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SPECIAL REPORT

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Pipeline Pressures And The Near-Term Inflation Outlook

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- We expect cyclical disinflation to resume, but the timeline has been pushed out.
- Our pipeline model suggests that the 3-month rate of core inflation will remain around 3% in the near term.
- Rate cuts will arrive in Q4 at the earliest, as the Fed awaits confirmation that disinflation has returned.
- Core goods inflation will stabilize close zero and core services will buck the disinflationary trend.
- Long-anticipated relief in the shelter component will be delayed further.

Forecasting inflation is difficult. Economists and policymakers have traditionally used Phillips Curve models, which rely on measures of the (GDP-based) output gap or the deviation of the unemployment rate from its full-employment level. This approach has a poor historical track record at best. Both supply and demand factors affect inflation and there is no indicator that can capture both dynamics. The pandemic shock further challenged the Phillips curve approach because massive shifts in supply and demand made it impossible to estimate the amount of slack in the economy or labor market at any point in time.

This *Special Report* describes our new regression-based model that captures the effects of changes in "pipeline" inflation. Pipeline inflation refers to pressures that have already accumulated further up the economic chain, such as producer prices or the labor market, but have yet to be reflected in final consumer prices.

Pipeline pressures are often quickly reflected at the consumer level, and this limits how far we can peer into the future using this methodology. As such, the model provides an inflation forecast for only the next three months. Moreover, pin-point accuracy is impossible because 3-month annualized rates of inflation are highly volatile.

That being said, we are hopeful that the model will provide useful information or guidance on the near-term direction of core PCE inflation, and whether it is likely to surprise the consensus to the upside or downside.

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Methodology Overview

Our model uses automatic relevance determination regression (ARD) to estimate the annualized 3-month rate of change of the main components of core Personal Consumption Expenditure (PCE). Core PCE inflation excludes food and energy, as these two categories are not only highly volatile but also set more by supply forces than demand. Excluding these items allow policymakers to have a better view on the overall trend in inflation.

In simple terms, ARD regression considers a large number of explanatory variables but retains only those that best explain movements in core inflation. Please refer to the **Appendix 1** for a list of explanatory variables.

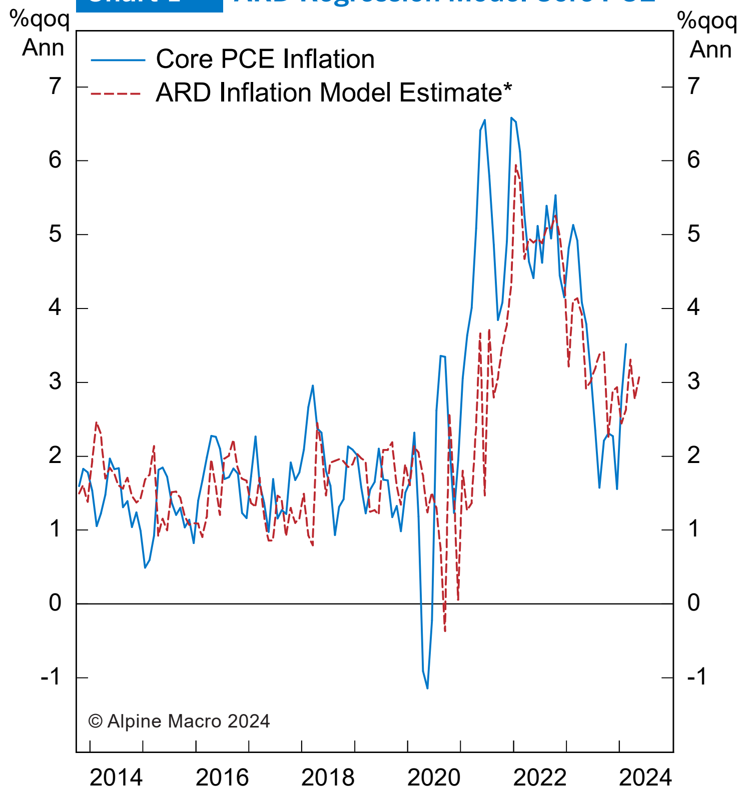
The ARD methodology, described in the **Appendix 2**, is well-suited for our forecasting needs as it sheds light on what is driving inflation in the post-pandemic world. It is the model that determines which factors are relevant for the inflation process and thereby eliminates pre-conceived biases.

We model inflation for the three components of core inflation separately, namely: core goods, core services excluding housing, and housing. This classification breakdown aligns with how the Fed thinks about the main inflation categories. We take a weighted average of the three sub-sectors to obtain a forecast for total core PCE inflation.

Model Results

Chart 1 presents the model's results. There are some obvious historical divergences, but keep in mind the inherent volatility of 3-month annualized inflation rate. As previously mentioned, pin-point estimates are impossible. The model is meant only to suggest the most likely direction of inflation over the next 3 months, given movements in pipeline prices that have already occurred over the previous 3-12 months.

Chart 1 ARD Regression Model Core PCE



*Alpine Macro proprietary model

The model sees the 3-month rate of change of core inflation decelerating only modestly in the coming months from its current pace of 3.5% to about 3%.

This forecast reflects a weighted average of the following three model forecasts:

Housing

Chart 2 presents the forecasts for housing inflation. The historical track record for this component is

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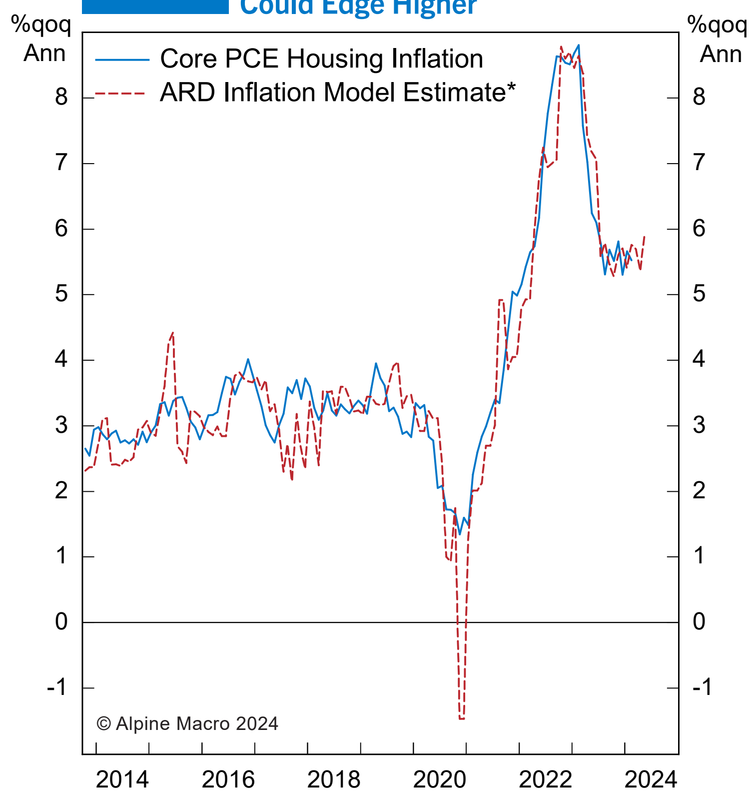
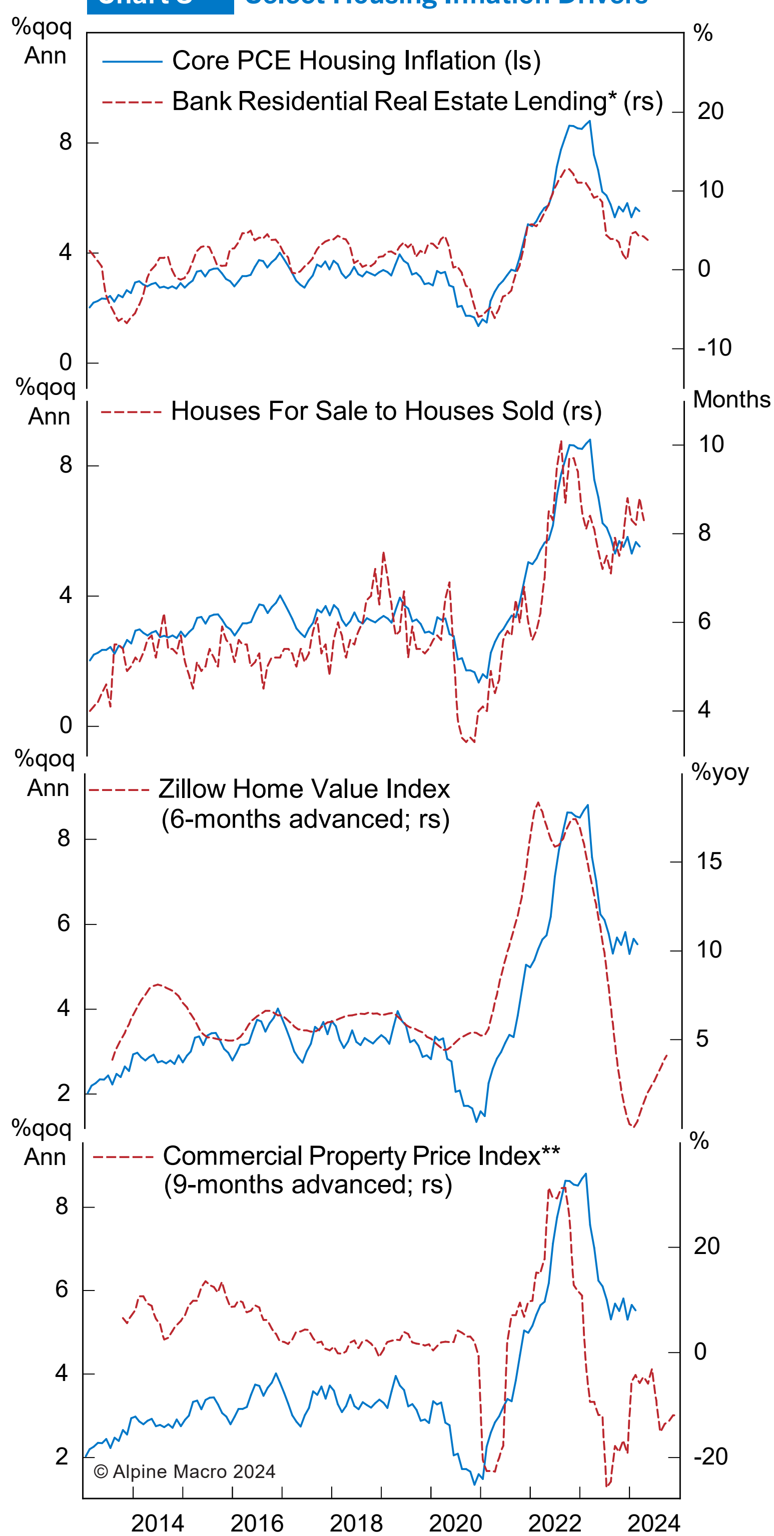
Chart 2 Housing Inflation Could Edge Higher



*Alpine Macro proprietary model

Chart 3 Select Housing Inflation Drivers



*Shown as 6-month change; source: Federal Reserve
**Shown as 6-month change; source: Green Street Advisors

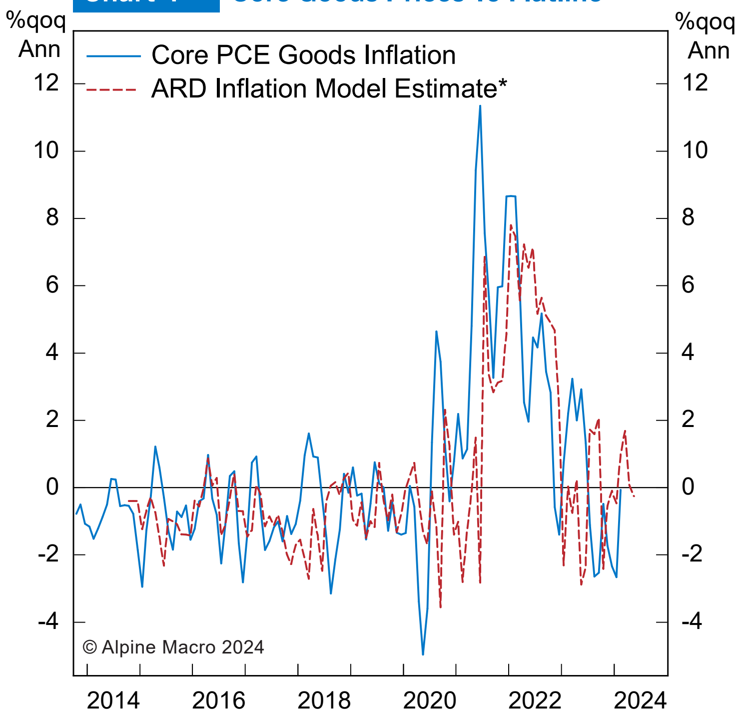
Table 1 Model Accuracy

	R-Squared
Housing	0.82
Core Goods	0.43
Core Services ex-housing	0.5

very good, providing an R-squared of 0.82 (**Table 1**). The model sees the quarterly annualized housing inflation rate reaching 5.9% by June, up from 5.6% over the latest 3-month period.

The model's estimate for near-term housing inflation is driven by the following factors, among several others (**Chart 3**):

Chart 4 Core Goods Prices To Flatline



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- Continued growth in real estate bank credit (6-month change)
- A rebound in the ratio of houses for sale to houses sold
- A recovery in the mortgage application refinancing index (12-month change)
- Rising Zillow home value index (12-month change)
- A moderation in the decline of CRE Prices (6-month change)

Core Goods

The model expects core goods inflation on a quarterly basis to stabilize around 0%, similar to the latest quarter-over-quarter reading and the pre-pandemic average (Chart 4). The model's track record for core goods inflation is the least accurate out of the three categories, with an R-squared of 0.43.

The relatively less certain results may be due to a shift in the composition of consumer spending on goods during the pandemic. The rise in e-commerce and changing consumer habits during the various lockdown episodes have disrupted consumption behavior.

The model's accuracy was better prior to the pandemic. As consumption patterns settle into a "new normal", we expect the core good model's accuracy to improve.

According to the model, the key factors currently keeping core goods inflation steady include (Chart 5):

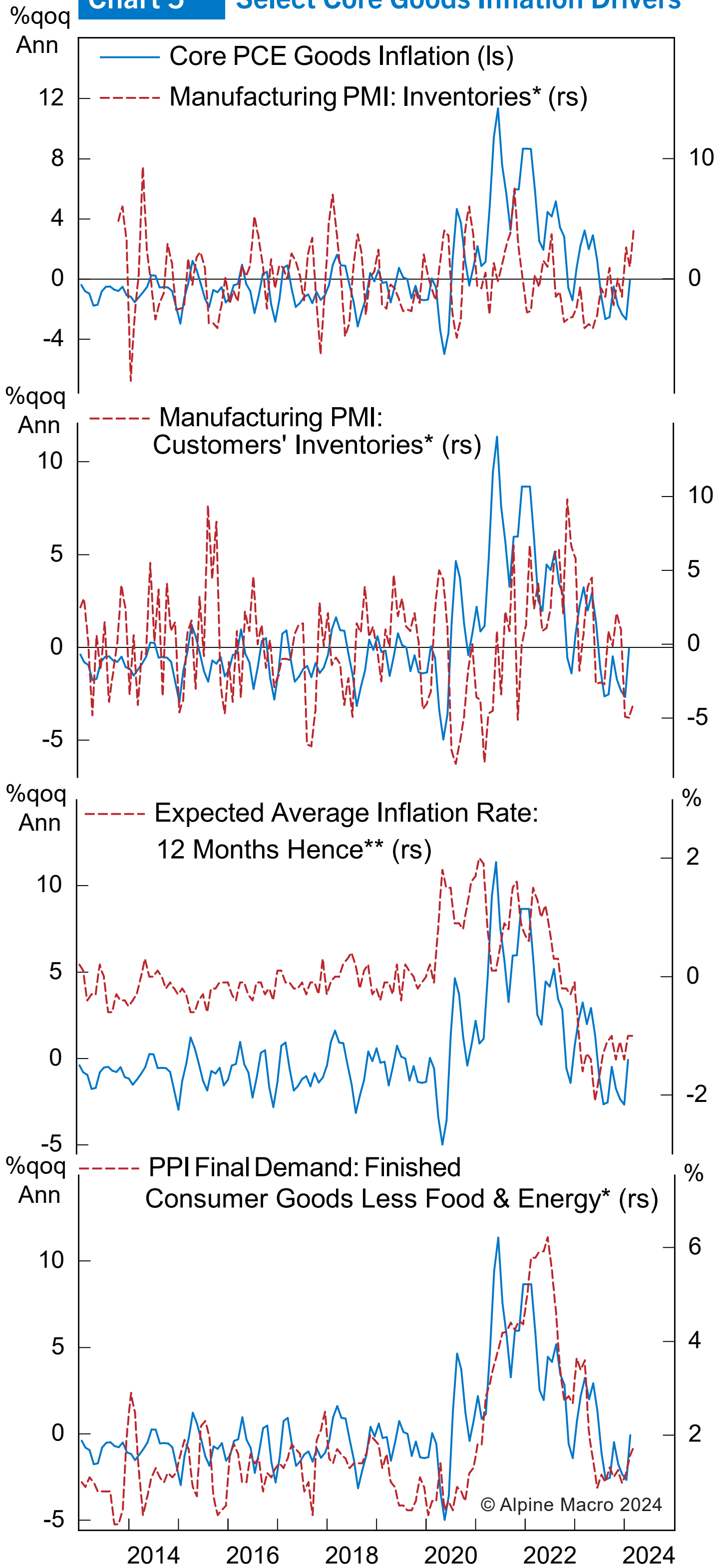
- A recovery in several PMI measures (3-month change)
- Stabilizing consumer confidence regarding inflation (12-month change)
- Stable unemployment rate (3-month change)
- Renormalization of government transfer receipts (12-month change)
- Final demand PPI for finished core consumer goods has mean reverted (3-month change)

Core Services Excluding Housing

As for the biggest component of core PCE, the model expects core services excluding housing inflation to trend towards 3.7% in the next quarter, a deceleration from the surprise surge in February's quarterly annualized rate of 4.5% (Chart 6).

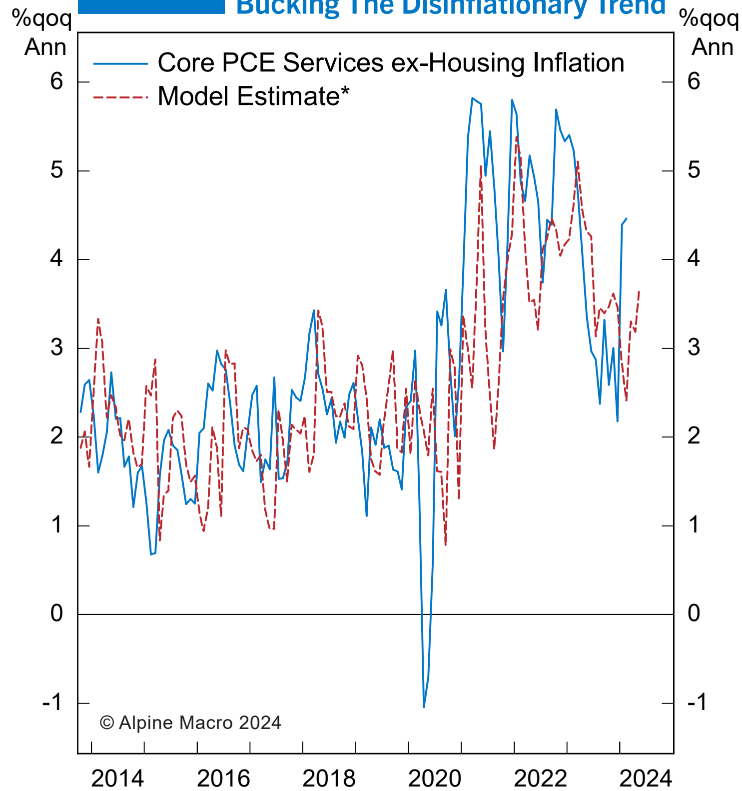
Nevertheless, the model's forecast for the next quarter illustrates a break from the downward trend in core services excluding housing inflation established throughout 2023. The forecast is also

Chart 5 Select Core Goods Inflation Drivers



*Shown as 3-month change
**Shown as 12-month change; source: Conference Board

Chart 6 Core Services Ex-Housing Inflation Bucking The Disinflationary Trend



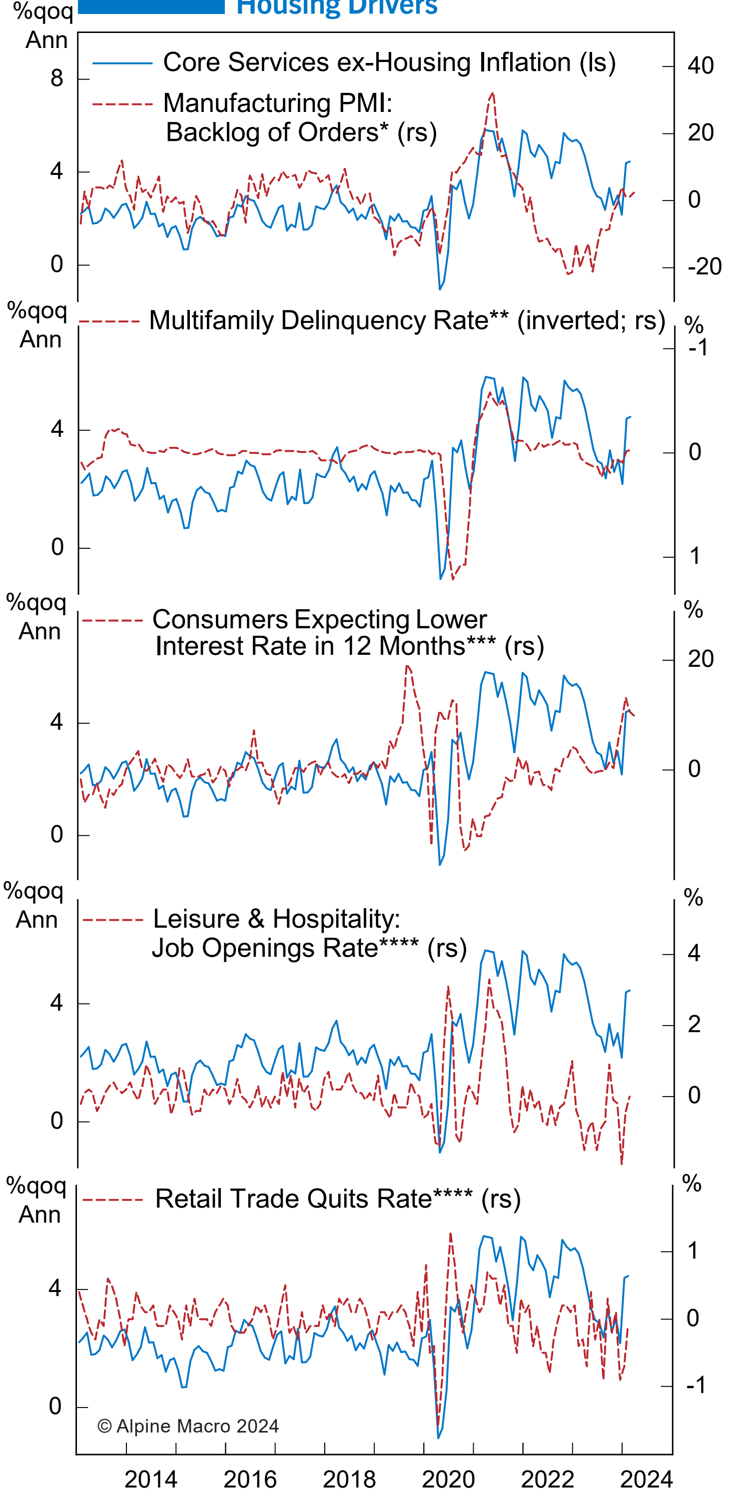
*Alpine Macro proprietary model

higher than the model's estimate for the previous quarter. This suggest that for the February surprise may not be a one-off and significant inflationary pressures still remain in this segment. The R-squared of this regression is around 0.5.

The latest rebound in the model forecast for core service inflation excluding housing is driven by the following (**Chart 7**):

- A rising backlog of orders from the PMI survey (12-month change)
- A topping delinquency rate in multifamily mortgages (6-month change)
- Increasing share of consumers expecting lower rates (6-month change)

Chart 7 Select Core Services Excluding Housing Drivers



*Shown as 12-month change
**Shown as 6-month change; source: Fannie Mae
***Shown as 6-month change; source: Conference Board
****Shown as 3-month change

- The opening and quit rates for service-sensitive sectors like leisure & hospitality as well as retail trade have rebounded (3-month change)

The model's results should not be viewed as point estimates. Rather, the forecast offers an indication for the trend in core inflation over the near-term based solely on pipeline pressures. Our tests show that the model offers predictive value that exceeds a simple autoregressive process.[1]

Investment Conclusion

The pipeline model suggests that investors should expect a slight moderation of 3-month inflation in the next few months relative to the past few months.

However, the deceleration will unlikely be enough to satisfy the Fed that disinflation has resumed. The Fed probably needs at least three benign inflation readings to consider easing policy. This means the FOMC may be on hold until Q4 at a minimum.

The main implication is that upward pressure on Treasury yields will continue in the near term, or at least will not ease much, unless the economy suddenly weakens substantially (which we do not expect).

We plan to update the model and report the results on a monthly basis.

Henry Wu
Senior Strategist & Head of Quantitative Research

1 The R-squared measures for an AR(1) process are -0.04, 0.84 and 0.18 for ○Core goods, housing and services excluding housing inflation, respectively.

Appendix 1
Input Data

We feed the model a wide range of explanatory variables that may explain pipeline inflation. The major categories include the following:

- Sector-level PPI measures including intermediate and final demand
- Labor market data: average hourly earnings, various employment and participation rates, sector-level JOLTS data, non-farm payrolls, UI claims
- Personal income and savings
- Sector-level PCE including nominal, real, and price indices
- Conference Board consumer confidence
- Retail sales and vehicle sales
- Mortgage rates and delinquencies
- Shipping indices, supply chain indices
- Durable goods orders
- ISM PMI
- Banking credit production data
- Housing data including new rent index, houses for sale to sold ratios, and housing affordability
- Industrial production

All inputs are cleaned and pre-processed using the following steps:

Explanatory variables are lagged to adequately account for the difference between the reference period and release date. For example, retail sales data for January is typically available in mid-February. Thus, when running the model at the beginning of February, we cannot assume to have January data. Instead, the data used for retail sales would reference December during backtesting.

Non-stationary variables are treated by taking the logged difference to produce rates of change. We included measures of 3-month, 6-month, and 12-month rates of change for every variable. Some explanatory variables may lead inflation for longer periods than others. Taking different rates of change allows the model to account for this difference in lead times.

We normalize all input data to allow for comparability. This process involves subtracting the mean and dividing by the standard deviation for each explanatory variable. Each series is transformed to have a normal distribution with mean zero and standard deviation of one.

We apply an activation function to the explanatory variables. We divided input variables by 2 and apply the hyperbolic tangent function. The hyperbolic tangent function limits the impact of outlier values. Dividing by 2 prior to the hyperbolic tangent function the magnifies the impact of smaller deviations from the mean.

Appendix 2
Model Configurations

We tested the model under three different learning periods before deciding on a rolling window approach which provided the most accurate results.

This approach trained the model on a short rolling window while trying to forecast the next period returns. Here's how it works:

(1) In the first iteration of the rolling window model, it would train on data from January 2011 to December 2012 to forecast inflation from December 2012 to March 2013.

(2) The second iteration would train the data from April 2011 to March 2013 and forecast inflation from March 2013 to June 2013.

(3) The third iteration would train the data from July 2011 to June 2013 and forecast inflation from June 2013 to September 2013. And so forth.

In the rolling window version, the model retrains and re-selects its explanatory variables at every iteration. The model adapts when the drivers of inflation change. However, this does not happen instantaneously. The model requires sufficient data points within its training period to shift to the new driver. This means that the model may lag at turning points but perform better when the drivers of inflation are relatively stable.

The model uses a 2-year rolling window for services inflation (both shelter and non-shelter) and a 3-year rolling window for core goods. The decision to restrict the learning window to a relatively short period of time was to allow the model to have out-of-sample results that consider only the post-pandemic period, given the likely regime change.

As the model is a fully mechanical process, not all of the selected explanatory variables make intuitive sense. Moreover, collinearity among the selected explanatory variables means that the coefficients of some variables will have opposite signs.

The number of explanatory variables the model will deem relevant in each iteration typically varies from 5-20. We are reasonably confident that the model is not overfitting as the rolling-window regression allows for extensive out-of-sample testing.

The rolling window is better suited than the traditional in-sample learning versus out-of-sample testing approach. The latter allows for very limited out-of-sample testing periods.

We also considered using a stretching window approach. This approach is similar to a rolling window. The training period would be allowed to stretch by one period rather than roll forward by one period in each iteration. Here's how it works:

(1) In the first iteration of the stretching window model, it would train on data from January 2011 to December 2015 to forecast inflation from December 2015 to March 2016.

(2) The second iteration would train the data from January 2011 to March 2016 and forecast inflation from March 2016 to June 2016.

(3) The third iteration would train the data from January 2011 to June 2016 and forecast inflation from June 2016 to September 2016. And so forth.

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This method created a sizable history for out-of-sample testing. However, the prediction results became increasingly inaccurate after the pandemic. This suggested that a regime change in the drivers of inflation has likely occurred. Because the model was calibrated to the pre-pandemic period, predictions were quite off. This is why we decide in favor a rolling window instead.

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