Did the Federal Reserve Break the Phillips Curve? Theory & Evidence of Anchoring Inflation Expectations Technical Appendix*

Brent Bundick† A. Lee Smith‡

March 2023

*Trenton Herriford, Logan Hotz, Emily Pollard, and Luca Van der Meer provided excellent research assistance, and we thank CADRE for computational and data support. The views expressed herein are solely those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Kansas City or the Federal Reserve System. This paper supersedes an older working paper titled, *Does Communicating a Numerical Inflation Target Anchor Inflation Expectations? Evidence & Bond Market Implications*, which contained a partial set of these results.

†Federal Reserve Bank of Kansas City. Email: brent.bundick@kc.frb.org

‡Federal Reserve Bank of Kansas City. Email: andrew.smith@kc.frb.org

A Derivation & Calibration of Theoretical Model

This section provides further details on the derivation and calibration of our theoretical model in Section 3 of the main text. Our model combines features from the previous works of Ireland (2007) and Leduc and Liu (2016). The key agents in our model are a representative household, a retail goods sector which produces differentiated products subject to nominal rigidities, an aggregation sector which aggregates the differentiated products into the final output, intermediate goods producers which hire labor in a frictional labor market, and a government which sets the short-term nominal interest rate and sets lump-sum taxes to finance unemployment benefits.

A.1 Households

The model features a representative household populated by a continuum of worker members which maximize utility from consumption and leisure:

$$\max \mathrm{E}_t \sum_{s=0}^{\infty} a_{t+s}\, \beta^s \left\{ \log\left(C_{t+s}\right) - \chi N_{t+s} \right\}$$

where C_t denotes consumption, N_t is the fraction of employed household members, χ denotes the disutility from working, β is the household's discount factor, and a_t is an exogenous preference shock which triggers unexpected fluctuations in household demand. The representative household chooses its consumption and bond holdings to maximize its utility subject to its budget constraint each period:

$$C_t + \frac{B_t}{P_t R_t} = \frac{B_{t-1}}{P_t} + W_t N_t + \phi_u(1 - N_t) + D_t - T_t, \qquad \forall t \geq 0,$$

where P_t denotes the aggregate price level, B_t denotes holdings of a nominal risk-free bond, R_t denotes the nominal interest rate, W_t denotes the real wage rate, ϕ_u denotes an unemployment benefit (the replacement ratio), D_t denotes profit income from ownership of intermediate goods producers and of retailers, and T_t denotes a lump-sum tax paid to the government. The household's optimal choices of consumption and bond holdings satisfy the following first-order conditions:

$$\lambda_t = \frac{a_t}{C_t}, \tag{1}$$

$$1 = \mathrm{E}_t \left\{ \left(\beta \frac{\lambda_{t+1}}{\lambda_t} \right) \left(\frac{R_t}{\Pi_{t+1}} \right) \right\}, \tag{2}$$

where $\Pi_t = P_t / P_{t-1}$ denotes the gross rate of inflation and λ_t denotes the nonnegative Lagrange multiplier on the household's budget constraint.

The discount factor of the household β is subject to shocks via the stochastic process a_t. We interpret these fluctuations as demand shocks since an increase in a_t induces households to consume more today for no technological reason. The stochastic process for these fluctuations is as follows:

$$\log(a_t) = \rho_a \log(a_{t-1}) + \sigma^a \varepsilon_t^a, \tag{3}$$

where ε_t^a is an independent and standard normal random variable.

A.2 Aggregation Sector

The aggregation sector uses $Y_t(i)$ units of each retail good produced by the retail goods-producing firm $i \in [0,1]$ to create the final output Y_t using the following constant returns to scale technology:

$$\left[\int_0^1 Y_t(i)^{\frac{\eta-1}{\eta}} di\right]^{\frac{\eta}{\eta-1}} \geq Y_t,$$

where $\eta > 1$ is the elasticity of substitution between differentiated products. Each intermediate good $Y_t(i)$ sells at nominal price $P_t(i)$ and each final good sells at nominal price P_t. The representative producer in the aggregation sector chooses Y_t and $Y_t(i)$ for all $i \in [0,1]$ to maximize the following expression of firm profits:

$$P_t Y_t - \int_0^1 P_t(i) Y_t(i) di,$$

subject to the constant returns to scale production function. Optimization results in the following first-order condition:

$$Y_t(i) = \left[\frac{P_t(i)}{P_t}\right]^{-\eta} Y_t. \tag{4}$$

The market for final output is perfectly competitive, and thus the aggregation earns zero profits in equilibrium. Using the zero-profit condition, the first-order condition for profit maximization, and the objective function, the aggregate price index P_t can be written as follows:

$$P_t = \left[\int_0^1 P_t(i)^{1-\eta} di\right]^{\frac{1}{1-\eta}}. \tag{5}$$

A.3 Retail Goods-Producing Firms

There exists a continuum of retail firms, each producing a differentiated product using a homogeneous intermediate good as input. The production function of a retail good of type $i \in [0,1]$ is given by

$$Y_t(j) = X_t(i), \tag{6}$$

where $X_t(i)$ is the input of intermediate goods used by retailer j and $Y_t(j)$ is the output. The retail goods producers are price takers in the input market and monopolistic competitors in the product markets, where they set prices for their products, taking as given the demand schedule in Equation (4) and the price index in Equation (5).

Firm i faces a quadratic cost to adjusting its nominal price $P_t(i)$:

$$\frac{\phi_P}{2}\left[\frac{P_t(i)}{\Pi_t^{LT} P_{t-1}(i)} - 1\right]^2 Y_t$$

where ϕ_P governs the magnitude of the adjustment costs. $\Pi_t^{LT} = \exp(\pi_t^{LT})$ is the gross rate of long-term inflation expectations which are determined by the following equation:

$$\pi_t^{LT} = (1-\rho^\pi)\,\pi^* + \rho^\pi \pi_{t-1}^{LT} + \delta^\pi \left(\pi_t - \pi_{t-1}^{LT}\right), \tag{7}$$

where $\pi_t = \log(\Pi_t)$ and $\pi^* = \log(\Pi^*)$, which is the central bank's, potentially implicit, inflation target. The coefficient δ^π determines the degree to which long-term inflation expectations are anchored. If $\delta^\pi = 0$, then long-term inflation expectations are fully anchored in the sense that they are invariant to realized inflation. On the other extreme, if $\delta^\pi > 0$, then inflation expectations are unanchored and drift with realized inflation.

Each retail firm producing good i chooses $P_t(i)$ to maximize its discounted present-value of profits:

$$\mathrm{E}_t \sum_{s=0}^{\infty}\left(\frac{\beta^s \lambda_{t+s}}{\lambda_t}\right)\left[\left(\frac{P_{t+s}(j)}{P_{t+s}} - q_{t+s}\right) Y_{t+i}(i) - \frac{\phi_P}{2}\left(\frac{P_{t+s}(i)}{\Pi_{t+s}^{LT} P_{t+s-1}(i) - 1}\right)^2 Y_{t+s}\right], \tag{8}$$

where q_t denotes the relative price of the intermediate good. In a symmetric equilibrium with $P_t(i) = P_t$ for all i, the optimal price-setting decision implies:

$$q_t = \frac{\eta-1}{\eta} + \frac{\phi_P}{\eta}\left\{\left(\frac{\Pi_t}{\Pi_t^{LT}}\right)\left(\frac{\Pi_t}{\Pi_t^{LT}} - 1\right) - \mathrm{E}_t\left[\left(\frac{\beta\lambda_{t+1}}{\lambda_t}\right)\left(\frac{\Pi_{t+1}}{\Pi_{t+1}^{LT}}\right)\left(\frac{\Pi_{t+1}}{\Pi_{t+1}^{LT}} - 1\right)\left(\frac{Y_{t+1}}{Y_t}\right)\right]\right\}. \tag{9}$$

A.4 The Labor Market

Our formulation of the labor market in our model closely follows Leduc and Liu (2016). At the beginning of each period, there exist N_{t-1} employed workers, u_t unemployed workers searching for jobs, and v_t vacancies posted by firms. Matches between unemployed workers and vacancies are created using a Cobb-Douglas matching function:

$$m_t = \mu u_t^\alpha v_t^{1-\alpha}, \tag{10}$$

where m_t is the number of successful matches, the parameter $\alpha \in (0, 1)$ denotes the elasticity of job matches with respect to the number of searching workers, and the parameter μ scales the matching efficiency. We define the job filling rate, the probability that an open vacancy is matched with a searching worker, as follows:

$$q_t^u = \frac{m_t}{v_t}. \tag{11}$$

We define the job finding rate, the probability that an unemployed and searching worker is matched with an open vacancy, as follows:

$$q_t^v = \frac{m_t}{u_t}. \tag{12}$$

There exist N_{t-1} workers in the beginning of period t. Each period, a fraction ρ of these workers lose their jobs. Thus, the number of workers who survive the job separation is $(1-\rho)N_{t-1}$. At the same time, m_t new matches are formed. Following the timing assumption in Blanchard and Galí (2010), we assume that new hires start working in the period they are hired. Thus, aggregate employment in period t evolves according to

$$N_t = (1-\rho)N_{t-1} + m_t. \tag{13}$$

With a fraction ρ of employed workers separated from their jobs, the number of unemployed workers searching for jobs in period t is given by

$$u_t = 1 - (1-\rho)N_{t-1}. \tag{14}$$

We assume full participation and define the unemployment rate as the fraction of the population who are left without a job after hiring takes place. Thus, we can write the unemployment rate as follows:

$$U_t = u_t - m_t = 1 - N_t. \tag{15}$$

A.5 Intermediate Goods Producers

Each intermediate goods firm produces a homogeneous intermediate good and hires at most one worker subject to search and matching frictions in the labor market. Since our model abstracts from changes in productivity, each firm employs a single worker who produces one unit of the intermediate good each period. If a firm finds a match, the firm obtains a flow profit in the current period after paying the worker. In the next period, the match may survive with probability $1 - \rho$ or dissolve with probability ρ. If the match dissolves, the firm posts a new job vacancy at a fixed cost κ units of the final good with the value V_{t+1}. Thus, the following Bellman equation captures the value of the firm:

$$J_t^F = q_t - W_t + \mathbb{E}_t \left\{ \left(\beta \frac{\lambda_{t+1}}{\lambda_t} \right) \left((1-\rho) J_{t+1}^F + \rho V_{t+1} \right) \right\}, \tag{16}$$

where q_t denotes the relative price of the intermediate good, W_t denotes the real wage, and λ_t is the representative household's marginal utility from consumption.

κ denotes the cost of posting a new vacancy in terms of final goods. The vacancy is filled with probability q_t^v, in which case the firm obtains the value of the match. Otherwise, the vacancy remains unfilled and the firm goes into the next period with the value V_{t+1}. Thus, the value of an open vacancy is given by

$$V_t = -\kappa + q_t^v J_t^F + \mathbb{E}_t \left[\frac{\beta \lambda_{t+1}}{\lambda_t} (1 - q_t^v) V_{t+1} \right]. \tag{17}$$

Free entry implies that $V_t = 0$ which implies:

$$\frac{\kappa}{q_t^v} = J_t^F, \tag{18}$$

which describes the optimal job creation decisions. The benefit of creating a new job is the match value J_t^F while the expected cost of creating a new job is the flow cost of posting a vacancy κ multiplied by the expected duration of an unfilled vacancy $1/q_t^v$.

If a worker is employed, he obtains wage income but pays a utility cost of working. In period $t+1$, the match is separated with probability ρ and the separated worker can find a new match with probability q_{t+1}^u. Thus, a separated worker fails to find a new job in period $t+1$ and enters the unemployment pool with probability $\rho(1-q_{t+1}^u)$. Otherwise, the worker continues to be employed. The marginal value of an employed worker (denoted by J_t^W) therefore satisfies the Bellman equation

$$J_t^W = W_t - \frac{\chi}{\lambda_t} + \mathbb{E}_t \left\{ \frac{\beta \lambda_{t+1}}{\lambda_t} \left[\left(1 - \rho(1 - q_{t+1}^u)\right) J_{t+1}^W + \rho(1 - q_{t+1}^y) J_{t+1}^u \right] \right\}, \tag{19}$$

where J_t^U denotes the value of an unemployed worker. An unemployed worker obtains the flow unemployment benefit ϕ_u and can find a new job in period $t+1$ with probability q_{t+1}^u. Thus, the value of an unemployed worker satisfies the Bellman equation

$$J_t^U = \phi_u + \mathbb{E}_t \left\{ \frac{\beta \lambda_{t+1}}{\lambda_t} \left[q_{t+1}^u J_{t+1}^W + (1 - q_{t+1}^u) J_{t+1}^U \right] \right\}. \tag{20}$$

Firms and workers bargain over wages in which the parameter b determines the bargaining weight. Leduc and Liu (2016) derive the following expression for the Nash bargaining wage.

$$W_t^N = (1-b)\left[\frac{\chi}{\lambda_t} + \phi_u\right] + b\left\{q_t Z_t + \beta(1-\rho)\mathbb{E}_t\left[\frac{\beta\lambda_{t+1}}{\lambda_t}\frac{\kappa v_{t+1}}{u_{t+1}}\right]\right\}. \tag{21}$$

The Nash bargaining wage is a weighted average of the worker's reservation value and the firm's productive value of a job match. By forming a match, the worker incurs a utility cost of working and forgoes unemployment benefits. By employing a worker, the firm receives the marginal product from labor in the current period and saves the vacancy cost from the next period.

Following Hall (2005) and Blanchard and Galí (2010), we assume actual wages adjust slowly to changing economic conditions:

$$W_t = W_{t-1}^{\gamma}\left(W_t^N\right)^{1-\gamma} \tag{22}$$

where W_t^N is the wage under Nash bargaining and $\gamma \in (0,1)$ represents the degree of real wage rigidity.

A.6 Monetary Policy

The central bank in the model sets its short-term nominal policy rate R_t to minimize deviations of inflation from long-term expectations:

$$\log\Big(R_t\Big) = \log\Big(R_{t-1}\Big) + \phi_\pi \log\Big(\Pi_t/\Pi_t^{LT}\Big), \tag{23}$$

where ϕ_π denotes the central bank's response to inflation deviations.

A.7 Government Policy

The government finances transfer payments for unemployment benefits through lump-sum taxes. We assume that the government balances the budget in each period so that

$$\phi_u(1-N_t) = T_t. \tag{24}$$

A.8 Equilibrium

In equilibrium, the markets for final consumption goods, intermediate goods, and the zero net-supply bonds ($B_t = 0$) all clear. Therefore, we can write the aggregate resource constraint:

$$C_t + \kappa V_t + \frac{\phi_P}{2}\left(\frac{\Pi_t}{\Pi_{t+1}^{LT}} - 1\right)^2 Y_t = Y_t. \tag{25}$$

A.9 Complete Model

We can write down the complete model as follows:

$$\lambda_t = \frac{a_t}{C_t}, \tag{26}$$

$$1 = \mathrm{E}_t \Bigg\{ \left(\beta \frac{\lambda_{t+1}}{\lambda_t} \right) \left(\frac{R_t}{\Pi_{t+1}} \right) \Bigg\}, \tag{27}$$

$$q_t = \frac{\eta - 1}{\eta} + \frac{\phi_P}{\eta} \left\{ \left(\frac{\Pi_t}{\Pi_t^{LT}} \right) \left(\frac{\Pi_t}{\Pi_t^{LT}} - 1 \right) - \mathrm{E}_t \left[\left(\frac{\beta \lambda_{t+1}}{\lambda_t} \right) \left(\frac{\Pi_{t+1}}{\Pi_{t+1}^{LT}} \right) \left(\frac{\Pi_{t+1}}{\Pi_{t+1}^{LT}} - 1 \right) \left(\frac{Y_{t+1}}{Y_t} \right) \right] \right\}, \tag{28}$$

$$m_t = \mu u_t^{\alpha} v_t^{1-\alpha}, \tag{29}$$

$$q_t^u = \frac{m_t}{v_t}, \tag{30}$$

$$q_t^v = \frac{m_t}{u_t}, \tag{31}$$

$$N_t = (1 - \rho) N_{t-1} + m_t, \tag{32}$$

$$u_t = 1 - (1 - \rho) N_{t-1}, \tag{33}$$

$$U_t = 1 - N_t, \tag{34}$$

$$Y_t = N_t, \tag{35}$$

$$\log \Big(R_t \Big) = \log \Big(R_{t-1} \Big) + \phi_\pi \log \Big(\Pi_t / \Pi_t^{LT} \Big) + \phi_y \log \Big(Y_t / Y_{t-1} \Big), \tag{36}$$

$$C_t + \kappa V_t + \frac{\phi_P}{2} \left(\frac{\Pi_t}{\Pi_{t+1}^{LT}} - 1 \right)^2 Y_t = Y_t, \tag{37}$$

$$J_t^F = q_t - W_t + \mathbb{E}_t \left\{ \left(\beta \frac{\lambda_{t+1}}{\lambda_t} \right) \Big((1 - \rho) J_{t+1}^F + \rho V_{t+1} \Big) \right\}, \tag{38}$$

$$\frac{\kappa}{q_t^v} = J_t^F, \tag{39}$$

$$W_t^N = (1-b)\left[\frac{\chi}{\lambda_t} + \phi_u\right] + b\left\{q_t Z_t + \beta(1-\rho)\mathbb{E}_t\left[\frac{\beta\lambda_{t+1}}{\lambda_t}\frac{\kappa v_{t+1}}{u_{t+1}}\right]\right\}, \tag{40}$$

$$W_t = W_{t-1}^{\gamma}\left(W_t^N\right)^{1-\gamma}, \tag{41}$$

$$\log(a_t) = \rho_a \log(a_{t-1}) + \sigma^a \varepsilon_t^a, \tag{42}$$

$$\log\Big(\Pi_t^{LT}\Big) = (1-\rho^\pi)\log\Big(\Pi^*\Big) + \rho^\pi \log\Big(\Pi_{t-1}^{LT}\Big) + \delta^\pi\Bigg(\log\Big(\Pi_t\Big) - \log\Big(\Pi_{t-1}^{LT}\Big)\Bigg). \tag{43}$$

To keep track of the model's predictions for inflation and the nominal interest rate, we also include the growth rates of inflation and the nominal interest rate as equations in our model:

$$g_t^\pi = \Pi_t/\Pi_{t-1}, \tag{44}$$

$$g_t^r = R_t/R_{t-1}. \tag{45}$$

A.10 Calibration and Solution Method

After writing the model in stationary form, we calibrate the parameters of the model and solve the model using a first-order approximation around the deterministic steady state. Table A.1 contains the calibrated parameters of our model. Since our model combines the frictional market specification of Leduc and Liu (2016) with the estimated macroeconomic model of Ireland (2007), we almost exclusively use the parameters from those papers in calibrating our model. Following Blanchard and Galí (2010), we set the matching elasticity parameter α and the wage bargaining parameter $b = 0.5$. Our calibration of job separations $\rho = 0.1$ implies a monthly job separation rate of roughly 3.5%. Consistent with calibration of Hall and Milgrom (2008), the replacement ratio of unemployment is set such that $\phi = 0.25$. The remaining labor market parameters are calibrated using the strategy in Section 4.1 of Leduc and Liu (2016) which implies a steady-state unemployment rate of $U = 0.064$ and a total cost of posting vacancies at roughly 2 percent of gross output. We set the real wage rigidity parameter $\gamma = 0.8$, which is in line with Gertler and Trigari (2009).

With a couple of exceptions, the remaining parameters are calibrated to match the values in Ireland (2007). We set the household discount factor $\beta = 0.9995$ and the elasticity of substitution across intermediate goods $\eta = 6$. For the persistence of the preference shock process, we calibrate $\rho_a = 0.9097$ to the estimated value of Ireland (2007). We set the volatility of the preference shock process $\sigma_a = 0.01$ such that a one standard deviation shock moves the demand shock process by one percent. For the monetary policy rule, we follow Ireland's assumption of full interest rate smoothing (a coefficient of one on lagged interest rates in the policy rule). We calibrate the policy response of inflation deviations $\phi_\pi = 0.8594$, the estimated value of Ireland (2007). With respect to the policy response to changes in the real economy, Ireland (2007) includes a nontrivial response of policymakers to changes in output growth. However, we find that including a response to output growth generates much larger (and likely counterfactual) fluctuations in inflation when we incorporate frictions in the labor market, so we remove this feature to generate more sensible inflation dynamics.

We calibrate the remaining parameters of the model (ρ^π, δ^π, Π^*, and ϕ_P), based on our empirical evidence from the main text. In particular, we calibrate $\delta^\pi = 0.27$, the point estimate from our baseline inflation compensation regression model over the 1999–2011 sample period. We calibrate π^* such that the model-implied constant in the reduced-form Phillips curve under drifting inflation expectations matches the average level of inflation (3.18%) over the 1999–2011 period. We then select values for ρ^π and ϕ_P to match two moments from our Phillips curve regressions over the 1999–2011 sample: the slope of the reduced-form Phillips curve as well as the slope of the expectations-augmented Phillips curve. We match these regression coefficients by running the same Phillips curve regressions on model-simulated data, then comparing the estimated coefficients based on model-simulated data with the sum of their squared deviations from their empirical counterparts. Importantly, we do not target any of the Phillips curve regression moments from the post-2012 sample as these serve as important tests of the model's predictions from anchoring.

Finally, we enter the non-linear model into Dynare and generate impulse response functions and model simulations based on a first-order perturbation to the non-linear model approximated around the deterministic steady-state.

B Additional Theoretical Model Results

In this section, we explore the sensitivity of the model's predictions for the anchoring of inflation expectations to plausible alternative parameter values.

B.1 No Real Wage Rigidity: γ

In our baseline model, we calibrated our labor market parameters to standard values from the literature (see Leduc and Liu (2016)). Beginning with early work by Blanchard and Galí (2010), papers often assume sticky real wages in models that combine search frictions and nominal rigidities. However, for our work, real wage rigidity is not necessary to generate reasonable impulse responses and the results with flexible wages generate very similar break test results for the reduced-form Phillips curve. Table B.1 below recalculates our baseline reduced-form Phillips curve regressions without sticky wages $\gamma = 0$, leaving all other parameters unchanged. Under this alternative calibration, the quantitative results are quite close to our baseline, suggesting that an econometrican would still detect a break even if we were to remove real wage rigidity from our model. The green dashed-dotted line in Figure B.1 shows that in our model, the impulse responses to a demand shock under drifting inflation expectations are similar under both rigid and flexible wages, which helps explain why our Phillips curve break tests are robust to this alternative calibration.

B.2 More Persistent Inflation Expectations: ρ^{π}

Our baseline model specification assumes that longer-term inflation expectations drift around a stationary longer-term inflation target. We calibrate the persistence of longer-term inflation expectations ρ_{π}, the degree of price rigidity Φ_P, and the central bank's inflation objective π^* such that the model matches the constant and slope of the reduced-form Phillips curve and the slope of the expectations-augmented Phillips curve prior to the anchoring of expectations. As shown in Table A.1, this calibration procedure results in a persistence parameter of $\rho_{\pi} = 0.93$, suggesting that the data prefers a persistent but stationary processes. However, prior work has modeled long-term inflation expectations as following a random walk (Gürkaynak, Sack and Swanson, 2005; Ireland, 2007). We can emulate this previous research by assuming a much more persistent process for inflation expectations, setting $\rho^{\pi} = 0.999$ (similar to the value estimated in Rudebusch and Swanson, 2012). Without adjusting other parameter values, the black dotted line in Figure B.1 shows even larger differences between inflation dynamics in the anchored and drifting regimes. Because of the amplification of inflation and inflation expectations in the drifting regime with $\rho^{\pi} = 0.99$, we find an even steeper pre-anchoring reduced-form Phillips curve slope and, hence, continue to detect a structural break in the Phillips curve post-anchoring in model-simulated data under this alternative calibration.

B.3 Smaller Pass-Through from Inflation Surprises to Long-Term Inflation Expectations: δ^{π}

We base our analysis of the model predictions that results from anchoring inflation expectations on the assumption that, prior to anchoring, inflation surprises pass-through to long-term inflation expectations according to $\delta^{\pi} = 0.27$. This value is based on our baseline inflation compensation regression model from 1999–2011 (Table 2 in the main text). However, there is some uncertainty on how to map this parameter into our theoretical model. For example, in the data, the inflation surprise is constructed from the month-over-month inflation rate. Moreover, in the monthly data there is one inflation surprise per period whereas, in the quarterly model, there would be three such surprises. In light of these issues, we demonstrate the robustness of the model's predictions to a conservatively much smaller value of $\delta^{\pi} = 0.27 - 1.65 \times 0.10$, which is the 5% left tail assuming a Normal distribution. We then recalibrate ρ^{π} and ϕ_P to again match the slope of the reduced-form Phillips curve as well as the slope of the expectations-augmented Phillips curve empirical estimates over the 1999–2011 sample. Table B.2 shows both reduced-form (left columns) as well as expectations-augmented (right columns) Phillips curve regressions estimated on model-simulated data under this alternative calibration of δ^{π}. The results in Table B.2 show that, even with a much smaller degree of drift with current inflation in the inflation expectations process, an econometrician confronted with small samples would still detect a break in the reduced-form Phillips curve but find stability in the expectations-augmented Phillips curve regressions.

C Additional Phillips Curve Empirical Results

In this section, we explore the robustness of the empirical results relating to the apparent instability in the reduced-form Phillips curve amid stability in the expectations-augmented Phillips curve post-2011.

C.1 HAR Inference of Phillips Curve Regression Model

For our Phillips curve regressions, we regress the inflation rate on the unemployment rate in levels. Since macroeconomic data tend to display significant persistence across months, Newey-West standard errors are used to address concerns of both heteroskedasticity and serial correlation in the regression residuals. Likewise, this follows other popular papers estimating similar Phillips curve regressions (such as Coibion and Gorodnichenko, 2015).

While we use the typical rule-of-thumb of 12 lags (for monthly data) when constructing our Newey-West standard errors, advancements in HAR inference underscore the tendency for these conventional Newey-West standard errors to over-reject the null hypothesis. Therefore, as a robustness check, we compute HAR standard errors using the quadratic spectral (QS) kernel to estimate the long-run variance together with Kiefer and Vogelsang (2005) fixed-b critical values in our Phillips curve regressions. We set the truncation parameter of the QS window to $v = 0.4T^{2/3}$ which follows Lazarus et al. (2018) who report reduced size distortions from this choice of long-run variance calculation. Table C.1 below reports these results. Our conclusions regarding the presence of a break in the reduced-form Phillips curve remain unchanged under these more conservative standard errors and critical values.

C.2 Stability of Expectations-Augmented Phillips Curve

The model's predictions for the effects of anchoring are for breaks in the reduced-form Phillips curve that are *not present* in the structural/expectations-augmented Phillips curve. In contrast, breaks in the expectations-augmented Phillips curve could reflect changes in structural parameters that govern the price setting process such as the frequency of price-adjustment, input shares, and labor markets (see Coibion and Gorodnichenko, 2015, for example). Given the evolution of market structures and labor markets, many of these deep structural parameters may well have shifted during our sample of study. In fact, what is perhaps most noteworthy about our break test results is that the post-2012 flattening in the reduced-form Phillips curve does not appear to be due to any of these potential changes to the price setting process and, instead, the recent flattening in the reduced-form Phillips curve can be largely explained by better anchored inflation expectations.

While we are conceptually interested in structural breaks in the reduced-form Phillips curve, it would be reassuring if there isn't a break in the expectations-augmented Phillips curve circa 2012. We therefore provide additional evidence that the post-2011 break we find in the reduced-form Phillips curve doesn't coincide with a break *near* 2012 in the expectations-augmented Phillips curve. To confirm this, we performed two robustness exercises. First, we conducted our Chow test ± 6-months January-2012. Second, we subjected both the reduced-form and expectations-augmented Phillips curve regressions to a breaktest at an unknown date (i.e. Andrews, 1993). The results are shown in Figure C.1. Panel A shows no evidence of a change in the slope of the expectations-augmented Phillips curve circa 2012. Panel B reinforces this finding by showing that the large and significant break in the reduced-form Phillips curve (black solid line) post-2011 does not coincide with any significant breaks in the expectations-augmented Phillips curve (blue solid line). Both of these findings underscore our conclusion that, post-2011, there is evidence of a break in the reduced-form Phillips curve despite evidence of relative stability in the expectations-augmented (or structural) Phillips curve.

D Additional High-Frequency Empirical Results

This section details additional results and sensitivity analysis of the high-frequency regressions presented in Section 4.1 of the main text.

D.1 Break in δ^{π}, Not Change in Nature of CPI Surprises

We now show that the break in the estimate of δ^{π} we document appears to reflect a change in the reaction of inflation expectations to CPI surprises rather than a change in the nature of CPI surprises. Table D.1 shows the summary statistics for CPI surprises both before and after 2012. The standard deviation of the Bloomberg core inflation surprises is equal to 0.07 prior to 2012 and 0.06 thereafter. Furthermore, the surprises in both samples are not significantly skewed nor do we find evidence that they are non-normal as the Jarque-Bera statistic falls below its critical value. The most notable difference between the two samples is the presence of an average downside inflation surprise after 2012. From the viewpoint of our regression model, this change in the distribution of inflation surprises has the potential to impact the intercept δ^0, but not the slope coefficient δ^{π}. However, Table 2 of the main text shows that we find no statistically significant evidence of a change in the regression intercept across the two sample periods.

D.2 Robustness to Alternative Data, Samples, & Specifications

Our baseline model shows that market-based measures of inflation expectations became less sensitive to news about inflation after the FOMC began to communicate a numerical inflation objective. We now examine the robustness of this finding to using: (i) alternative measures of nominal compensation and food and energy price controls, (ii) data samples that exclude the global financial crisis, and (iii) specifications that allow for more gradual parametric change. Under all of these alternative specifications, we continue to find evidence that nominal compensation became unresponsive to inflation news after the FOMC communicated an explicit inflation objective.

In our baseline inflation compensation model, we proxy forward inflation expectations by using inflation compensation measured from inflation-indexed bonds. However, TIPS yields may contain a non-trivial, time-varying liquidity premium, which could distort our measure of inflation expectations.[1] Our baseline model also uses the weight of core goods and services in the overall CPI basket, along with the headline and core CPI surprises, to infer the information content emanating from food and energy components. While this weight varies little month to month, its value is not exactly known in real time. To address both of these concerns, we estimate the following alternative regression model around CPI releases:

$$\Delta y_t^{LT} = \delta^0 + \delta^\pi \pi_t^{core} + \delta^f \pi_t^{food} + \delta^e \pi_t^{energy} + \varepsilon_t, \tag{46}$$

where Δy_t^{LT} is the one-day change in the 1-year, 9-year forward nominal rate and π_t^{food} and π_t^{energy} are the one-day percent changes in the Goldman Sachs agricultural and energy price indexes, respectively.[2] We refer to this as the *forward rate model*.

Rather than using inflation compensation measured from inflation-indexed bonds, this alternative model uses far-forward measures of nominal interest rates as a proxy for long-term inflation expectations. Although real factors could influence this measure of forward compensation, Gürkaynak, Sack and Swanson (2005) argue that most macroeconomic models predict that, following a disturbance, real variables would return to their steady state values before nine years. In addition, this specification uses the change in spot prices for food and energy inputs instead of the implied surprise from the CPI measure of food and energy prices. Given that timely information on the previous month's food and energy prices is already available to bond investors at the time of the CPI release, the change in spot prices for food and energy inputs might be a more appropriate control for these non-core items on the day of the CPI release.

Using this alternative forward rate model, the regression results in Table D.2 show a

[1] As long as this premium is uncorrelated with core inflation surprises, our baseline results remain unbiased.

[2] We calculate nominal forward rates from the yield on constant maturity zero coupon bond yields as described in Gürkaynak, Levin and Swanson (2010).

decline in the response of inflation compensation to inflation news following the adoption of the inflation target.[3] Before 2012, nominal compensation significantly comoved with inflation surprises. However, after 2012, nominal compensation became unresponsive.[4] The general robustness of our findings using the forward rate model is important as we move to our analysis of the BOJ's adoption of a numerical inflation target. For Japan, we lack data on real (inflation-indexed) bonds and the knowledge about the weight of core components in the CPI basket. Thus, we cannot estimate our preferred inflation compensation model. However, we can estimate the forward rate model for Japan.

Using this alternative model, tests for a structural break at an unknown date also suggest a break in the coefficient on the core inflation surprise around 2010. The solid black line in Panel B of Figure D.1 plots the Chow test sequence for δ^{π} using the forward rate regression model over time. As in the baseline inflation compensation regression model, shown in Panel A, we see a clear peak in the time series of the test statistic in the first half of 2010. However, there is also a sharp spike in the sequence of Chow tests in late 2008. Both the 2008 and 2010 breaks fail to exceed the 10% critical value of the Andrews-Quandt test in the second panel of Figure D.1. The presence of two local maxima could signal either two breaks or, based on the timing, instability during the financial crisis. This latter possibility of instability in the regression model due to the global financial crisis leads us to further examine the robustness of our candidate break dates.

If we drop the precipice of the global financial crisis, we find evidence indicating the presence of a single structural break in early 2010. We first show that the break test results for our baseline inflation compensation regression model are robust to dropping the financial crisis from our sample. For our baseline inflation compensation model, Table D.3 shows that we estimate the exact same break date of May 2010 for the core inflation coefficient when we drop the fourth quarter of 2008 and first quarter of 2009 from the estimation. Table D.4 similarly shows that the estimated break date for the forward rate model is February of 2010 and that break is statistically significant using the Andrews-Quandt test and the Andrews-Ploberger test. Robustness of the estimated break dates to dropping the financial crisis is further apparent in the blue dotted lines in Panels A and B of Figure D.1, which plot the time series of the Chow test statistics for samples that exclude the financial crisis. For

[3] We no longer scale the core CPI surprises by the weight of core components in the CPI basket in the forward rate specification.

[4] While the Chow test statistic for a break after 2012 is slightly below the critical value, the p-value of the Chow test for δ^{π} is 0.1003, indicating that our findings are generally robust.

both the inflation compensation (Panel A) and forward rate (Panel B) models, the presence of a peak in the time series of the break statistics in 2010 is insensitive to the inclusion or exclusion of the financial crisis. This finding suggests that the source of instability in the response of forward bond yields to inflation surprises occurring around 2010 is not simply a reflection of financial market volatility but, instead, is likely due to deeper structural change.

Finally, rolling-window regressions of our forward rate model also indicate a similar decline in δ^π that we observe in our baseline inflation compensation model. Panel C of Figure D.1 reproduces the rolling-window regression estimates of δ^π using 10-year rolling samples for our baseline regression model, as shown in the main text, for comparability. Panel D of Figure D.1 then illustrates the time variation in δ^π from the forward rate regression model in Equation (46). We observe the same pattern of structural change as in our baseline inflation compensation regression model. Early in the sample, prior to 2012, δ^π is estimated to be statistically significant and positive. However, the point estimate of δ^π begins to decline in 2010 and falls to values not different from zero by 2012. The results of these alternative specifications provide further evidence that the FOMC's decision to communicate a numerical inflation objective helped better anchor US inflation expectations.

D.3 Alternative Horizon for Breakeven Inflation Compensation

In our baseline high-frequency event-study regression, we use the daily change in the 1-year, 9-year forward breakeven inflation compensation around CPI announcements. However, we can also analyze the change in other horizons of forward inflation breakevens around these announcements. Figure D.2 below plots the breaktest coefficient on the core CPI inflation surprise along with 90% confidence intervals across many horizons. These tests show that the sensitivity of forward inflation compensation declined across all horizons after 2012 and significantly so for horizons beyond 9 years, showing that our results are robust to using alternative horizons of far-forward inflation compensation.

E SVAR Model of Household Inflation Expectations

In this section, we provide further details and results from our VAR model of household's inflation expectations that is presented in Section 4.2 of the main text.

E.1 Data and VAR Model

We analyze impulse responses from a four variable structural VAR model to detect a potential change in the degree to which household's longer-term inflation expectations are anchored since 2012. We include m/m annualized CPI energy inflation and m/m annualized CPI food inflation in addition to m/m annualized overall CPI inflation to account for the documented fact that some consumer prices, such as gasoline and grocery prices, are more important than others in shaping household inflation expectations (Coibion and Gorodnichenko, 2015; Cavallo, Cruces and Perez-Truglia, 2017). We add to these CPI inflation measures the median 5- to 10-year inflation expectation from the University of Michigan's Survey of Consumers.

We model these series as a VAR(3) over two distinct samples: January 1999 - December 2011 and January 2012 - December 2019 on the basis of lag-selection criteria which recommend 1 or 2 lags depending on the sample and the criteria. The start date of the recent sample period, January 2012 - December 2019, is dictated by the Federal Reserve's January 2012 adoption of an inflation target. It is precisely this change in FOMC communication that we wish to analyze. The start date of the early sample period, January 1999 - December 2011, is selected to align with the regression samples used for other specifications in the main text. Finally, to make the results comparable across samples, we scale the shocks to have the same impact effect on the driving variable (i.e. energy inflation, food inflation, or overall inflation) in both samples.

We conduct inference on the estimated VAR models from a Bayesian perspective. In particular, error bands are calculated by assuming a non-informative conjugate (Normal-Inverse Wishart) prior over the VAR lag coefficients and covariance matrix. Our exact implementation follows Koop and Korobilis (2010) closely. 68% error bands are calculated based on 10,000 draws from the posterior distribution of the identified impulse responses.

E.2 Shock Identification

The timing of CPI data releases relative to when the household survey data are collected naturally lends itself to identification by zero short-run restrictions. In particular, we use a recursive identification strategy with the following ordering: CPI energy inflation, CPI food inflation, the median of households' expectations for inflation over the next 5 to 10 years, and CPI inflation. This ordering allows us to identify 3 inflation shocks: an energy inflation shock, a food inflation shock, and a core inflation shock. Our recursive identification strategy aims to identify these shocks based on the following sequence of surveys and data releases.

We assume that households are aware of energy and food inflation in the current month when they respond to the University of Michigan survey. After all, the typical household frequents gasoline stations, grocery stores, and restaurants at least once a week. Therefore, our shock identification allows for inflation in salient goods, namely gasoline and food, to influence their inflation expectations within the current month. This argues for ordering energy and food inflation ahead of households' expectations for inflation over the next 5 to 10 years in our recursively identified VAR model. We distinguish energy from food inflation shocks by ordering energy inflation ahead of food inflation. Our assumption is that an exogenous increase in energy prices can spillover to food prices within the month, perhaps through transportation and delivery costs. Conversely, we assume that an exogenous increase in food inflation can't spillover to energy inflation within the month.

Finally, we identify a core inflation shock on the basis of the timing of the consumer interviews conducted by the University of Michigan. Every month, the University of Michigan calls more than 500 households to conduct interviews. These interviews are conducted beginning either late in the previous month or early in the current month. Importantly, the final interviews are always completed before the end of the current month. So, in March for example, the first interview is conducted on February 26 and the last interview is completed by March 24. Importantly for our identification strategy, the CPI report for the reference month is always released the following month. For example, the March CPI report is released sometime in early April. Therefore, the assumption we make is that households' long-term inflation expectations can't respond within the month to the CPI release. After all, even a consumer that is eagerly awaiting the latest BLS report on price inflation in the current month won't be able to acquire this information until the following month. This argues for ordering CPI inflation after households' expectations for inflation over the next 5 to 10 years in a recursively identified VAR model.[5] Since we order energy and food inflation ahead of inflation expectations and CPI inflation, we interpret the orthogonalized innovation to CPI inflation as a core inflation shock.

E.3 Additional SVAR Results

Figure 6 in the main text shows a meaningful change in the impulse responses of longer-term inflation expectations in response to each of the three shocks we identify. In particular, these

[5] Leduc, Sill and Stark (2007), Clark and Davig (2011), Leduc and Sill (2013) use a similar justification for their recursive identification schemes.

impulse responses suggest that energy inflation, food inflation, and core inflation surprises no longer feed through to households' longer-term inflation expectations after 2012.

In this section, we show that, in contrast to longer-term inflation expectations, households' near-term inflation expectations continued to respond to these inflation surprises after 2012. In particular, we now repeat the above analysis but replace households' expectations for inflation over the next 5 to 10 years with households' expectations for inflation over the next 1 year. In Figure E.1, we observe statistically significant revisions of households' 1-year inflation expectations in response to both energy and food inflation shocks.

These results serve two purposes. First, they show that anchoring longer-term inflation expectations need not eliminate fluctuations in near-term inflation expectations. Recall that, in response to energy inflation shocks, which Coibion and Gorodnichenko (2015) demonstrate are a primary driver of household near-term inflation expectations, longer-term inflation expectations show little response after 2012. Therefore, these results help to further reconcile our conclusions with those in Coibion and Gorodnichenko (2015) since they illustrate the disparate behavior of households' near-term and longer-term inflation expectations in response to salient price changes in the post-2012 sample. Second, these results demonstrate that the nature of inflation shocks didn't fundamentally change over the two samples. In particular, households continued to revise their near-term inflation expectations after 2012 in much the same way they did prior to 2012. Instead, what changed in the latter sample period is the degree to which these revisions in near-term inflation expectations lead to corresponding revisions in their longer-term inflation expectations.

References

Andrews, Donald WK. 1993. "Tests for parameter instability and structural change with unknown change point." *Econometrica*, 821–856.

Blanchard, Olivier, and Jordi Galí. 2010. "Labor markets and monetary policy: A New Keynesian model with unemployment." *American Economic Journal: Macroeconomics*, 2(2): 1–30.

Cavallo, Alberto, Guillermo Cruces, and Ricardo Perez-Truglia. 2017. "Inflation expectations, learning, and supermarket prices: Evidence from survey experiments." *American Economic Journal: Macroeconomics*, 9(3): 1–35.

Clark, Todd E, and Troy Davig. 2011. "Decomposing the Declining Volatility of Long-term Inflation Expectations." *Journal of Economic Dynamics and Control*, 35(7): 981–999.

Coibion, Olivier, and Yuriy Gorodnichenko. 2015. "Is the Phillips curve alive and well after all? Inflation expectations and the missing disinflation." *American Economic Journal: Macroeconomics*, 7(1): 197–232.

Gertler, Mark, and Antonella Trigari. 2009. "Unemployment fluctuations with staggered Nash wage bargaining." *Journal of Political Economy*, 117(1): 38–86.

Gürkaynak, Refet S., Andrew Levin, and Eric Swanson. 2010. "Does Inflation Targeting Anchor Long-Run Inflation Expectations? Evidence from the U.S., U.K, and Sweden." *Journal of the European Economic Association*, 8(6): 1208–1242.

Gürkaynak, Refet S, Brian Sack, and Eric Swanson. 2005. "The sensitivity of long-term interest rates to economic news: evidence and implications for macroeconomic models." *American Economic Review*, 95(1): 425–436.

Hall, Robert E. 2005. "Employment fluctuations with equilibrium wage stickiness." *American Economic Review*, 95(1): 50–65.

Hall, Robert E, and Paul R Milgrom. 2008. "The limited influence of unemployment on the wage bargain." *American Economic Review*, 98(4): 1653–74.

Hansen, Bruce E. 1997. "Approximate asymptotic p values for structural-change tests." *Journal of Business & Economic Statistics*, 15(1): 60–67.

Ireland, Peter N. 2003. "Endogenous Money or Sticky Prices." *Journal of Monetary Economics*, 50: 1623–1648.

Ireland, Peter N. 2007. "Changes in the Federal Reserve's Inflation Target: Causes and Consequences." *Journal of Money, Credit and Banking*, 39(8): 1851–1882.

Kiefer, Nicholas M., and Timothy J. Vogelsang. 2005. "A New Asymptotic Theory for Heteroskedasticity-Autocorrelation Robust Tests." *Econometric Theory*, 21(6): 1130–1164.

Koop, Gary, and Dimitris Korobilis. 2010. *Bayesian Multivariate Time Series Methods for Empirical Macroeconomics.* Now Publishers Inc.

Lazarus, Eben, Daniel J Lewis, James H Stock, and Mark W Watson. 2018. "HAR inference: Recommendations for practice." *Journal of Business & Economic Statistics*, 36(4): 541–559.

Leduc, Sylvain, and Keith Sill. 2013. "Expectations and Economic Fluctuations: An Analysis Using Survey Data." *Review of Economics and Statistics*, 95(4): 1352–1367.

Leduc, Sylvain, and Zheng Liu. 2016. "Uncertainty shocks are aggregate demand shocks." *Journal of Monetary Economics*, 82: 20–35.

Leduc, Sylvain, Keith Sill, and Tom Stark. 2007. "Self-Fulfilling Expectations and the Inflation of the 1970s: Evidence from the Livingston Survey." *Journal of Monetary Economics*, 54(2): 433–459.

Rudebusch, Glenn D., and Eric T. Swanson. 2012. "The Bond Premium in a DSGE Model with Long-Run Real and Nominal Risks." *American Economic Journal: Macroeconomics*, 4(1): 105–143.

Table A.1: Calibrated Model Parameters

Parameter	Description	Value	Source
β	Household Discount Factor	0.9995	Ireland (2007)
χ	Disutility of Working Scalar	0.476	Leduc and Liu (2016)
θ	Elasticity of Substitution Intermediates	6.0	Ireland (2003)
α	Share Parameter in Matching Function	0.5	Blanchard and Galí (2010)
μ	Matching Efficiency	0.645	Leduc and Liu (2016)
ρ	Job Separation Rate	0.1	Monthly Separation Rate of 3.5%
ϕ_u	Flow Benefit of Unemployment	0.25	Hall and Milgrom (2008)
κ	Vacancy Cost	0.14	Leduc and Liu (2016)
b	Nash Bargaining Parameter	0.5	Blanchard and Galí (2010)
γ	Real Wage Rigidity	0.8	Gertler and Trigari (2009)
ϕ_P	Cost of Adjusting Nominal Prices	270	Calibrated to Match Phillips Curve
ρ^π	Persistence of Inflation Expectations	0.93	Calibrated to Match Phillips Curve
Π^*	Central Bank Inflation Target	1.008	Calibrated to Match Phillips Curve
ϕ_π	Central Bank Response to Inflation	0.8594	Ireland (2007)
ρ_a	Preference Shock Persistence	0.9097	Ireland (2007)
σ_a	Preference Shock Volatility	0.01	Implies 1% Demand Shock

Table B.1: Reduced-Form Phillips Curve Regressions Under Alternative Wage Setting

	Model Simulations			**Model Simulations**		
	With Real Wage Rigidity $\gamma = 0.8$			No Real Wage Rigidity $\gamma = 0.0$		
	1999–2011	2012–2019	1999–2019	1999–2011	2012–2019	1999–2019
Constant	3.18^{***}	3.18^{***}	3.18^{***}	3.18^{***}	3.18^{***}	3.18^{***}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Unemployment Rate	-0.19^{***}	-0.09^{***}	-0.19^{***}	-0.20^{***}	-0.10^{***}	-0.20^{***}
	(0.04)	(0.02)	(0.04)	(0.03)	(0.02)	(0.03)
Constant $\times\ \mathcal{I}_{t\geq 2012}$			0.00			0.00
			(0.03)			(0.03)
Unemployment Rate $\times\ \mathcal{I}_{t\geq 2012}$			0.10^{**}			0.11^{***}
			(0.04)			(0.04)
Observations	156	96	252	156	96	252
R^2	0.34	0.37	0.35	0.48	0.45	0.48

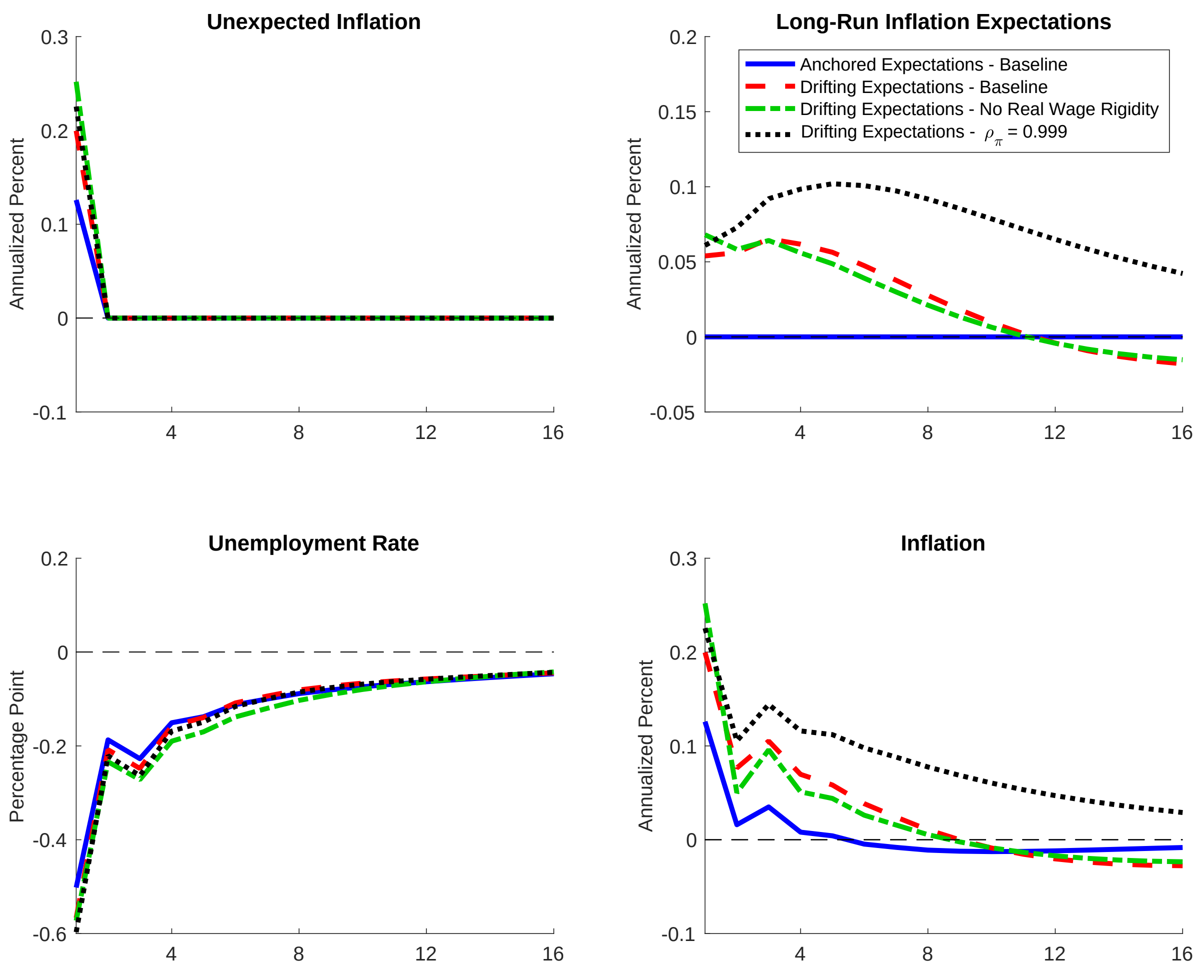
Bootstrapped standard errors are shown in parenthesis. $^{*}p < 0.10$,$^{**}p < 0.05$,$^{***}p < 0.01$
See Section B for details.

Table B.2: Reduced-Form Phillips Curve Regressions Under Alternative Degree of Pass-Through from Inflation Surprises to Long-Term Inflation Expectations

	Model Simulations			**Model Simulations**		
	Reduced-Form Phillips Curve			Expectations-Augmented Phillips Curve		
	1999–2011	2012–2019	1999–2019	1999–2011	2012–2019	1999–2019
Constant	3.18^{***}	3.18^{***}	3.18^{***}	-0.00	0.00	-0.00
	(0.02)	(0.04)	(0.02)	(0.03)	(0.02)	(0.02)
Unemployment Rate	-0.19^{***}	-0.12^{***}	-0.19^{***}	-0.18^{***}	-0.17^{***}	-0.18^{***}
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Constant $\times \mathcal{I}_{t\geq 2012}$			0.00			0.00
			(0.04)			(0.03)
Unemployment Rate $\times \mathcal{I}_{t\geq 2012}$			0.07^{**}			0.01
			(0.04)			(0.03)
Observations	156	96	252	156	96	252
R^2	0.56	0.37	0.53	0.55	0.53	0.56

Bootstrapped standard errors are shown in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$
See Section B for details.

Figure B.1: Impulse Responses to a Demand Shock Under Drifting & Anchored Expectations



Note: The figure shows the impulse responses in the theoretical model to a one standard deviation aggregate demand (preference) shock under anchored and drifting inflation expectations, with the latter shown for various alternative model calibrations. See Section B for details.

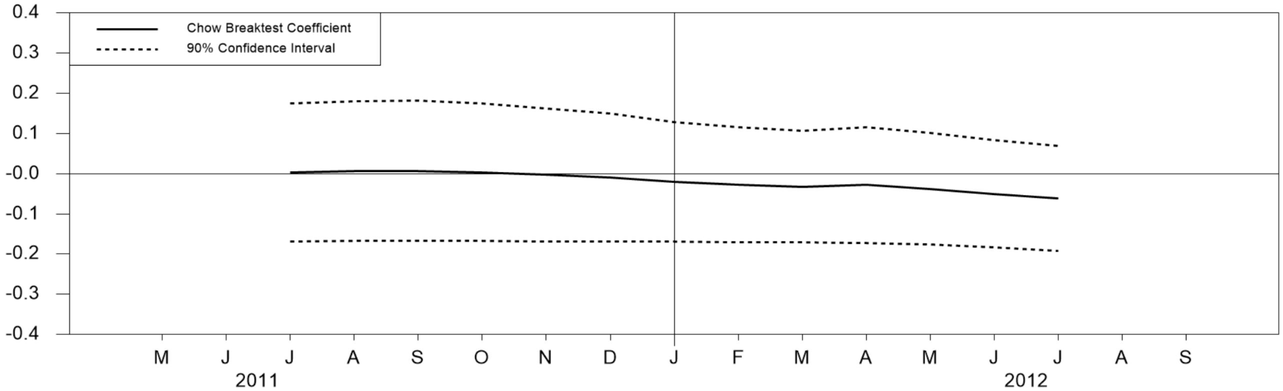
Table C.1: Robustness: US Reduced-Form Phillips Curve Regressions with HAR Standard Errors

	Newey-West Standard Errors			**HAR Standard Errors**		
	Core Inflation			Core Inflation		
	1999-2011	2012-2019	1999-2019	1999-2011	2012-2019	1999-2019
Constant	3.18^{***}	2.22^{***}	3.18^{***}	3.18^{***}	2.22^{***}	3.18^{***}
	(0.22)	(0.22)	(0.22)	(0.24)	(0.22)	(0.22)
Unemployment Rate	-0.19^{***}	-0.04	-0.19^{***}	-0.19^{***}	-0.04	-0.19^{***}
	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)
Constant $\times\ \mathcal{I}_{t\geq 2012}$			-0.96^{***}			-0.96^{**}
			(0.28)			(0.28)
Unemployment Rate $\times\ \mathcal{I}_{t\geq 2012}$			0.15^{***}			0.15^{**}
			(0.04)			(0.05)
Observations	156	96	252	156	96	252
R^2	0.49	0.09	0.45	0.49	0.09	0.45

Note: Core Inflation is measured as the year/year percent change in the CPI excluding food and energy. Standard errors are shown in parenthesis. For the regressions on the left panel, we use Newey-West standard errors with 12 lags. For the regressions on right panel, we use HAR robust standard errors (a QS kernel with $v = 0.4T^{2/3}$ cosine terms) and fixed-b asymptotic critical values from Kiefer and Vogelsang (2005). $^{*}p < 0.10$,$^{**}p < 0.05$,$^{***}p < 0.01$

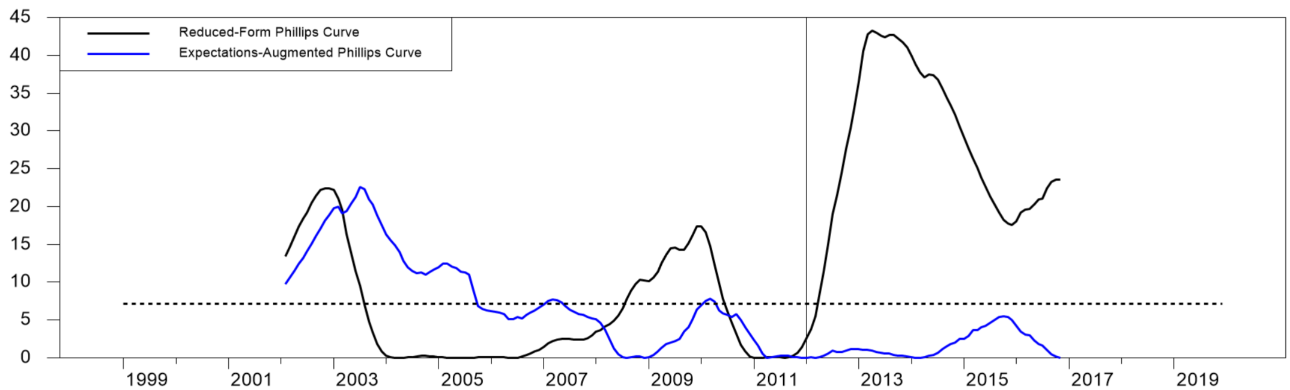
Figure C.1: Robustness of Phillips Curve Structural Break Evidence Post-2011

**Panel A: Expectations-Augmented Phillips Curve:
Chow Test Robustness to Different Candidate Break Dates for Unemployment Rate**



Note: Positive (negative) values indicate a flatter (steeper) Phillips curve slope.

**Panel B: Phillips Curve Regressions:
Breaktest Sequences at an Unknown Date for Unemployment Rate**



Note: Vertical line denotes January 2012. Dashed horizontal line denotes breaktest critical value.

Both panels use monthly data from January 1999 through December 2019. For Panel B, 15% of the observations on the ends of the sample are not examined as break points. 10% critical values are obtained from Andrews (1993) for $\pi_0 = 0.15$ and $p = 1$.

Table D.1: Summary Statistics of US Core CPI Inflation Surprises

	1997–2011	2012–2019
Mean	−0.00	−0.02
	[0.63]	[0.01]
Standard Deviation	0.07	0.06
Skewness	0.13	−0.23
	[0.48]	[0.37]
Kurtosis	−0.35	0.21
	[0.35]	[0.69]
Jarque-Bera	1.40	1.00
	[0.50]	[0.61]
Observations	179	96

Note: p-values in brackets.

Table D.2: Chow Test: US Forward Rate Model

	Estimation Sample		
Δ 1-Year, 9-Year Fwd Nominal Rate	1997–2011	2012–2019	1997–2019
Constant	-0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.01)
Core CPI surprise	0.10^{*}	-0.04	0.10^{*}
	(0.06)	(0.06)	(0.06)
GS Agriculture Price Index	0.00	0.02^{**}	0.00
	(0.01)	(0.01)	(0.01)
GS Energy Price Index	0.00	0.01^{***}	0.00
	(0.00)	(0.00)	(0.00)
Constant $\times \mathcal{I}_{t \geq 2012}$			-0.00
			(0.01)
Core CPI surprise $\times \mathcal{I}_{t \geq 2012}$			-0.14
			(0.09)
GS Agriculture Price Index $\times \mathcal{I}_{t \geq 2012}$			0.01
			(0.01)
GS Energy Price Index $\times \mathcal{I}_{t \geq 2012}$			0.00
			(0.00)
Observations	179	95	274
R^2	0.04	0.12	0.06

Note: Eicker-White standard errors in parenthesis. $^{*}p < 0.10$,$^{**}p < 0.05$,$^{***}p < 0.01$

Table D.3: Structural Break Tests at an Unknown Date: US Inflation Compensation Model Excluding Financial Crisis

		Structural Break Test	
Δ 1-Year, 9-Year Fwd Breakeven Inflation		Andrews-Quandt	Andrews-Ploberger
	Break Date	Test Statistic	Test Statistic
Constant	2003:05	1.33	0.11
		[0.95]	[1.00]
Core CPI surprise	2010:05	9.61**	2.40**
		[0.03]	[0.03]
Food & Energy CPI surprise	2011:08	3.39	0.45
		[0.48]	[0.48]
All Coefficients	2010:05	12.46*	3.61*
		[0.09]	[0.09]
Residual Variance	2003:04	3.28	1.06
		[0.50]	[0.18]

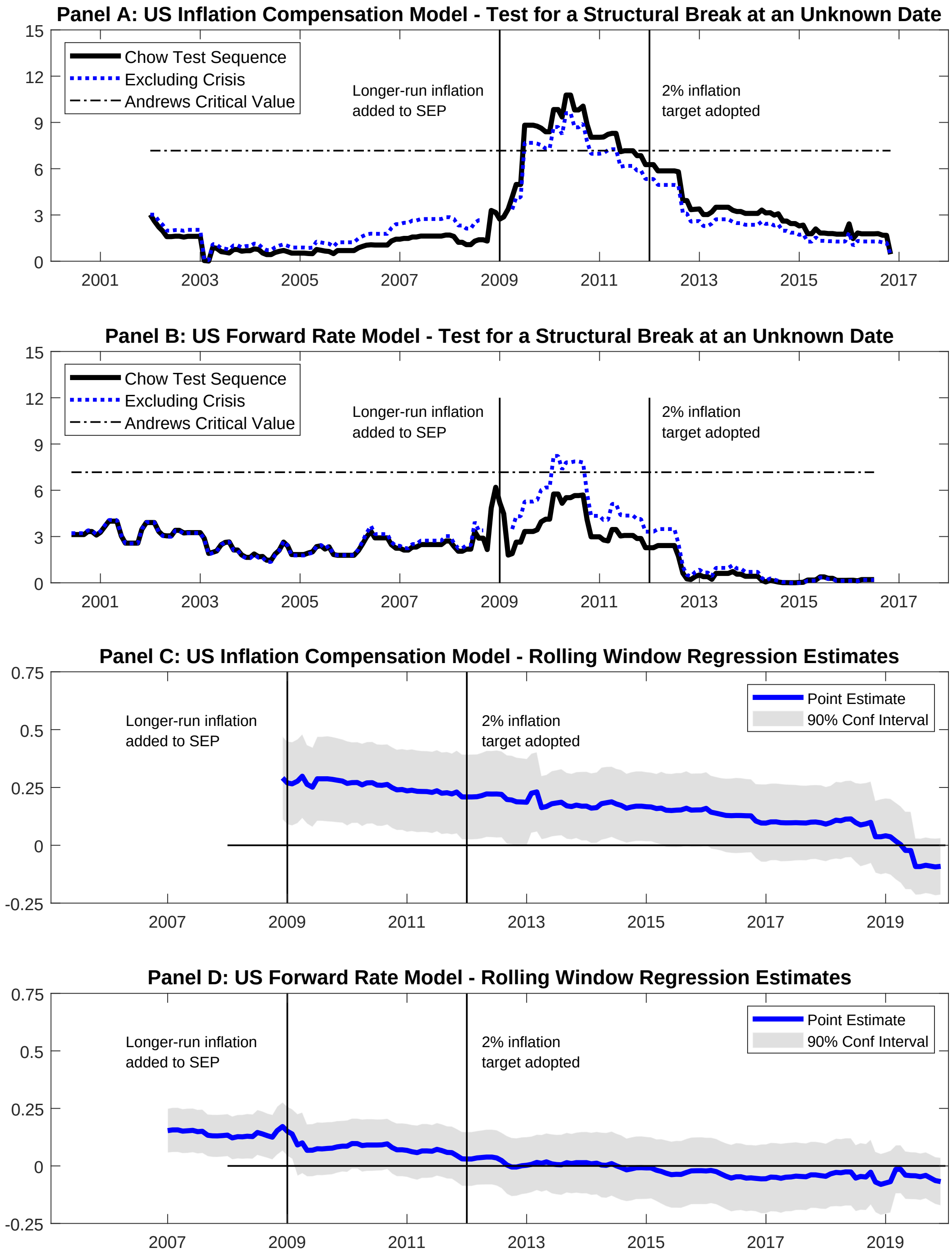
Note: Approximate asymptotic p-values from Hansen (1997) in brackets.
Observations: 245. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table D.4: Structural Break Tests at an Unknown Date: US Forward Rate Model Excluding Financial Crisis

		Structural Break Test	
Δ 1-Year, 9-Year Fwd Nominal Rate		Andrews-Quandt	Andrews-Ploberger
	Break Date	Test Statistic	Test Statistic
Constant	2013:11	2.83	0.54
		[0.59]	[0.41]
Core CPI surprise	2010:02	8.22*	1.85*
		[0.06]	[0.06]
GS Agriculture Price Index	2003:09	5.23	1.27
		[0.22]	[0.13]
GS Energy Price Index	2011:05	4.18	0.63
		[0.35]	[0.35]
All Coefficients	2010:02	12.74	3.87
		[0.17]	[0.15]
Residual Variance	2013:11	2.66	0.68
		[0.63]	[0.32]

Note: Approximate asymptotic p-values from Hansen (1997) in brackets.
Observations: 268. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

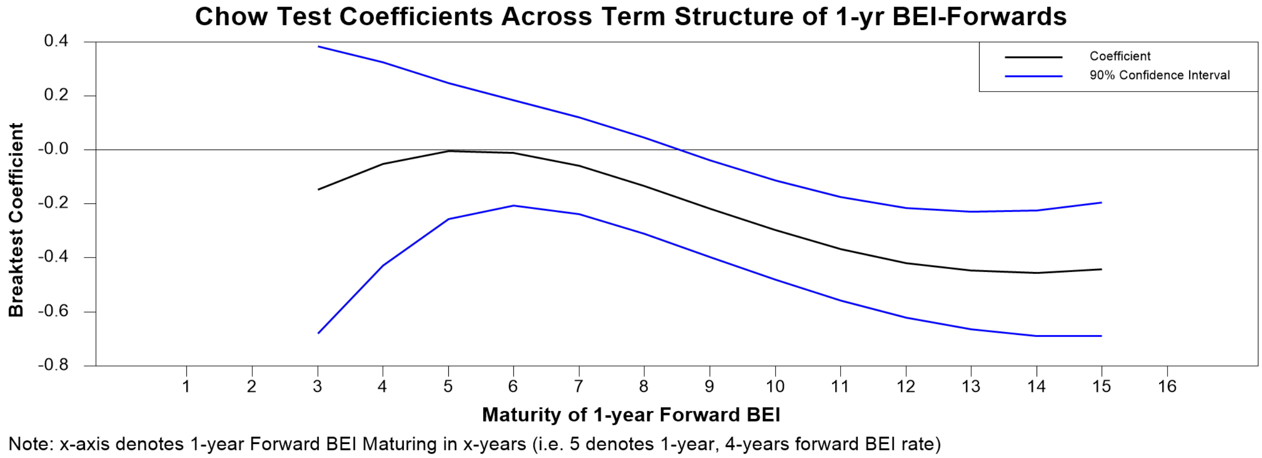
Figure D.1: Robustness of High-Frequency Regressions



Panels A and B Note: Each panel shows the sequence of Chow test statistics as a function of candidate break dates. For each model, 15% of the observations on the ends of the sample are not examined as break points. 10% critical values are obtained from Andrews (1993).

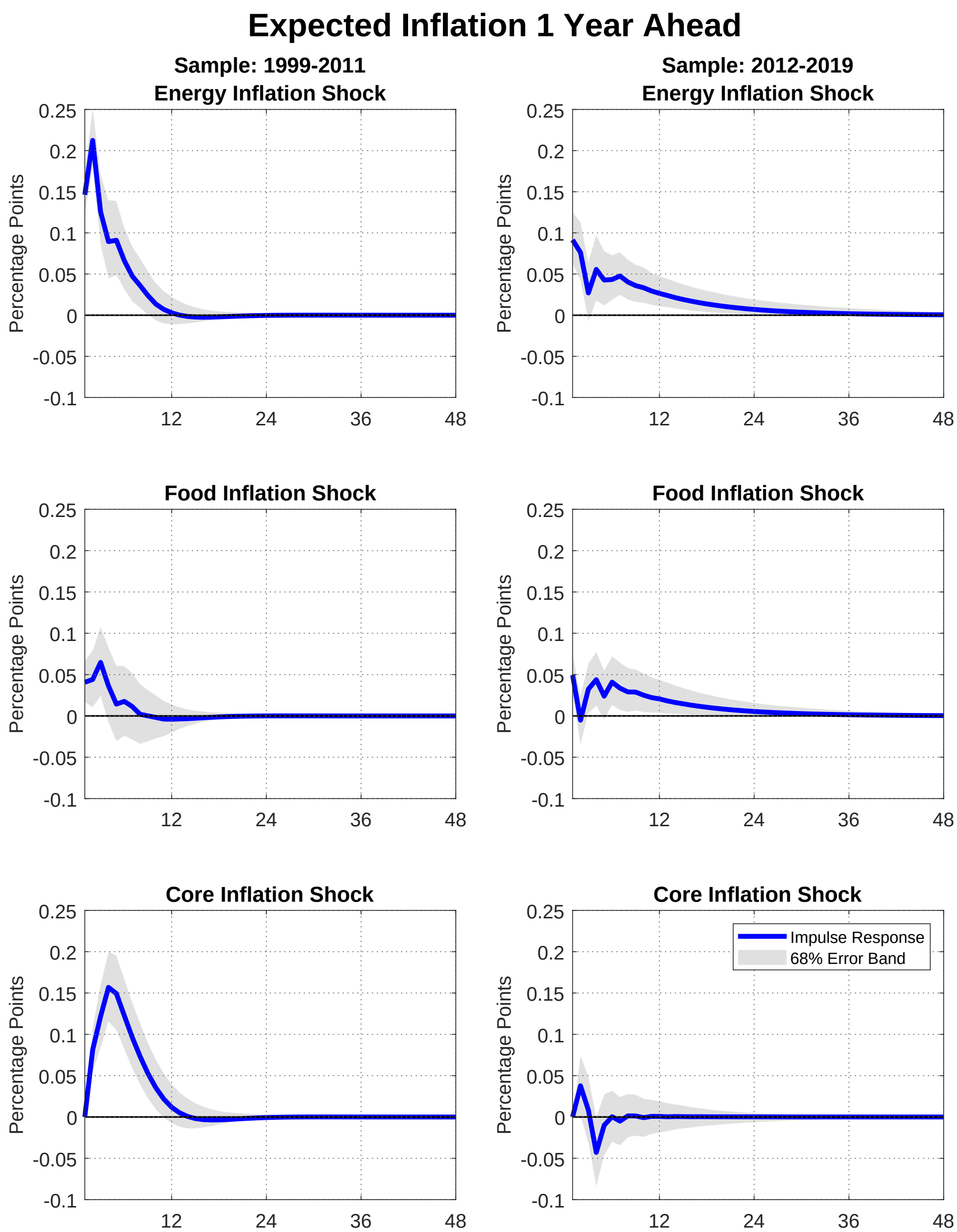
Panels C and D Note: Each panel shows the sequence of estimates of δ^{π} as a function of time. The date on the x-axis denotes the end of the 10-year rolling sample. The 90% confidence intervals are computed as the point estimate plus or minus 1.645 times the Eicker-White standard error.

Figure D.2: Robustness of Structural Break in Baseline Regression Across Various Horizons of Breakeven Inflation



Note: This chart shows the chow test coefficeint for a break in Janaury 2012 in the baseline regression model for various horizons of breakeven inflation rates. Each horizon of forward inflation rates is a separate regression using monthly data from January 1999 through December 2019.

Figure E.1: VAR Impulse Responses of Household's Near-Term Inflation Expectations



Note: The figure shows VAR-estimated impulse responses of household's near-term inflation expectations in response to various inflationary impulses. The impulse responses in the left column are estimated from 1999–2011. The impulse responses in the right column are estimated from 2012–2019. Each VAR model is estimated on monthly data comprised of CPI energy inflation, CPI food inflation, near-term inflation expectations collected from the University of Michigan Survey of Consumers, and CPI inflation. The CPI inflation series enter the VAR in month-over-month inflation rates, annualized.