers in the total labor force	2001	Thailand National Statistical Office
Average Wage	The compensation, in cash or in kind, received by employees in exchange for their labor	2001	Thailand National Statistical Office
Debt-to-GDP ratios	The percentage of government debt to GDP	2001	The Bank of Thailand

Table A4: Foreign factor variables

Variables	Description	Data Availability	Source
Export volume	Aggregate world export volume	2000	CPB Netherlands Bureau for Economic Policy Analysis
Import price	Prices of imported goods and services landed into the country during the period	2000	Thailand's Ministry of Commerce
Exchange Rate	Value of US dollar in terms of Thai Baht	1994	The Bank of Thailand
Nominal Effective Exchange Rate (NEER)	The weighted average of bilateral exchange rates of the baht vis-à-vis Thailand's 25 major trading partners and competitors	1994	The Bank of Thailand
Real Effective Exchange Rate (REER)	NEER adjusted for relative prices between that of Thailand and major trading partners and competitors	1994	The Bank of Thailand
Terms of trade	The ratio between export price index and import prices index	1995	Thailand's Ministry of Commerce
Commodity price	Average of non-energy commodity prices	1960	The World Bank
Trade balance	Net export (export less import) of goods	1995	The Bank of Thailand
Imports	Transactions involving movements of goods into Thailand over a specific period	1995	Thailand's Ministry of Finance
Exports	Transactions involving movements of goods into Thailand over a specific period	1995	Thailand's Ministry of Finance
World Trade Volume	Aggregate world trade in commodities	2000	CPB Netherlands Bureau for Economic Policy Analysis
World Manufactured Product (PPI)	Aggregate industrial production including value added in mining, utilities, and manufacturing	2000	CPB Netherlands Bureau for Economic Policy Analysis

Table A5: Financial Conditions variables

Variables	Description	Data Availability	Source
Credit spread	The spread of government bond yield and corporate bond yield (AA-3Y)	2001	The Thai Bond Market Association
Equity returns	The returns of the Stock Exchange of Thailand's SET index	1975	The Stock Exchange of Thailand
CBOE Volatility Index (VIX)	Index representing the market's expectations for volatility over the coming 30 days	2000	CBOE Global Markets
Merrill Lynch Option Volatility Estimate index (Move)	The implied yield volatility of a basket of one-month over-the-counter options	2002	Intercontinental Exchange
The Chicago Fed's National Financial Conditions Index (NFCI)	Weighted average of 105 indicators of risk, credit, and leverage in the financial system	1971	Federal Reserve Bank of Chicago
Minimum loan rate (MLR)	The rate that commercial bank charges its most creditworthy major borrowers on loans with pre-specified repayment schedules.	1983	The Bank of Thailand
Policy rate	The rate that the Monetary Policy Committee announced in conducting monetary policy under the inflation-targeting framework.	2000	The Bank of Thailand
Equity volatility	Monthly standard deviation computed from equity daily return for the SET index	1998	Bloomberg

Table A6: Energy Specific Factors Variables

Variables	Description	Data Availability	Source
Energy retail price	Weighted average of domestic retail oil price	2002	Thailand's Ministry of Energy
Energy prices	Weighted average of energy commodity prices	1960	The World Bank
Oil spread	WTI Electronic Energy Future Continuation 4 minus Future Continuation 1	2000	Reuters
Oil Fund	Value of Thailand's oil fund used to adjust domestic retail oil price	2002	Thailand's Ministry of Energy
Dubai oil price	Dubai oil price	1995	PTT Public Company Limited
World oil demand	World liquid fuels consumption	1990	U.S. Energy Information Administration
World oil Supply	World crude oil NGPL and other liquids production	1990	U.S. Energy Information Administration
Oil inventory	World net inventory withdrawals, total crude oil and other liquids	2001	U.S. Energy Information Administration

Table A7: Raw Food specific factors Variables

Variables	Description	Data Availability	Source
World food price	Weighted average international price of five commodity group price	1994	The Food and Agriculture Organization
Agricultural production	Average quantity of any crop and livestock	2005	Thailand's Office of Agricultural Economics
Agricultural price	Average price of any crop and livestock	2005	Thailand Office of Agricultural Economics
Farm income	Summary of income and expenses that occurred during a specified accounting period	2005	Thailand Office of Agricultural Economics
Oceanic Niñno Index (ONI)	The rolling 3-month average sea surface temperatures in the east-central tropical Pacific. When the Oceanic Niño Index is -0.5 or lower, indicating the region is cooler than usual.	2005	International Research Institute for Climate and Society

B Regression Results

Table B1: Core inflation results

Variable	10th	30th	50th	70th	90th
(intercept)	0.22	-0.07	-0.35	-0.68 *	-0.39
	(0.14)	(0.18)	(0.21)	(0.40)	(0.45)
Inflation expectations	0.18 *	0.45 ***	0.74 ***	1.22 ***	1.38 ***
	(0.11)	(0.13)	(0.12)	(0.22)	(0.20)
LEI	0.09 **	0.11 **	0.03	0.04	0.07
	(0.04)	(0.05)	(0.07)	(0.07)	(0.05)
Wage	0.07 ***	0.05 ***	0.06 ***	0.03	0.01
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
World Production	0.27 ***	0.23 **	0.11	0.01	-0.04
	(0.10)	(0.09)	(0.09)	(0.07)	(0.05)
NEER	0.00	-0.06 **	-0.06 **	-0.08 **	-0.06 **
	(0.03)	(0.03)	(0.03)	(0.04)	(0.02)
Credit Spread	-0.01 ***	-0.01 ***	-0.01 ***	-0.01 ***	-0.02 ***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
World Food Price	0.02	0.00	0.00	0.01	0.04 ***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
N	210	210	210	210	210
τ	0.10	0.30	0.50	0.70	0.90
R^1	0.27	0.19	0.25	0.31	0.43
AIC	434.63	423.07	437.20	459.80	458.31
AIC	461.41	449.85	463.98	486.58	485.09

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table B2: Raw food price inflation results

Variable	**10th**	**30th**	**50th**	**70th**	**90th**
(intercept)	-4.25 ***	-1.80	-0.01	2.51	5.40
	(0.83)	(1.19)	(1.17)	(0.95)	(1.59)
LEI	0.96 **	0.68 **	0.43 *	-0.06	0.41
	(0.47)	(0.32)	(0.23)	(0.32)	(0.69)
VIX	0.21 ***	0.22 ***	0.21 ***	0.20 ***	0.22 ***
	(0.05)	(0.06)	(0.05)	(0.05)	(0.08)
Retail oil price	0.04	0.14 **	0.15 **	0.20 **	0.14
	(0.08)	(0.07)	(0.06)	(0.09)	(0.11)
World food price	0.21 *	0.23 ***	0.24 ***	0.29 **	0.51 ***
	(0.11)	(0.06)	(0.06)	(0.12)	(0.15)
ONI	-0.57	0.00	-0.27	-0.03	-0.51
	(0.78)	(0.33)	(0.38)	(0.59)	(1.07)
N	171	171	171	171	171
τ	0.10	0.30	0.50	0.70	0.90
R^1	0.14	0.20	0.22	0.25	0.30
AIC	993.14	952.20	954.34	981.70	1048.26
AIC	1011.99	971.05	073.19	1000.55	1067.11

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table B3: Energy price inflation results

Variable	10th	30th	50th	70th	90th
(intercept)	-13.59 ***	-0.49	5.10 ***	8.47 ***	16.14 ***
	(3.08)	(2.56)	(1.36)	(1.69)	(2.90)
NEER	-0.30	0.21	-0.10	-0.13	-0.15
	(0.63)	(0.48)	(0.23)	(0.32)	(0.69)
NFCI	7.38	2.06	5.21 *	5.51 **	3.46
	(4.94)	(3.24)	(2.66)	(2.79)	(2.70)
Oil spread	1.68 **	1.29	0.58 *	0.69	1.67
	(0.82)	(0.84)	(0.35)	(0.65)	(1.02)
World oil supply	-5.11 ***	-2.50 **	-0.33	0.16	1.11
	(1.78)	(1.19)	(0.91)	(1.02)	(1.37)
World oil demand	0.10	1.16 *	0.85 *	0.45	2.51
	(1.13)	(0.65)	(0.48)	(0.79)	(2.05)
N	209	209	209	209	209
τ	0.10	0.30	0.50	0.70	0.90
R^1	0.14	0.05	0.03	0.04	0.05
AIC	1743.82	1651.74	1610.12	1645.11	1734.58
AIC	1763.87	1671.80	1630.17	1665.16	1754..63

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table B4: Headline inflation results

Variable	**10th**	**30th**	**50th**	**70th**	**90th**
(intercept)	-2.61 *	-2.05 ***	-2.95 ***	-4.62 ***	-4.79 ***
	(1.32)	(0.47)	(0.48)	(0.43)	(0.71)
Inflation expectations	1.26 *	1.36 ***	2.13 ***	3.49 ***	3.94 ***
	(0.52)	(0.25)	(0.33)	(0.30)	(0.42)
LEI	0.55 **	0.49 ***	0.29 ***	0.14	0.05
	(0.18)	(0.12)	(0.08)	(0.09)	(0.09)
Wage	-0.09	-0.03	0.01	-0.02	0.10
	(0.07)	(0.05)	(0.04)	(0.04)	(0.05)
World Production	1.32 ***	0.20	0.06	-0.25	-0.30 *
	(0.34)	(0.18)	(0.14)	(0.15)	(0.15)
NEER	-0.20 *	-0.04	0.01	-0.00	-0.03
	(0.08)	(0.05)	(0.04)	(0.04)	(0.05)
Credit Spread	-0.02 **	-0.00	-0.01	-0.01 *	-0.02 **
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
World oil demand	0.23	0.07	0.07	0.08	0.07
	(0.17)	(0.07)	(0.07)	(0.05)	(0.10)
World oil supply	0.58 **	0.05	0.09	0.18 *	0.19
	(0.20)	(0.18)	(0.12)	(0.08)	(0.14)
World Food Price	0.00	0.05 *	0.07 ***	0.05 **	0.05
	(0.04)	(0.02)	(0.02)	(0.02)	(0.03)
N	210	210	210	210	210
τ	0.10	0.30	0.50	0.70	0.90
R^1	0.25	0.23	0.28	0.33	0.47
AIC	907.90	840.73	798.88	786.12	815.33
AIC	941.37	874.20	832.35	819.59	848.80

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$