Good Inflation, Bad Inflation: Implications for Risky Asset Prices

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Abstract

In times of market-perceived "good inflation," when inflation news is positively correlated with real economic growth, shocks to expected inflation substantially reduce corporate credit spreads and raise equity valuations. Meanwhile in times of "bad inflation," these effects are attenuated and the opposite can take place. These dynamics naturally arise from an equilibrium asset pricing model with a time-varying inflation-growth relationship and persistent macroeconomic expectations. Using inflation swap prices we study how expected inflation is priced in firm-level credit spreads and equity returns, and uncover evidence of a time-varying inflation beta.

Keywords: Inflation Risk, Time Variation, Asset Prices, Stock-Bond Correlation

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1 Introduction

The rise of global inflation in the aftermath of the COVID-19 pandemic has reignited enormous interest among policymakers, academics, and market participants regarding the pricing of inflation risk in financial markets. On a high frequency basis, recent studies show that asset prices continue to react rapidly to inflation news conveyed through macroeconomic announcements or following informative central bank speeches; while at a lower frequency, other studies show that inflation risk continues to be an important source of systematic movements in financial markets.[1]

In this paper, we study the inflation sensitivity of firm-level corporate credit spreads and equity returns, and focus on a relatively novel dimension – its time-variation.[2] Our empirical findings show that in times of market-perceived "good inflation," when inflation news is positively correlated with real economic growth, shocks to expected inflation (i.e., inflation risk) substantially reduce spreads and raise equity valuations. Meanwhile, in times of "bad inflation," when inflation news is negatively correlated with real economic growth, these effects are attenuated and, in some instances, can also be reversed.

We motivate our analysis using an economic model that features time-varying inflation risk and persistent macroeconomic expectations (i.e., long-run risks). Relative to Bansal and Yaron (2004) and Bansal and Shaliastovich (2013), we embed a time-varying covariance between expected real growth and inflation shocks which, by definition, determines the good and bad nature of expected inflation movements. While shocks to expected inflation raise discount rates in all regimes, they affect a firm's real cash flows and asset prices in an asymmetric manner. In a good inflation regime, the positive cash flow reaction leads to an increase in equity valuations and a decline of credit spreads through reduced default risk. The opposite story holds in bad inflation regimes.

Our model provides a number of implications that guide our empirical analysis. First, the endogenous, model-implied bond-stock return correlation behaves one-to-one with the real growth-inflation covariance. While we would like to measure this covariance on a real-time basis in the data, our framework shows that the bond-stock correlation measure serves as an

[1] Recent work that employ a high frequency approach to these questions include Chaudhary and Marrow (2023), Gil de Rubio Cruz, Osambela, Palazzo, Palomino, and Suarez (2023), Knox and Timmer (2023), and Kroner (2023). Prominent work focused on the pricing of inflation risk include Bansal and Shaliastovich (2013), Ajello, Benzoni, and Chyruk (2019), Bhamra, Dorion, Jeanneret, and Weber (2022), Fang, Liu, and Roussanov (2023), and Bonelli (2023).

[2] Some recent papers have focused on the time variation of priced macroeconomic risk. Elenev, Law, Song, and Yaron (2023) show that macroeconomic announcements affect equity markets more in bad times. Cieslak and Pflueger (2023) discuss "good" and "bad" inflation over time, and how they relate to demand versus supply-driven shocks. Finally, Boons, Duarte, de Roon, and Szymanowska (2020) focus on the time-varying, asset pricing implications of inflation risk and show qualitatively similar findings using low frequency data.

excellent proxy. Second, the model clearly displays that when the covariance is significantly positive (i.e., a good inflation regime) equity returns (credit spreads) positively (negatively) respond to expected inflation shocks. Finally, our model also speaks to the importance of persistent expectations. When the long-run mechanism in expected growth is attenuated, there is less variability in the bond-stock correlation and expected inflation shocks are less important, on an absolute basis, for asset prices.[3]

In the empirical analysis, we directly test for the time-varying nature of financial markets' sensitivity to movements in expected inflation. We design an empirical strategy centered around expected inflation information revealed by macroeconomic announcements using daily and intraday movements of five year inflation swaps. As these swaps are market-based contracts concerning longer-term inflation expectations, they allow us to better link to the long duration cash flows present in credit and equity securities.[4] Furthermore, we restrict our analysis to macroeconomic announcements that are informationally relevant for inflation expectations, during which traders price in new information and swap movements display a greater degree of variation.[5] Because the real growth-inflation covariance is not directly observable at high frequencies, we follow one of the model's main implications and use the bond-stock correlation, which we can conveniently track on a daily basis.

All told, our empirical strategy focuses on the transmission of announcement news into inflation swaps, which proxy for the relevant inflation expectations embedded into equities and credit markets. Before presenting the conditional results, we first show that, unconditionally, daily movements in expected inflation reduce credit spreads and increase equity prices. Specifically, a one standard deviation (1-σ) movement in expected inflation reduces 5-year CDS spreads by 1 basis point and increases equity returns by 40 basis points, over a 1-day horizon. These results are consistent with the unconditional behavior of our model calibrated to the post 2000's bond-stock correlation in our empirical sample.

We next turn to our main results and document the time-varying sensitivity of financial markets to changes in inflation expectations. In particular, we show that the sensitivity depends on the market perception of the relationship between inflation news and future real economic growth. Using our model result, we embed an interaction term in our baseline panel

[3] The link that our model draws between the real-nominal covariance and the bond-stock correlation is similar to the New-Keynesian model discussion in Cieslak and Pflueger (2023). Meanwhile, Chernov, Lochstoer, and Song (2023) and Jones and Pyun (2023) study the role of consumption growth persistence towards the variability of the bond-stock correlation.

[4] Additionally, Diercks, Campbell, Sharpe, and Soques (2023) show that swaps provide better forecasts of future inflation than survey-based measures.

[5] We focus on macroeconomic announcements related to CPI, core CPI, PPI, core PPI, GDP, and nonfarm payrolls. We choose this set of announcements as their survey-based surprises are significantly priced in intraday inflation swap markets.

regression that combines the change in swap rates on macroeconomic announcement days and the lagged 3-month stock-bond return correlation.[6] We find robust evidence that a reduction in this correlation (i.e., more of a "good" inflation environment), leads to a larger reduction in credit spreads and increase in equity returns. For example, when the correlation is two standard deviations lower relative to its mean, the marginal response of CDS spreads across all firms with respect to a 1-σ movement in expected inflation is negative 2.1 b.p, while the equity return sensitivity is positive and equal to 0.81%. An analogous interpretation holds in the other direction.

We show additional empirical results of interest, outside the scope of our model. Using a decomposition similar to the one in Berndt, Douglas, Duffie, and Ferguson (2018), which takes into account estimates of expected default rates and losses given default, the large majority of credit market effects operates through the risk premium channel.[7] In the cross section, our findings are strongest for riskier firms, as there is a strong interaction between time variation and heterogeneity in inflation beta. Finally, when we compare our bond-stock correlation measure with alternative drivers of inflation beta in the literature (e.g., the nominal-real covariance measure from Boons et al. (2020)), it outperforms in many horse race tests.

One potential critique of our analysis using daily movements in swap rates is that it does not necessarily reflect exogenous shocks to expected inflation. To tackle this concern, we study higher frequency, 60-minute changes in inflation swaps surrounding relevant macroeconomic announcements. First, we show that swap rates significantly adjust on an intraday basis with respect to macroeconomic surprises, lending credibility to the announcements we focus on. We next display that intraday movements in swaps are priced significantly in daily credit spreads and equity returns, particularly in a time-varying manner. Consistent with our findings using daily measures, when inflation and growth risks are positively related vis-a-vis the stock-bond return correlation, shocks to *intraday* expected inflation reduce credit spreads and increase returns.

To better understand the source of the priced inflation risk, we decompose the intraday movements of inflation swaps using a heteroskedasticity approach (e.g., Rigobon and Sack (2004)). Following Gürkaynak, Kisacikoğlu, and Wright (2020), we take advantage of the greater variance in swap prices across all maturities on announcement days (vs. non-

[6] All correlation measures are computed in a rolling fashion, using daily data. We test multiple measures including a 6-month measure and one that accounts for inflation swap changes instead of Treasury bond returns.

[7] Palazzo and Yamarthy (2022) show that the risk premium calculation in Berndt et al. (2018) that takes into account the entire term structure of default probabilities, can be approximated using estimates of the losses given default and the probability of default over the horizon of the CDS.

announcements), and identify a latent factor orthogonal to macroeconomic surprises. All told, this latent factor helps explain more than 60% of the total variation in the 5-year swap. We show that the latent component in inflation swap changes is a key driver for credit and equity markets, and helps drive the time-variation in inflation risk pricing. Moreover, focusing purely on headline macroeconomic surprises (e.g., CPI or PPI) leaves out a significant inflation-related driver that affects asset prices.

We discuss existing literature over the remainder of this section. In section 2, we provide a description of the model mechanism that motivates our empirical analysis. In Section 3, we provide more details regarding the key data used in our study, while section 4 focuses on our empirical tests.

Related Literature

Our paper relates to a broad set of economic research studying asset prices reaction to macroeconomic news, the state dependency in the pricing of these news, and structural models designed to examine how inflation news in particular affects equity and credit markets. We provide a partial summary of this broad research area in what follows.

While a large strand of the high frequency asset pricing literature has focused on the transmission of monetary policy shocks measured over a narrow window (e.g., Gürkaynak, Sack, and Swanson (2005), Bernanke and Kuttner (2005), Gürkaynak et al. (2020), Swanson (2021)), more recent papers have focused on inflation surprises. Gil de Rubio Cruz et al. (2023) show that firm-level close-to-open returns react negatively to CPI surprises, and that core CPI surprises matter more than headline surprises, which include the more volatile items food and energy.[8] Similar to Pearce and Roley (1988), the authors find that firm-level characteristics (e.g., leverage and firm size) matter for the transmission in the cross section. Knox and Timmer (2023) also show that stock prices decline following a positive inflation surprise, more so for firms with low market power. Chaudhary and Marrow (2023) focus on 1-day movements in inflation swaps surrounding CPI announcements and show that increases in swap-implied inflation expectations increase equity prices. We also follow a swap-based identification strategy surrounding multiple macroeconomic announcement days. However, relative to Chaudhary and Marrow, we additionally investigate corporate credit securities (credit default swaps), focus on the time-variation and cross-sectional heterogeneity of inflation sensitivities, and provide high-frequency evidence.

Recent papers have also studied the state dependency in pricing macroeconomic risks. Elenev et al. (2023) use a wide array of macroeconomic announcements (capacity utilization,

[8]Surprises denote the difference between realized inflation measures and the median economist survey taken shortly prior to the announcement day.

nonfarm payrolls, CPI, GDP, among others) and show that stock markets react more steeply when the output gap is higher and short-term rates are expected to increase (i.e., a more adverse state). Relative to this work, we focus exclusively on inflation announcements and examine reactions in both equity and credit markets. Furthermore, we focus on the inflation-growth relationship as the key state dependent driver. An early paper that discusses the state-dependency in the pricing of CPI surprises is Knif, Kolari, and Pynnönen (2008), where the authors characterize the response of monthly equity prices to CPI surprises, as a function of underlying manufacturing capacity utilization. Similarly, Gil de Rubio Cruz et al. (2023) show that the stock market sensitivity to inflation surprises is the largest during periods when inflation expectations and the output gap are well above their long-run values.

A more closely related paper to ours is Boons et al. (2020), where the authors show that the covariance between inflation and future consumption growth helps determine the inflation risk premium. In states where the covariance is deeply negative, high inflation beta stocks serve as hedges and the inflation risk premia is lower, if not negative. Meanwhile in positive covariance states, the risk premia increases substantially. While our testing environment is significantly different and we do not focus on measuring the inflation risk premium, we also find that an alternative higher frequency measure of the inflation-growth covariance, the stock-bond correlation, matters for the pricing of expected inflation risk in equity returns and credit spreads.[9] Another recent paper that studies state dependency with respect to inflation news is Kroner (2023), who shows that the transmission of inflation surprises into risk-free bond yields is higher when inflation is higher to begin with. Among many other differences, the focus of our work is the transmission of changes in inflation expectations into risky asset prices and the role of the stock-bond return correlation in shaping this transmission mechanism.

Structural models of asset prices have also examined the link to inflation risk. Bansal and Shaliastovich (2013) show in a long-run risks endowment economy that a negative relationship between future expected real growth and lagged expected inflation is needed to generate an upward-sloping term structure of interest rates. Relative to their framework, both Burkhardt and Hasseltoft (2012) and Song (2017) embed a time-varying relationship between shocks to expected growth and expected inflation in an equilibrium long-run risks model. Using regime-switching models they show evidence consistent with a real-nominal covariance shift in the early 2000's. Our model is conceptually similar to both of these works, however we additionally price credit securities (CDS) and derive time-varying in-

[9]In Boons et al. (2020) the nominal-real covariance is based on the coefficient arising from a rolling, monthly regression of future consumption growth on CPI inflation. They use a longer sample at lower frequency, to be able to significantly detect shifts in the covariance sign.

flation beta for both equity returns and credit spreads as a direct model output. Bhamra et al. (2022) extend the debt pricing literature with exogenous cash flows (e.g., Leland and Toft (1996)) to embed sticky leverage (i.e., debt with fixed nominal coupon) and sticky cash flows. Increases in expected inflation reduce credit spreads and equity valuations, based on these assumptions. A model that is closer in spirit to ours is the one in Boons et al. (2020), where the authors also augment an endowment-based asset pricing model with Epstein-Zin preferences to discuss equity market behavior. The key wrinkle is that future consumption growth directly depends on past shocks to overall inflation and this time-varying coefficient helps determine the sign of the inflation risk-premium. Relative to Boons et al., we also use an endowment economy style model but directly embed persistent expectations (long-run risks) as they more directly map to the inflation swaps in the data. We also show that the persistence of expected growth matters tremendously for the model's empirical relevancy. Similar to the regime-switching covariance in our model, Kang and Pflueger (2015) highlights the importance of the cyclicality of inflation shocks towards credit spreads, in the context of a real business cycle model. Finally, Gomes, Jermann, and Schmid (2016) shows that a drop in inflation, when debt contracts are nominally written, leads to higher credit spreads and reduced economic activity, via a general equilibrium feedback effect.

2 Economic Model

We theoretically motivate our empirical analysis using an equilibrium asset pricing model that studies how inflation risk is priced in credit and equity markets. In particular, the model explicitly shows that the covariance of inflation and real growth risks is one-to-one with the sign and magnitude of the endogenous bond-stock correlation.[10] This result is key to justify the use of the latter variable as a "real-time" measure of the inflation-growth relationship in the data. Further, the variation in the covariance determines the time-varying beta of risky asset prices to expected inflation news. Towards the end of this section, we discuss the model-implied testable implications.

2.1 Setup

The model is an extension of the long-run risks endowment economy of Bansal and Shaliastovich (2013). We choose a long-run risks framework as the data suggest that movements in

[10] This finding aligns with previous literature explaining the switch in the sign of the bond-stock correlation during the late 1990s. David and Veronesi (2013), Campbell, Pflueger, and Viceira (2020) and Fang et al. (2023) attribute this change to the changing correlation between consumption growth and inflation, that is, the nominal channel.

the expected component of inflation are what matter for asset prices. Real and nominal fundamentals, that is consumption growth and inflation, are partially determined by persistent components as follows:

$$
\begin{aligned}
\Delta c_{t+1} &= \mu_c + x_{ct} + \sigma_c \varepsilon_{c,t+1}, \\
\pi_{t+1} &= \mu_\pi + x_{\pi t} + \sigma_\pi \varepsilon_{\pi,t+1}, \\
X_t \equiv \begin{pmatrix} x_{ct} \\ x_{\pi t} \end{pmatrix} &= \Pi X_{t-1} + \Sigma_{t-1}\eta_t, \\
\Sigma_t &= \begin{pmatrix} \sigma_{xc} & \sigma_{xc\pi}(s_t) \\ 0 & \sigma_{x\pi} \end{pmatrix},
\end{aligned}
$$

where x_{ct} and $x_{\pi t}$ indicate expected growth and expected inflation, respectively, and the residual components (ε_i) represent short-run noise. Π is the transition matrix for X_t and $\sigma_{xc\pi,t} = \sigma_{xc\pi}(s_t)$ indicates a time-varying covariance that is independently regime-switching. The regimes follow an N-state Markov probability matrix:

$$
\mathbb{P}(s_t | s_{t-1}) = \begin{pmatrix} p_{11} & \cdots & p_{1N} \\ \vdots & \ddots & \vdots \\ p_{N1} & \cdots & p_{NN} \end{pmatrix},
$$

where p_{ij} is the probability of transitioning from state i to j and $\sum_j p_{ij} = 1$ for all states i.

We intentionally place the regime switching parameter in the composite shock process for growth expectations, as this assumption delivers a direct link between the expected growth level and orthogonalized expected inflation shocks. As will be clear in our empirical setting, one can interpret the daily changes in highly persistent inflation swaps as shocks to expected inflation, and this interpretation serves to motivate our setup. However, we are not the first ones to adopt a regime-switching approach as Burkhardt and Hasseltoft (2012) and Song (2017), among others, place regime switches in both the covariance matrix and transition matrix of X_t, and estimate these parameters. That said, our goal is to highlight a mechanism that works through the expected inflation channel in a clear and parsimonious manner.

In line with the literature, the representative investor has Epstein and Zin (1989) recursive preferences:

$$
V_t = \left[(1-\delta) C_t^{\frac{1-\gamma}{\theta}} + \delta \left(\mathbb{E}_t \left(V_{t+1}^{1-\gamma} \right) \right)^{\frac{1}{\theta}} \right]^{\frac{\theta}{1-\gamma}},
$$

where δ is the time discount factor, γ the risk aversion, and ψ the intertemporal elasticity of substitution (IES). The preference for the early resolution of uncertainty is determined by $\theta \equiv \frac{1-\gamma}{1-\frac{1}{\psi}}$. As shown in Epstein and Zin (1989), the investor's (log) pricing kernel takes the form:

$$m_{t+1} = \theta \log \delta - \frac{\theta}{\psi}\Delta c_{t+1} - (1-\theta) r_{c,t+1},$$
$$r_{c,t+1} = \kappa_0 + \kappa_1 pc_{t+1} - pc_t + \Delta c_{t+1},$$

where m is the stochastic discount factor, Δc is the log-growth rate of consumption, pc is the log price-to-consumption ratio, and r_c indicates the return on an asset that pays off the aggregate consumption tree as a dividend. Using the log-linear return approximation from Campbell and Shiller (1988), we write the log return in a linear form above, where κ_0 and κ_1 are constants that are a function of the average pc.[11] Moreover, for any asset i, including the consumption-paying asset, the Euler condition holds:

$$\mathbb{E}_t \left[\exp\left(m_{t+1} + r_{i,t+1}\right)\right] = 1.$$

In the analysis that follows, we mainly focus on the consumption asset as a stand in for aggregate equity returns. While the level and volatility of this asset return will be less than their empirical counterparts for the aggregate stock market returns, we are mostly focused on its cyclical properties, which make it similar to a hypothetical, levered dividend claim. It is straightforward to extend the model to focus on such a levered claim, as done in Bansal and Yaron (2004).

2.1.1 Model Solution and Risk-Free Nominal Bonds

To solve the model, one needs to characterize the equilibrium price-consumption ratio. Based on the Euler equation restriction and fundamental assumptions, we can show that the price-consumption ratio takes the form:

$$pc_t = A_1' X_t + A_2(s_t),$$

where A_1 is a set of loadings on expected growth and inflation and A_2 is a regime switching component. These loadings satisfy the following restrictions:

[11] Based on a first-order approximation of log returns, $\kappa_1 = \exp(\overline{pc})/(1+\exp(\overline{pc}))$ and $\kappa_0 = \log(1+\exp(\overline{pc})) - \kappa_1 \overline{pc}$, where $\overline{pc}$ is the model-implied average pc. In the model solution we ensure that κ_0, κ_1, and $\overline{pc}$ are consistent with one another.

$$A_1 = (1 - \frac{1}{\psi}) \times (I - \kappa_1 \Pi')^{-1} e_1,$$

$$\theta A_2(s_t) = \theta \log \delta + (1-\gamma)\mu_c + \theta\kappa_0 + \frac{1}{2}(1-\gamma)^2\sigma_c^2 + \frac{1}{2}\theta^2\kappa_1^2 A_1' \Sigma_t \Sigma_t' A_1 + \log\left\{\sum_{j=1}^{N} p_{ij} \exp\left(\theta\kappa_1 A_2(s_j)\right)\right\} \quad \text{for } i = 1, \ldots, N.$$

For a given set of fundamental parameters, A_1 can be solved directly while A_2 is solved numerically.[12] For explicit details regarding the model solution, see Appendix B.

To compute the bond-stock return correlation we need to use both the nominal return on the consumption claim, $r_{c,t+1} + \pi_{t+1}$, and the nominal return on a risk-free bond. The return on an n-period zero-coupon, risk-free bond (purchase at t, sell at $t+1$) is given by:

$$\exp\left(r_{f,t+1}^{\$,n}\right) = \frac{P_{f,t+1}^{\$,n-1}}{P_{f,t}^{\$,n}} = \exp\left(p_{f,t+1}^{\$,n-1} - p_{f,t}^{\$,n}\right),$$

where $P_{f,t}^{\$,n}$ indicates the price of a nominal risk-free bond at time t that matures at $t+n$, and its lowercase is the same in log terms. We can show that the log price takes the form:

$$p_{f,t}^{\$,n} = P_1^{n'} X_t + P_2^n(s_t),$$

where state loadings are maturity specific. Similar to the methodology in Ang and Piazzesi (2003), we first derive the coefficient values for a 1-period risk-free bond and then show that $\left\{P_1^{n'}, P_2^n(s_t)\right\}$ can be solved recursively, as a function of the maturity $n-1$ coefficients. Using this approach, we compute nominal bond prices and corresponding bond returns. Again, Appendix B provides explicit details.

2.1.2 Pricing CDS

We also extend the model to speak to the pricing of inflation risk in credit markets. While the long-run risks literature largely focuses on asset pricing implications for equity and bond markets, less work has examined its implications for credit markets. Augustin (2018) is an exception, as the author studies sovereign CDS implications at the country level, that arise from an estimated credit risk model with exogenous default rates, Epstein-Zin preferences, and long-run risk fundamentals. Our model uses many elements of Augustin (2018) as a

[12] If we allow Π to be strictly diagonal, pc_t does not load on $x_{\pi t}$ and we recover the original setting from Bansal and Yaron (2004).

starting point, but embeds the time-varying covariance of expected real and nominal shocks.

As given in Berndt et al. (2018), the CDS of maturity K periods is a rate C_t that satisfies:

$$\Delta C_t \sum_{k=1}^{K/\Delta} \mathbb{E}_t \left[\tilde{M}^{\$}_{t+k\Delta} \left(1 - D_{t,(k-1)\Delta}\right) \right] = \sum_{k=1}^{K/\Delta} \mathbb{E}_t \left[\tilde{M}^{\$}_{t+k\Delta} \times (1-R) \times D_{t+(k-1)\Delta,\Delta} \right] \tag{1}$$

where the left (right) hand side indicates expected payments from the protection holder (seller). Δ denotes the length of time between payments and $\tilde{M}^{\$}_{t+z}$ is the nominal SDF from t to $t+z$. $D_{t,z}$ denotes a default indicator between t and $t+z$. For simplicity, we assume constant losses given default given by $1-R$, and that default occurs shortly before the end of each period.

Assuming a quarterly frequency and that payments are made each quarter ($\Delta = 1$), we can write the 5-year CDS as:

$$\begin{aligned} C_t &= \frac{\sum_{k=1}^{20} \mathbb{E}_t \left[\tilde{M}^{\$}_{t+k} \times (1-R) \times D_{t+k-1,1} \right]}{\sum_{k=1}^{20} \mathbb{E}_t \left[\tilde{M}^{\$}_{t+k} \left(1 - D_{t,k-1}\right) \right]} = \frac{\sum_{k=1}^{20} \mathbb{E}_t \left[\tilde{M}^{\$}_{t+k} \times (1-R) \times (S_{t,t+k-1} - S_{t,t+k}) \right]}{\sum_{k=1}^{20} \mathbb{E}_t \left[\tilde{M}^{\$}_{t+k} S_{t,t+k-1} \right]} \\ &= (1-R) \times \left(1 - \frac{\sum_{k=1}^{20} \mathbb{E}_t \left[\tilde{M}^{\$}_{t+k} S_{t,t+k} \right]}{\sum_{k=1}^{20} \mathbb{E}_t \left[\tilde{M}^{\$}_{t+k} S_{t,t+k-1} \right]} \right) \end{aligned} \tag{2}$$

where $S_{t,z}$ indicates a survival dummy variable as of time $t+z$.

We follow Augustin (2018) and Doshi, Elkamhi, and Ornthanalai (2018) and assume that default dynamics are exogenous and related to key state variables. While we understand this is a simplification, it allows us to compute CDS prices in closed form and speak to our object of interest – the inflation sensitivity in CDS spreads. Realized default at $t+1$ is given by:

$$D_{t,1} = \begin{cases} 0 & \text{w/probability } \exp(-\lambda_t), \\ 1 & 1 - \exp(-\lambda_t), \end{cases}$$

where the realization is conditionally independent of all other variables in the model. The ex-ante probability (hazard rate) is based on $\lambda_t = \beta_{\lambda 0}(s_t) + \beta'_{\lambda x} X_t$. This formulation does not guarantee that $\lambda_t > 0$ but it allows us to maintain tractability of CDS prices, given the regime switching covariance matrix for X. In our quantitative exercise, we ensure a positive λ_t by calibrating $\beta_{\lambda 0}$ and $\beta_{\lambda x}$ appropriately.[13]

To solve for CDS prices, we need to compute $\mathbb{E}_t \left[\tilde{M}^{\$}_{t+k} S_{t,t+k} \right]$ and $\mathbb{E}_t \left[\tilde{M}^{\$}_{t+k} S_{t,t+k-1} \right]$

[13] One downside of the linear hazard rate formulation is that it restricts the countercylicality of λ_t. To ensure that $\lambda_t > 0$ for $\beta_{\lambda 0}$ and $\beta_{\lambda x \pi} = 0$, we set $\beta_{\lambda xc} > -\frac{\beta_{\lambda 0}}{\max(x_{ct})}$. This limits the volatility of default rates and resulting CDS spreads. Despite this limitation, the model generates reasonable quantitative behavior of CDS spread changes.

for all k, using the Epstein-Zin nominal SDF formulation and long-run risk fundamentals introduced earlier. Using the Law of Iterated Expectations and conditional independence assumption of default, we can show that:

$$\mathbb{E}_t\left[\tilde{M}^{\$}_{t+k} S_{t,t+k}\right] = \mathbb{E}_t\left[\tilde{M}^{\$}_{t+k} \exp\left(-\sum_{j=1}^{k} \lambda_{t+j-1}\right)\right] = \exp\left(B_1^{k\prime} X_t + B_2^k(s_t)\right)$$

$$\mathbb{E}_t\left[\tilde{M}^{\$}_{t+k} S_{t,t+k-1}\right] = \mathbb{E}_t\left[\tilde{M}^{\$}_{t+k} \exp\left(-\sum_{j=1}^{k-1} \lambda_{t+j-1}\right)\right] = \exp\left(C_1^{k\prime} X_t + C_2^k(s_t)\right)$$

which are exponentially affine in the state and a regime-switching coefficient. The coefficients $\left\{B_1^k, B_2^k(s_t), C_1^k, C_2^k(s_t)\right\}$ depend on the fundamental parameters of the model and are solved using a recursive numerical algorithm. Using these results, we can write the model-implied CDS as:

$$C_t = (1-R) \times \left(1 - \frac{\sum_{k=1}^{20} \exp\left(B_1^{k\prime} X_t + B_2^k(s_t)\right)}{\sum_{k=1}^{20} \exp\left(C_1^{k\prime} X_t + C_2^k(s_t)\right)}\right) \tag{3}$$

which is numerically tractable and solves quickly. See Appendix B for explicit details.

2.2 Model Results

In this subsection, we describe the model's key mechanism, illustrate the baseline calibration, and discuss comparative statics. Finally, we highlight how the long-run risk mechanism interacts with the time-varying covariance of expected growth and inflation risks.

2.2.1 Key Mechanism

Before describing our baseline calibration, we start by examining the model's key mechanism: the role of the covariance parameter governing the joint dynamics of expected inflation and growth shocks ($\sigma_{xc\pi}$). In particular, we show that this parameter, which has a clear economic interpretation, directly connects to the stock-bond correlation. In this exercise, we assume that $\sigma_{xc\pi}$ is constant across regimes, and we set it to different values to examine the model's performance. Preference and other fundamental parameters are set to target quarterly values from the data. As we change parameter values, we also ensure that the unconditional variance of expected growth does not change.[14]

Figure 1 displays the model-implied bond-stock correlation based on simulated nominal stock and 5-year bond return data. The y-axis shows the correlation while the x-axis denotes

[14]This is done by directly re-sizing the constant parameter, σ_{xc} in the growth equation.

the covariance parameter. Focusing on the solid blue line, the bond-stock return correlation is monotonically decreasing in the covariance. Put differently, when expected inflation shocks are more positively correlated with consumption growth ($\uparrow \sigma_{xc\pi}$) – an environment where inflation is relatively better for real cash flows – the stock-bond correlation reduces and bond returns become more of a hedge. The reason being that potential shocks to expected inflation naturally reduce bond prices (lead to negative bond returns) while increasing the payoffs of the consumption asset (positive stock returns). A similar but opposite interpretation holds when inflation shocks are more negatively correlated with consumption growth.

Furthermore, this exercise suggests that the model generates sizable variation in the bond-stock correlation. While there is no regime switching present here, embeddding movements in $\sigma_{xc\pi}$ can generate plausible variation in the correlation and explain the patterns we later discuss in the data. For the remainder of this section, we incorporate time-variation in $\sigma_{xc\pi}$ and examine its implications.

2.2.2 Baseline Calibration

As it is standard in the long-run risks literature, we numerically calibrate the model at a quarterly frequency. That said, the mechanisms we discuss hold at higher frequencies, as we show in our empirical analysis. In the calibration, we make two simplifying assumptions. First, the autoregressive matrix Π is set to be diagonal with no cross dependencies. This assumption allows for a clean interpretation of the covariance parameter as the sole source of the real-nominal interaction. Second, we fix the number of regimes to $N = 2$ so that we can speak to distinctive "good" and "bad" inflation regimes.

The top panel of Table 1 lists the baseline parameter values. Some parameters are taken straight from the literature (e.g., $\gamma, \delta, \Pi_{cc}, \Pi_{\pi\pi}$) while others are calibrated. Putting aside the inflation-growth covariance parameter, we calibrate the fundamental parameters (those of $\Delta c, \pi$) to match, or get reasonably close to first and second moments of consumption growth and inflation, between 1968Q4 and 2019Q4.[15] We also match the unconditional volatilities of expected real growth and inflation, constructed using survey data from the Survey of Professional Forecasters (SPF) and the methodology in Bansal and Shaliastovich (2013).

As shown in Figure 1, the "good inflation" regime with $\sigma_{xc\pi} > 0$ produces a negative stock-bond correlation, while the "bad inflation" regime produces the opposite. Because much of our data sample (post 2000's) lies in the former, we calibrate $|\sigma_{xc\pi}(s_1)| > |\sigma_{xc\pi}(s_2)|$, with $\sigma_{xc\pi}(s_1) > 0$ and $\sigma_{xc\pi}(s_2) < 0$. Hence s_1 is our good inflation regime, where orthogonal shocks to expected inflation feedback positively to expected growth. Conditional transition

[15] We do not include data beyond 2019Q4 to avoid the extreme volatility induced by the COVID-19 episode.

probabilities on the regime (p_{11}, p_{22}) are chosen to be equal, with an average regime length of 8 - 10 quarters.

In terms of credit parameters we calibrate the recovery rate (R) and default parameters ($\beta_{\lambda 0}, \beta_{\lambda x}$) which govern the hazard rate function. We set $R = 0.4$ in line with the panel average of Markit recovery rates. To simplify the model $\beta_{\lambda 0} = 0.505\%$ across both regimes to target a 2% annual default rate, close to the empirical average.[16] Finally, we only allow λ_t to depend on x_{ct} as default rates tend to significantly correlate with economic growth measures. We calibrate $\beta_{\lambda xc} < 0$ to generate reasonable countercyclicality of default rates and volatility of CDS spreads.

Based on these parameter values, we solve the model and simulate $40,000$ quarters, including a burn-in period. Beyond the macro moments, the bottom panel of Table 1 shows that the model does a reasonable job with the annualized nominal risk-free rate (4.63%), which is close to the average 3M Treasury bill rate over time. Similarly, the model produces a substantial annual equity premium (.91%), that would be similar to the $\sim 5\%$ seen in the data if we employed a levered dividend claim. The average, annualized 5Y CDS spread in the model is substantial (1.34%) with a reasonable volatility of credit spread movements (5.4 basis points). The behavior of credit spreads in the model is particularly noteworthy given the parameter restrictions on the hazard rate ($\beta_{\lambda xc}$).

In terms of bonds and stocks, the unconditional asset correlation in the model is -15% as the dynamics from the "good inflation" regime dominate.[17] Specifically within the good regime, the correlation is on average -45%, while within the bad regime it is 28%. These values are reasonable in comparison with the ones documented in the empirical part.

To further understand the model and the time-varying inflation sensitivities, we use the simulated return and credit spread data to run simple univariate regressions:

$$\begin{aligned} r_{ct} - r_{ft} &= \beta_0 + \beta_1 \Delta x_{\pi t} + \varepsilon_t, \\ \Delta s_t^{5Y} &= \beta_0 + \beta_1 \Delta x_{\pi t} + \varepsilon_t. \end{aligned}$$

If our intuition is accurate, we would expect $\Delta x_{\pi t}$, which embeds the time-varying covariance, to have differential effects on equity returns and credit spreads across the two regimes. In the bottom six rows of Panel B of Table 1, we show that this is indeed the case. On average, a standard deviation increase in $\Delta x_{\pi t}$ is associated with a 23 basis point increase in the

[16] Based on Moody's EDF data, the average 5Y default probability is roughly 1.1%. We calibrate average default rates a bit higher to get closer to the CDS spread level in the data.

[17] As the correlation is negative, long-term bond returns pay off when the return on consumption are lower and act as a hedge. As a result, prices on long-term nominal bonds are higher leading to a negative bond risk premium (i.e. $E\left[r_f^{5Y,\$} - r_f^{\$}\right] < 0$).

consumption return. In regime 1, the good regime, this coefficient balloons to 93 basis points; while in the bad regime, a movement in expected inflation is associated with a 48 basis point decline. Similar results obtain for model-implied CDS spreads. A positive shock to inflation expectations results in a 1.6 basis point reduction unconditionally. This increases in magnitude, to 6.3 basis points in good inflation regimes. Meanwhile, the sign flips and credit spreads increase in bad regimes.

Across both asset classes, the model shows a qualitatively consistent behavior. In good inflation environments, when the bond stock return correlation is more negative, equity returns (credit spreads) increase (decrease) at a greater rate with respect to expected inflation movements. The opposite takes place in bad inflation environments.

2.2.3 Comparative Statics

To better understand the model mechanisms, we examine how the model performs under different parameter configurations and compare them to the baseline. Similar to the exercise in Figure 1, when changing parameters that are related to the persistence or volatility parameters of X, we make sure that the unconditional moments of X are held fixed.

We begin by looking at a model where the covariance channel is completely shut off, that is where $\sigma_{xc\pi} = 0$ across both regimes. This counterfactual helps us determine how much of the asset price response and stock-bond correlation is driven by this channel. Results from this test are presented in the first column of Table 2. We see that the absolute size of the bond-stock correlation has shrunk close to zero (0.09) and similarly, the degree to which inflation shocks are priced in risky asset prices is significantly reduced. Now, a standard deviation movement in expected inflation shocks only moves returns by about 1 basis point in absolute terms, compared to the 23 basis points in the baseline (Model 4). Similarly, CDS spreads move by roughly 0.01 basis points in response to the same shock.[18]

Next, we examine how the model performs under $\sigma_{xc\pi}(s_1) = 6 \times 10^{-4}$ and $\sigma_{xc\pi}(s_2) = -6 \times 10^{-4}$, a symmetric calibration of the covariance parameter (Model 2). Under this configuration, we see that the model generates a greater absolute bond-stock correlation in the bad regime versus the good regime, thus determining an unconditional bias towards the bad regime. This result tells us that some asymmetry in $\sigma_{xc\pi}$ (biased towards the good regime) is needed to capture the post 2000 patterns. That said, all regime-specific interpretations are similar to the ones for the baseline case.

Finally, we focus on the role of the growth-related long run risk parameter, Π_{cc}. Intuitively, if expected inflation shocks are embedded into x_c in a more long-lived manner, they will matter for asset prices to a greater degree. Starting from Model 2, where $\Pi_{cc} = 0.95$, we

[18] Any small discrepancies of model 1 statistics across regime are due to small sample error in simulation.

lower this parameter to 0.85 and examine the model's performance in Column (3) of Table 2. First and foremost, we observe that the annualized risk premium shrinks from 88 to 37 basis points, an outcome consistent with the traditional long-run risk mechanism. More interestingly, we see that the magnitudes of the regime-specific stock bond correlation, equity return betas, and CDS betas all shrink.

We can more directly see this result in Figure 1, where the dashed red line conveys the model-implied return correlation under a lower persistence of the expected growth component ($\Pi_{cc} = 0.85$). Similar to earlier, as $\sigma_{xc\pi}$ increases, the return correlation reduces. However, the bond-stock correlation is much less sensitive to movements in the covariance term relative to the baseline (i.e., the slope is less negative). Because expected inflation shocks are embedded for a shorter duration of time on average (following the reduced Π_{cc}), a movement in the covariance parameter governing the expected inflation shock means less for the correlation of assets that embed long term cash flows. Due to a similar logic, the magnitude of the equity return and CDS betas shrink in absolute size as well. It is also worth noting that a lower persistence of the expected growth component makes it more challenging for the model to generate a negative bond-stock correlation, which is a robust feature in the data.

2.2.4 Summary

Our model economy clearly illustrates the effect of bad and good inflation regimes on risky asset prices. More importantly, the model shows that, in the presence of persistent expectations, the bond-stock return correlation is one-to one with the covariance between expected inflation and growth shocks. Because this covariance term is not directly observable in the data on a high frequency basis, we instead use the bond-stock return correlation, as suggested by the model, to empirically test whether expected inflation movements are priced in a time-varying manner.

3 Data

In this section, we describe the main data used to investigate how inflation risk is priced in credit and equity markets. There are four key objects of interest: inflation swap spreads, firm-level corporate CDS spreads, firm-level equity returns, and the time-varying correlation between the aggregate stock market and Treasury bond returns. All measures are available daily and we focus on their behavior surrounding key macroeconomic releases, from

August 2004 to October 2023.[19] Asset pricing data go back further but our joint dataset is constrained by the availability of inflation swap spreads. As described below, we also incorporate intraday inflation swap prices to show that the daily dynamics are robust when we focus on a more causal setting.

Inflation Swaps. Inflation swaps are traded instruments that convey expectations of future inflation. Broadly speaking, the swap contract involves the exchange of two cash flow legs – a fixed leg payment equal to the contract rate and a floating payment equal to realized CPI inflation over the contract length. By no-arbitrage, the contract rate denotes "expected inflation," but because it is a traded security with future payoffs it also contains a risk premium component.[20]

Inflation swaps are useful for our study in a number of ways. As swaps are market contracts concerning longer-term inflation expectations, they allow us to more directly link prices of assets with longer duration cash flows to the relevant inflation views of market participants. This is different than looking at CPI inflation surprises, for example, which focus on a very recent backwards-looking realization. Alternatively, one could use inflation surveys (e.g., Survey of Professional Forecasters or Blue Chip) to proxy for inflation expectations. An issue with surveys is that they are available at a much lower frequency (monthly or quarterly) to allow us to examine concurrent asset price responses on CPI release days. Additionally, Diercks et al. (2023) show that inflation swaps provide better forecasts of future inflation than survey-based measures. Moreover, breakeven inflation implied by TIPS also provides an alternative measure of inflation expectations that is comparable. Using swaps allow us to get around some of the liquidity issues that are prevalent in TIPS markets (see e.g., Fleming and Sporn (2013), D'Amico et al. (2018)).

In our study, we use daily swap spreads from Bloomberg and focus on the 5-year horizon to match the maturity of our CDS data. Time series of these swap rates are displayed in the top panel of Figure 2. One year rates are generally more volatile than five or ten year rates, however the three rates tend to move together. The bottom panel of the same figure displays the relationship between the 5-year swap and 5-year breakeven inflation implied by TIPS (5-year constant maturity nominal yield minus 5-year constant maturity TIPS). As

[19]Specific announcements of interest include CPI, PPI, GDP (initial release), and nonfarm payroll employment. As discussed in greater detail in the next section, we choose these announcements because the surprises they generate are closely related to movements in inflation swaps in a tight window.

[20]We recognize that this latter inflation risk premium might be non-trivial and time-varying, however Bahaj, Czech, Ding, and Reis (2023) use transaction-level data of traded UK inflation swaps to show that the supply of long-horizon inflation protection is very elastic, reflects fundamentals, and incorporates new information quickly. That said, in Appendix A we show that the large majority of time-varying beta with respect to inflation compensation is driven by physical inflation expectations, using estimates from D'Amico, Kim, and Wei (2018).

expected, the two are highly correlated and similar in level. As shown in Panel A of Table 3, the average swap rate term structure is upward sloping on macroeconomic release days, ranging from 1.9% (1-year) to 2.4% (10-year). Meanwhile, daily changes in the 5-year swap rate on macroeconomic announcement days display a standard deviation of 4.9 basis points.

In our empirical analysis, we also study higher frequency inflation swap prices to capture precise movements in expected inflation surrounding macroeconomic release times. These data are collected through Refinitiv Tick History and are available on a minute-by-minute basis going back to October 2007. Despite the shorter sample, we are still able to examine asset pricing behavior surrounding over 622 announcements. As all of the key announcements occur at 8:30 AM ET, we compute swap price changes in a 60 minute window (15 minute before and 45 minutes after), similar to the wide window shock in Gürkaynak et al. (2005). In Panel C of Table 3, we display the behavior of the intraday swap change ($\Delta\pi^{idswap,5Y}$). Across all 622 macroeconomic releases, 5-year inflation swaps display a volatility of roughly 3.3 b.p in the one hour window. This is fairly large considering that the daily swap change standard deviation is 4.9 basis points.

Corporate CDS and Equity Returns. In our study, we incorporate firm-level asset prices in credit and equity markets, as they help with identifying level and time-varying effects related to changes in inflation expectations. We use single-name CDS data to proxy for corporate credit risk and collect firm-level CDS quotes from Markit at the 5-year maturity, as it is the most liquid and often traded maturity. Quotes represent the bid-ask average from multiple reporting dealers. We use CDS that are linked to bonds that are senior and unsecured (tier category SNRFOR) and are based on the no restructuring (XR) docclause. We remove all data that correspond to the *Financials, Utilities*, and *Government* sectors in Markit. These empirical specifications are very similar to those used in Berndt et al. (2018). Daily equity returns are from CRSP and we match them to our CDS panel on a CUSIP basis.[21] To control for outlier values in both CDS spreads and equity returns, we winsorize all data at the 0.5% level.

Relative to corporate bonds, there are multiple reasons why CDS data are ideal for our study. First, as CDS are insurance contracts tied to default events of firms, they reflect a risk spread that does not depend on the choice of a risk-free rate. Second, because CDS contracts are traded frequently by a number of institutions (hedge funds, banks, insurance companies, etc.) relative to corporate bonds that trade infrequently, they are less susceptible to pricing frictions that arise from illiquidity and imperfect information (see Bai and Collin-Dufresne

[21] We use 6-digit CUSIP identifiers to match the two datasets. As well known in CRSP, there are a number of duplicate firm-level CUSIP's often referring to different share classes, and we only keep returns that exhibit the largest time series for each firm.

(2019)). Finally, a longer-standing literature suggests that CDS lead corporate bonds in price efficiency, which is relevant when we think of the pricing of inflation risk (e.g., Blanco, Brennan, and Marsh (2005), Lee, Naranjo, and Velioglu (2018)).

In Panel B of Table 3, we provide summary statistics of CDS and equity returns on macroeconomic announcement days. The average 5-year CDS spread in our sample is 2.26% and exhibits a significant degree of skewness and kurtosis. The daily (1-day) change in CDS spreads displays notable variation (8.4 basis points), and ranges from -52.5 to 65.3 b.p. Finally, daily equity returns average 3.2 basis points. The sample size of equity returns is much smaller than CDS as the merged sample yields a significantly lower number of firms ($\sim$ 650 firms) while the larger CDS sample contains roughly 1400 firms.

Stock-Bond Correlation. A key part of our analysis is to examine the time-variation in the inflation beta of credit and equity markets, and how this variation relates to fundamental economic drivers. We do that by focusing on measures that relate to the *inflation-growth* relationship. A precise measure of this object would help us understand whether inflation movements are the result of positive real growth ("good inflation") or might harm real activity in the future ("bad inflation"). As Cieslak and Pflueger (2023) suggest in different language, inflation can be supply-driven, as it was in the second half of the 20th century, or demand-driven, as it has been more recently. Our hypothesis is that the pricing implications of both types of inflation would be different for risky asset prices.

As our model suggests, a starting point to measure the inflation-growth relationship is to examine the return correlation of stocks and US Treasury bonds. Granted, the bond-stock correlation is an imperfect proxy as both bonds and stocks are a function of other types of shocks; they are not "pure" indicators of inflation and growth, respectively. That said, the bond-stock correlation serves as a good proxy for our exploration. In the top panel of Figure 3, we display rolling 3-month (3M) and 6-month (6M) correlations of daily aggregate stock returns and bond returns, where value-weighted stock returns are taken from Ken French's database and daily US Treasury bond returns are computed using zero-coupon 5-year yields.

As well documented in other studies, the stock-bond return correlation is significantly positive until the late 1990's and switches to a relatively negative correlation regime afterwards. This is evident in the bottom panel of Figure 3, where we explicitly focus on the sample that overlaps with our inflation swap data (July 2004 and after). While there are pockets of positive correlation over the last 20 years (e.g., mid 2000's and the last two years), the overall trend suggests a shift from bad to good inflation regimes.

Despite the shift toward a good inflation regime, our data still show a great degree of variation in the correlation measures. For example, the average 3-month correlation over the shorter sample ranges from -78% to 54%. In what follows, we exploit this variation in the correlation measures to better understand the amplification role that the underlying inflation-growth relationship plays.

4 Empirical Results

Our empirical analysis starts by discussing results unconditionally before focusing on the time variation of expected inflation beta. In line with the model's implications, we show how the stock-bond correlation serves as a reasonable proxy for the real growth-inflation relationship and empirically affects the pricing of inflation risk. We also discuss more causal evidence based on higher frequency price movements of inflation swaps.

Our empirical design hinges on information revealed by macroeconomic announcements. In particular, we focus on days where there are data releases related to key price movements (consumer price index and producer price index) or economic activity (nonfarm payroll and initial GDP release). As we show towards the end of this section, market participants do react to macroeconomic announcements surprises on these event days by revising their inflation expectations. By one simple measure, the variance of swap movements is larger on announcement days than non-announcement days, anywhere from 2 to 3.5 times larger.[22]

4.1 Unconditional Pricing of Inflation Risk

We start by examining daily changes in credit risk on event days, and relate them to movements in swap rates. Our baseline specification is:

$$\Delta s_{it} = \beta_i + \beta_\pi \Delta \pi_t^{swap} + \beta_s s_{i,t-1} + \varepsilon_{it}, \tag{4}$$

where s_{it} indicates the 5-year CDS spread for firm i at time t. The dependent variable, $\Delta s_{it} \equiv s_{it} - s_{i,t-1}$, indicates the 1-day change in CDS spreads, while $\Delta\pi^{swap}$ is the 1-day change in 5-year swap rates. We control for firm fixed effects (β_i) and lagged CDS spreads ($s_{i,t-1}$) as these might also mechanically affect the daily change in CDS, and we cluster standard error by firm-date, as there might be greater co-movement of asset prices on event days. Markit dealer quotes are taken throughout the day. However, because all of our announcements occur before the start of trading hours in the US, it is plausible that the change variable will capture new information related to inflation expectations.

[22]The degree of variance differences, between announcement and non-announcements days is dependent on the inflation swap maturity. Using swap prices in a tight window around typical news release timings, on a daily basis, we can show that 2- and 3-year swaps display the highest degree of variance increases.

The first two columns of Table 4 present the baseline results. We find that a positive change in inflation swaps significantly reduces CDS spreads, that is higher expected inflation unconditionally reduces credit risk. At the 1-day horizon, a one standard deviation change in inflation swaps is associated with a one basis points reduction in CDS. While the magnitude of the coefficient might seem small, such a change corresponds to about 12% of the daily standard deviation in CDS rate changes during macroeconomic announcement days. We also show in column (2) that the coefficient grows over time: five days out, the response more than doubles up to 2.2 basis points.

Next, we show that equity markets react to changes in inflation expectations in a qualitatively consistent manner. We are not the first to examine the relationship between equities and inflation risk. Gil de Rubio Cruz et al. (2023) use high frequency data to show that equities respond in a negative manner to core CPI inflation surprises, defined as the gap between realized core CPI and pre-announcement survey forecasts. Meanwhile, in a recent work that also uses inflation swaps, Chaudhary and Marrow (2023) shows that movements in expected inflation lead to positive returns for aggregate stock returns.

Similar to the baseline CDS regression, our baseline equity specification takes the form:

$$R_{it} - R_{ft} = \beta_i + \beta_\pi \Delta\pi_t^{swap} + \beta_X' X_{i,t-1} + \varepsilon_{it}, \tag{5}$$

where the dependent variable indicates 1 or 5-day excess equity returns ($t-1$ to t) for an individual firm. Lagged variables ($X_{i,t-1}$) include CDS spreads and excess returns. Results for this test are provided in columns (3) and (4) of Table 4. Column (3) suggests that following a one standard deviation change in inflation swaps, excess stock returns for the average firm increase by 38 basis points, an economically and statistically significant change which corresponds to 17% of the daily standard deviation in equity returns during relevant macroeconomic announcement days. In a five-day window, excess returns increase further up to 42 basis points (column (4)). Taking into account the CDS results from columns (1) and (2), the average response of asset prices to expected inflation movements is qualitatively consistent across the full sample. Positive movements in inflation swaps are good news for firms, as realized equity returns increase and CDS spreads decrease. These results are also consistent with the average negative stock-bond return correlation in our sample, which broadly indicates a good inflation regime.

4.2 Time Variation in Inflation Beta

While the data display robust evidence that unconditionally inflation risk benefits valuations by increasing stock prices and decreasing credit risk, this average effect masks time-variation and potential reversals. In this subsection, we focus precisely on this dimension, and study how inflation risk is priced over time. Our hypothesis is that the existing relationship between expected inflation and growth matters significantly for valuation purposes.

Based on the model, we concluded that the endogenous inflation beta for asset prices depended on the (regime-specific) covariance between expected real growth and expected inflation:

$$\begin{aligned} \Delta s_t &= \beta_0 + \beta_1 \left(\sigma_{xc\pi,t-1}\right) \Delta x_\pi \\ &\approx \beta_0 + \beta_1 \left(\tilde{\rho}_{t-1}\right) \Delta x_\pi , \end{aligned}$$

where β_1, the credit sensitivity to expected inflation movements, depends on $\sigma_{xc\pi,t-1}$. Simultaneously we showed that the real-nominal covariance was one-to-one with the bond stock correlation, $\sigma_{xc\pi} \sim \tilde{\rho}$. Putting these ideas together, testing for time-variation amounts to including an interaction term combining movements in expected inflation and the stock-bond correlation, as shown in the second line of the above expression.

In the empirical implementation, the key measure we test is related to the aggregate stock market and Treasury bond return correlation at the 3-month horizon. For robustness, we also examine the correlation at the 6-month horizon.[23] We augment the specification in Equation 4 and include an interaction term:

$$\Delta s_{it} = \beta_i + \beta_\pi \Delta\pi_t^{swap} + \beta_\rho \tilde{\rho}_{t-1} + \beta_{\rho\pi} \left(\tilde{\rho}_{t-1} \times \Delta\pi_t^{swap}\right) + \beta_X' X_{i,t-1} + \varepsilon_{it}, \qquad (6)$$

where $\tilde{\rho}$ is one of the proposed correlation measures. It is key that this correlation is taken at the $t-1$ date, so as to ensure that the news ($\Delta\pi_t^{swap}$) is not taken into account in the ex-ante measurement. We also standardize $\tilde{\rho}$ so that $\beta_{\rho\pi}$ indicates the additional sensitivity to changes in inflation swap when $\tilde{\rho}$ is one standard deviation $(1-\sigma)$ higher.

Results from this test are displayed in Table 5. The first column indicates the average change similar to previous results. In column (2), we show that a standard deviation reduction in $\tilde{\rho}$ (a movement of about 0.28) leads to a 0.61 b.p. larger reduction in credit spreads following an increase in inflation swaps. Column (3) also displays that similar results hold when we focus on a slower moving (longer term) measurement of the stock-bond correlation.

Our results have an intuitive explanation. Because bonds returns convey negative real payoffs on inflation, and stock returns are correlated with longer-term growth expectations, the $\tilde{\rho}$ can be interpreted as a (negative) measure of the inflation-growth correlation. When it takes a lower value this is suggestive that any shocks to expected inflation would be relatively

[23] In the Appendix, we also substitute our bond-stock return correlation measure with one based on inflation swaps and market returns. We show that results are robust and in some cases even stronger.

interpreted as "good inflation" news. Meanwhile when the correlation is more positive, as it was briefly in the mid-2000's, mid-2010's, and very recently, it is interpreted as "bad" news. In a consistent manner, when $\tilde{\rho}$ is very negative the CDS response becomes amplified downwards (if $\tilde{\rho} = -2$, the total response to $\Delta\pi^{swap}$ is $-2.03 = -0.81 - 2 \times .61$). The reverse is true when the correlation becomes more positive. In this case, a large positive bond-stock correlation can produce an increase in credit risk following an increase in expected inflation (if $\tilde{\rho} = 2$, the total response to $\Delta\pi^{swap}$ is $0.41 = -0.81 + 2 \times .61$).

In the right-most columns of Table 5, we investigate similar relationships related to the time-varying inflation beta of equity returns. While the average 1-day response to a standard deviation movement in expected inflation is 38 basis points, this response is greatly amplified when markets convey an environment of "good inflation" news. More precisely, if $\tilde{\rho} = -2$, the total response to the excess return would be is $0.79\% = 0.35 + 2 \times .22$ (column 5). This story is in line with our hypothesis and the evidence in CDS markets as well. Results are robust (statistically and economically) when we focus on the 6-month measure (column 6).

The equity-related results presented in Table 5 are similar in spirit with the underlying intuition in Boons et al. (2020), where the authors show that inflation risk is priced in stock markets in a time-varying manner, and that this time-variation is related to the degree of growth predictability by inflation. While the authors use lower frequency (monthly) data to make this point, we believe that our higher frequency tests centered around relevant macroeconomics announcement days reinforce these arguments.

Overall, our analysis provides convincing evidence that inflation risk is priced in a time-varying manner across credit and equity markets. News regarding inflation expectations bolster valuations (i.e., reduce CDS, increase equity returns) at a greater rate when movements regarding long-run inflation are associated with future economic expansions. At the same time, positive movements in inflation expectations bolster valuations at a lower rate (or potentially hurt valuations) when these news are associated with future economic slowdowns.

4.2.1 Additional Results

The previous results validate the model's prediction about the time-varying nature of financial markets' sensitivity to changes in expected inflation. In this subsection, we extend the empirical analysis to explore dimensions that are outside the model but are economically relevant. First, we examine how much of the time variation in inflation beta can be attributed to credit risk premia versus expected losses. Second, we explore the heterogeneity in the time-varying inflation response across different credit risk profiles. Finally, we examine alternative measures from the literature that might capture the nominal-real covariance and show how they compare to the bond-stock correlation.

Credit Risk Premia. Corporate credit spreads contain information with respect to risk-neutral compensation for default risk ("expected losses") as well as a risk premium component that reflects the comovement of investor marginal utility and losses in default. Because credit default swaps are standardized in their cash flows, we can examine whether the previously documented pricing of inflation risk arises from risk premia or the expected losses component.

To decompose CDS spreads into these two components we approximate the methodology in Berndt et al. (2018), which we describe briefly here. Similar to the pricing equation in the model section, the CDS spread at a given maturity is the annualized rate C_t, such that:

$$\Delta C_t \sum_{k=1}^{K/\Delta} \mathbb{E}_t \left[\tilde{M}^{\$}_{t+k\Delta} \left(1 - D_{t,(k-1)\Delta}\right) \right] = \sum_{k=1}^{K/\Delta} \mathbb{E}_t \left[\tilde{M}^{\$}_{t+k\Delta} \times L_{t+(k-1)\Delta,\Delta} \times D_{t+(k-1)\Delta,\Delta} \right]$$

The only difference relative to Equation (1) is that we allow for losses given default to be time-varying above. By definition the expected loss component is one where we assume risk neutrality of the SDF. Along with two other assumptions (conditional independence of recovery rates from realized default and martingale nature of recovery rates), one can transform the above equation to receive:

$$ExpLoss_t = \frac{L_t \sum_{k=1}^{K/\Delta} d_{t,k\Delta} \mathbb{E}_t \left[D_{t+(k-1)\Delta,\Delta} \right]}{\Delta \sum_{k=1}^{K/\Delta} d_{t,k\Delta} \mathbb{E}_t \left[1 - D_{t,(k-1)\Delta} \right]}$$

where $ExpLoss_t$ is the expected loss component and $d_{t,k\Delta}$ is the time t discount rate of a cash flow at $t + k\Delta$. Inherent in this expression is that the decomposition is firm, time, and maturity specific.

While Berndt et al. (2018) compute $ExpLoss_{it}$ using this nonlinear functional form, we use the approximation from Palazzo and Yamarthy (2022), where the authors show that $L_t \times \mathbb{E}_t \left[D_{t+(k-1)\Delta,\Delta} \right]$, the product of loss given default and the (annualized) probability of default over the course of the CDS contract, is close in level terms and highly correlated to the fully nonlinear form that accounts for the term structure of default probabilities. Using this approximation is convenient as it a straightforward formula requiring two pieces of data: recovery rate estimates (available from Markit) and default probability estimates (from Moody's). After obtaining $ExpLoss_{it}$, the credit risk premium is defined as the additive residual, $RiskPrem_{it} = s_{it} - ExpLoss_{it}$.

Using this decomposition, we can test whether our overall CDS results arise from expected losses or risk premia. We do so by modifying Equation (6) as follows:

$$\Delta y_{it} = \beta_i + \beta_\pi \Delta\pi_t^{swap} + \beta_\rho \tilde{\rho}_{t-1} + \beta_{\rho\pi}\left(\tilde{\rho}_{t-1} \times \Delta\pi_t^{swap}\right) + \beta_X' X_{i,t-1} + \varepsilon_{it}, \tag{7}$$

where we additionally control for the lagged expected loss component ($ExpLoss_{i,t-1}$) on the right-hand side and Δy_{it} is either $\Delta RiskPrem_{it}$ or $\Delta ExpLoss_{it}$.

Table 6 reports the results. The sample size in these tests shrinks by roughly half, as the measurement of expected losses requires matching Markit to Moody's EDF data. That said, the average sensitivity of 5-year CDS changes to expected inflation is roughly equal to the coefficient obtained with the larger sample (-0.90 b.p.), as reported in column (1). Meanwhile, columns (2) and (3) suggest that the large majority of inflation sensitivity operates through the risk premium channel.[24] Close to two-thirds of the overall sensitivity is attributable to $\Delta RiskPrem$.

More importantly, column (4) suggests that even in a limited CDS-EDF matched sample, the stock-bond correlation plays a key role in affecting the response of CDS to changes in expected inflation. Coefficient estimates are virtually unchanged in magnitude relative to the full-sample estimates in Table 5. In columns (5) and (6), we break down the interaction coefficient and show that risk premia again accounts for the large portion of the interaction term. Put differently, time-varying market perceptions of inflation and growth drive the pricing of inflation risk in risk premia, which influence overall credit spreads. Note that the interaction term is also significant in the expected loss component, which suggests that the physical probability of default (times loss given default) also responds in a consistent fashion. In columns (7) through (9) we show that these results are robust to using a longer window correlation between risk-free bond and stock returns.

Cross-Section of Time Variation. Credit spreads exhibit a great degree of skewness and kurtosis. In particular, firms with low distances to default and greater financial constraints display increased sensitivities to aggregate risk (e.g., Palazzo and Yamarthy (2022)).

In what follows, we combine the cross-sectional heterogeneity with time variation to study potential interaction effects. We re-examine the results from Equation (6) by CDS-based risk group. Using an intuitive measure of risk – a cross-sectional sort of CDS spreads on the day *prior* to the macroeconomic announcement, we report results in Table 7.[25] CDS-based regressions are reported in columns (1) through (4) and equity in columns (5) through

[24] In theory, coefficients from the $\Delta ExpLoss$ and $\Delta RiskPrem$ should add up to the overall Δs regression. However, there are minor discrepancies in the table. These discrepancies arise from a winsorization of all firm-level dependent and independent variables.

[25] We run separate regressions by risk group to avoid a triple interaction term.

(8). To facilitate comparisons to the average effect, the first column of each set repeats an earlier result regarding the time-varying nature of inflation risk pricing, across all firms. There are two main takeaways: (a) the *average* response is amplified in riskier firms and (b) the degree of time-variation increases for riskier firms. Put together, there are amplified effects for riskier firms when the bond-stock correlation is in the tail of its distributions.

These findings clearly illustrate the need to jointly think about the cross-section and time-variation of inflation beta. The baseline result in Column (1) shows that credit spreads decline by 0.81 basis points following an increase in inflation expectations. For a relatively risky firm however (group 5), when the bond-stock correlation is particularly negative ($\tilde{\rho} = -2$), the overall response is more than six times as large ($-1.99 - 2 \times 1.45 = -4.89$ b.p.).

Alternative Measures of Time Varying Inflation While our model ties a direct link between the bond-stock return correlation and the nominal-real covariance, the former is potentially a noisy proxy in the data as nominal bond and stock returns are a function of many different variables beyond inflation and real growth risks, respectively. Here, we examine whether a monthly measure suggested by Boons et al. (2020) – the nominal-real covariance measured through a time series regression – serves as a better proxy. Additionally, Elenev et al. (2023) show the importance of the output gap towards the macroeconomic news sensitivity of equity markets. Along these lines, we test whether a monthly measure of economic slack, capacity utilization, is relevant for the time variation of inflation beta.

To construct the regression-based covariance measure, we follow the methodology from Boons et al.. We collect aggregate, monthly nondurables and services consumption data from NIPA, and deflate it using the PCE price index. We further normalize it by population over time to create a real, per capita consumption time series. We run the following predictive regression:

$$\Delta C_{s+1:s+12} = \alpha_t + \beta_t \Pi_s + e_{s+1:s+12}, \quad \text{for } s = 1, \ldots, t-12$$

where Π_s reflects the monthly PCE inflation rate and $\Delta C_{s+1:s+12}$ is the future, annual consumption growth rate. In the baseline specification, as described above, this regression is an expanding window specification estimated using weighted least squares. Greater weight is placed on recent observations using an exponential decay function, with a half life of 60 months. In our panel regression analysis, we also test a simpler rolling regression coefficient (standard OLS) over the past 60 months. All three measures, including capacity utilization, are displayed in Appendix Figure A2.

The top panel displays both the expanding and rolling window coefficients with respect to inflation (β_t). As expected, the expanding window (EW) approach significantly smooths out the behavior of the covariance. The signs of the EW coefficient are significantly negative in the pre-2000 period and increase in the early 2000's until they reach a positive sign in the 2010's. This is qualitatively consistent with the behavior of the stock-bond correlation. The bottom panel displays an adjusted version of capacity utilization, displaying the deviations between the utilization index and its average over the past 12 months. As the raw index is a very persistent series, we try to measure its innovations by computing such deviations.

In Table 8, we repeat our baseline tests from Equation 6 but replace our bond stock correlation with the measures described above. As before, all measures are standardized within the interaction effect term, and we take the value that is available prior to the announcement day. In the top panel we focus on changes in CDS surrounding macroeconomic announcements. Columns 2 and 3 show that the nominal real covariance measures (expanding (EW) and rolling (RW)) display expected coefficients. When the covariance is more positive (more of good inflation environment), CDS spreads tend to reduce further in response to swap movements. While the sign on the capacity utilization coefficient is reasonable, implying that greater slack leads to a more positive credit outcome, the coefficient is statistically insignificant. In columns 5 - 7, we horse race the bond-stock correlation measure with the three measures discussed above and show that the former is a stronger driver of the time-varying inflation beta.

In the bottom panel, we conduct a similar set of exercises with respect to equities. Again both regression-based covariance measures are significant drivers of the time-variation while capacity utilization is insignificant (columns 2 - 4). Within the horse race regressions, the bond stock correlation is more important relative to two of the three measures. Only the expanding window covariance measure is marginally more important (.19 vs. 15). In summary, our analysis shows that the bond-stock correlation is a strong indicator for good and bad inflation regimes, particularly so in credit markets.

4.3 Evidence from High Frequency Swap Prices

While the earlier findings are economically and statistically significant, it is natural to question causality. As daily swap prices can reflect the endogenous formation of inflation and growth beliefs, it might be difficult to interpret their movements as exogenous shocks to expected inflation. In this subsection, we tackle this issue by focusing on the behavior of inflation swap prices in a narrower window surrounding macroeconomic news announcements.

4.3.1 Baseline Results

We begin by providing more information regarding the macroeconomic announcements of interest. As shown in Appendix Table A1, all six announcements are released on a monthly or quarterly basis at 8:30 AM EST. Hence, we gather inflation swap data on a daily basis from 8:15 AM to 9:15 AM EST, reflecting a 60 minute window. To ensure that financial markets are not simultaneously driven by both macroeconomic news and monetary policy related interest rate expectations, we drop the few days with FOMC announcements. In total this leaves us with 622 monthly and quarterly announcements, based on the merged sample with intraday inflation swap data, as the latter data from Refinitiv TickHistory are available starting from October 2007.

Before conducting any analysis, we want to confirm that these announcements are of relevance for inflation swaps. To this end, we project 60-minute changes in inflation swaps onto standardized surprise measures, each of which conveys the difference between a realized value and the corresponding Bloomberg median economist survey value:

$$\Delta\pi_t^{idswap,5Y} = \beta_0 + \beta_s \varepsilon_t^s + \eta_t. \tag{8}$$

In the above equation, s indicates one of the surprises of interest, {*corecpi, cpi, nonfarm, gdp, coreppi, ppi*}. In Table 9, we report the results from this regression.

A standardized movement in *corecpi* or *cpi* surprises strongly affects inflation swaps (1.7−1.9 b.p.), as one would expect. Looking at the other variables, they all show up significant on a univariate or a multivariate basis as given in the final column. The results in Table 9 give confidence that these announcements are relevant for examining the behavior of expected inflation.[26] Interestingly, the r-squared values are never greater than 31% individually and 12% on a pooled basis. This result plays a role in the next subsection as we explore the non-surprise component that are important in inflation swaps.

As the high frequency movements in swap rates can be interpreted as shocks to inflation expectations, due to its pure dependence on the news release, we modify our earlier credit spread regression,

$$\Delta s_{it} = \beta_i + \beta_\pi \Delta\pi_t^{idswap} + \beta_\rho \tilde{\rho}_{t-1} + \beta_{\rho\pi}\left(\tilde{\rho}_{t-1} \times \Delta\pi_t^{idswap}\right) + \beta_X' X_{i,t-1} + \varepsilon_{it}, \tag{9}$$

replacing the daily change in swaps with the intraday change. As $\Delta\pi_t^{idswap}$ is more interpretable as a shock, these results get closer to the causal effect of expected inflation on asset prices. Table 10 reports the results. In column (1), we look at the unconditional response of CDS spread changes to daily movements in swaps. As the sample has changed, we confirm that the baseline results from Table 4 continue to hold. In column (2) we show that stan-

[26]While not reported here, we first examined a broader set of announcements based on those studied in Gürkaynak et al. (2020). We find that other announcements (e.g., hourly earnings, unemployment, retail sales) are not as influential for inflation swaps.

dardized movements in higher frequency inflation swaps reduce overall credit risk, albeit at a subdued rate. These results are improved significantly however in column (4). We show that once we include the interaction effect between the lagged stock-bond return correlation and the intraday change in swaps, the *time variation* is strongly significant, albeit at a lower magnitude. Both the average and time-varying coefficient in this regression are directly in line with the story conveyed through daily data.

In columns (5) – (8), we repeat these tests using daily equity returns as a dependent variable. We find again that intraday movements in swaps get priced significantly in a time-varying manner. One might interpret the smaller magnitudes of coefficients in the intraday regression as a negative result. However, we view it as financial markets being slow to react. Over the course of the day as inflation swaps price in economic information, markets react and the response gets propagated to credit and equity markets.

4.3.2 Latent Component in Inflation Swaps

High-frequency event studies, which focus on the response of asset prices to particular news releases, struggle to fully explain movements in asset prices (see Gürkaynak et al. (2020)). This challenge arises because these studies primarily focus on headline surprises from news releases, thus overlooking non-headline information contained in announcements. Underscoring this idea, the final column of Table 9 shows that surprises only account for up to 12% of the variance in intraday swap movements surrounding macroeconomic announcements.

We address this challenge using a heteroskedasticity-based approach (e.g., Gürkaynak et al. (2020)). In particular, the variance of the residual (non-surprise) component of intraday swap movements on announcement days is substantially larger than that of non-announcement day changes. We statistically show this result in Appendix Figure A1. As a result, swap residuals are heteroskedastic depending on whether there is an announcement each day.

Having established this, we follow the Gürkaynak et al. methodology and identify a latent factor orthogonal to macroeconomic news surprises using a one-step estimator via the Kalman filter. Specifically, we use intraday inflation swap data taken over the same time window on announcement and non-announcement days, to estimate the following model:

$$y_t^i = \beta_i' s_t + \gamma_i d_t f_t + \eta_t^i \tag{10}$$

where y_t^i is the vector of 60-minute window intraday changes in inflation swaps rate across various maturities i (1, 2, 3, 5, 7, and 10 years), and s_t is the vector of surprises. If there is an announcement on a particular day's window, d_t takes a value of 1 (otherwise 0) and

f_t is an I.I.D. $\mathcal{N}(0,1)$ latent variable that captures the unobserved surprise component. The estimated latent factor is common across all inflation swap maturities, however the loadings across maturity might vary (γ_i). In the Appendix (Table A2), we present the estimation results.[27] We find that incorporating the latent factor significantly increases explanatory power, allowing us to explain the majority of inflation swap curve movements during announcement dates. Specifically, the addition of the latent factor increases the explanatory power for the 5-year inflation swap rate by 65 percentage points.

Next, we break down intraday changes in inflation swaps into headline (surprises) and non-headline (latent factor) components,

$$\begin{aligned} \Delta\pi_t^{idswap,i} &= \beta_i' s_t + \gamma_i d_t f_t + \eta_t^i, \\ &= \Delta\pi_t^{surp,i} + \Delta\pi_t^{latent,i} + \eta_t^i, \end{aligned}$$

for a maturity i. Focusing on the 5-year maturity, we modify our previous credit spread regression to separately incorporate both headline and non-headline components:

$$\begin{aligned} \Delta s_{it} = \beta_i + \beta_{\pi_s}\Delta\pi_t^{surp} + \beta_{\pi_l}\Delta\pi_t^{latent} + \beta_\rho\tilde{\rho}_{t-1} + \\ \beta_{\rho\pi_s}\left(\tilde{\rho}_{t-1} \times \Delta\pi_t^{surp}\right) + \beta_{\rho\pi_l}\left(\tilde{\rho}_{t-1} \times \Delta\pi_t^{latent}\right) + \beta_X' X_{i,t-1} + \varepsilon_{it}. \end{aligned} \tag{11}$$

The results of this regression are presented in Table 11. In column (1), we look at the unconditional response of CDS spread changes to surprise and latent factor components. Consistent with the estimation results, the largest response comes from the latent factor. Column (2) shows that once we incorporate the interaction effect between the lagged stock-bond return correlation and the surprises and latent factor, the *time variation* remains very significant. Despite the fact that average surprises are statistically insignificant, the surprise and latent factor, along with their time-varying coefficients in this regression, corroborate the narrative outlined in our baseline analysis. Once again, in columns (3) to (4), we replicate these tests using daily equity returns as the dependent variable. While these results are a bit weaker than the CDS-based regressions, we observe that the latent factor is priced unconditionally (column (3)) and in a time-varying fashion (column (4)). The same cannot be said for the surprise component. In conclusion, these intraday findings offer further evidence that shocks to inflation expectations are priced with significant time variation and beyond a headline surprise component.

[27] We thank Gürkaynak et al. for kindly making their Kalman Filter code available to the public. While their application involves identifying a latent factor in high-frequency asset price movements (interest rate and equity futures), we adapt their code to an inflation swap setting.

4.4 Robustness and Extensions

We conduct additional robustness exercises and extensions in Appendix A. Among these exercises, we test TIPS-based measures of inflation expectations, examine whether time-variation in the pricing of inflation swaps truly relates to inflation expectations (as opposed to risk premia), and ensure that our results are not driven by low liquidity periods in inflation swap markets or traded CDS that are less liquid.

As we show in the bottom panel of Figure 2, TIPS-based inflation expectations (constant maturity 5-year nominal yield minus constant maturity 5-year TIPS), broadly tracks well with our swap measure. To ensure that our results are not specific to the expected inflation measure we have chosen, we re-conduct our main analysis using 5-year breakeven inflation, $\Delta\pi^{be,5Y}$. The results confirm that our fundamental economic mechanism holds regardless of the expected inflation measure.

While swap prices express real-time market expectations of inflation, their movements may contain a risk premium component. To confirm that our empirical results are driven by physical expectations of inflation, in line with our model's predictions, we use inflation expectations estimates derived in D'Amico et al. (2018) where the authors use a term structure model fitted to TIPS and nominal yields. After showing that their daily inflation compensation measure is priced in a time-varying manner in CDS and equities, we find that estimates using inflation expectations alone are virtually identical.[28] Obviously these results are specific to the model D'Amico et al. (2018) estimate, however we are able to provide some evidence that physical expectations of inflation are largely responsible for the time-varying beta.

Inflation-linked products can suffer from low liquidity (e.g. Fleming and Sporn (2013), Diercks et al. (2023)). As a result, it is important to confirm that our findings are not driven by periods where swap markets display greater turbulence and mispricing. While we do not have direct data on dealer trading volume in these markets, we use an alternative measure related to "disagreement" across similar inflation products. In a frictionless environment, one might imagine that swaps and breakeven inflation would display prices that closely align with each other, while in a low liquidity environment the amount of disagreement could be larger. We show in the Appendix that indeed our results are driven by periods where the absolute difference in swap versus breakeven inflation is smaller. We show similar results using the absolute difference between swap rates and the D'Amico et al. (2018) inflation compensation measure mentioned above.

[28]The inflation compensation measure we use from D'Amico et al. is a model-driven one that differs from inflation swap or TIPS-implied breakeven inflation. The reason being, they also adjust for a illiquidity premium that affects TIPS markets.

As the Dodd-Frank Act led to greater standardization and regulation of CDS trading, the size of the single name CDS market has decreased over time (e.g., Boyarchenko, Costello, and Shachar (2020)). As a result, it is natural to ask whether our results are being driven by low liquidity in CDS markets. To test these issues, we look at the number of participating dealers for a given reference entity. If a firm's CDS has a greater number of dealers this might suggest greater liquidity. We show that our results actually strengthen when we focus on firms with a larger number of dealers each announcement day. Moreover, the reduction in single name trading volume over time does not impact the price informativeness of CDS prices with respect to inflation risk.

Though it has trended positive for short periods of time, the bond-stock return correlation has been mostly negative after 2000, making it is difficult to detect discrete sign switches in inflation beta. To understand whether sign switches are a possibility, we extend our equity panel back to the 1980's and use the earlier mentioned inflation compensation data from D'Amico et al. (2018) surrounding macroeconomic announcements. We show that indeed in negative (positive) correlation regimes, the equity beta is positive (negative). While we are unable to extend the credit sample due to a lack of data, these results suggest the good and bad inflation pricing dynamics are present over a longer time span.

Our results have focused on time-variation using the bond-stock return correlation as a key statistic. We also use an alternative measure which correlates daily changes in inflation swap prices to market returns and re-examine our main regressions. Regardless of horizon and consistent with our main result, increases in the prior swap-market correlation (more of a good inflation environment), leads to a further reduction in CDS spreads following an expected inflation shock. Equity markets provide a qualitatively similar result. Moreover, using the swap-based correlation measure does not affect our results and in some cases increases the statistical significance.

5 Conclusion

We study how expected inflation is priced in firm-level corporate credit spreads and equity prices, and shed light on the time variation in their inflation sensitivities. In times of market-perceived "good inflation," when inflation news is positively correlated with real economic growth, movements in inflation risk substantially reduce spreads and raise equity valuations. Meanwhile in times of "bad inflation," the effects are reversed. These dynamics are strongest for riskier firms and operate largely through a risk premium channel. A long-run risks framework provides a parsimonious economic mechanism that explains these dynamics and highlights the key role played by the covariance of expected growth and inflation shocks.

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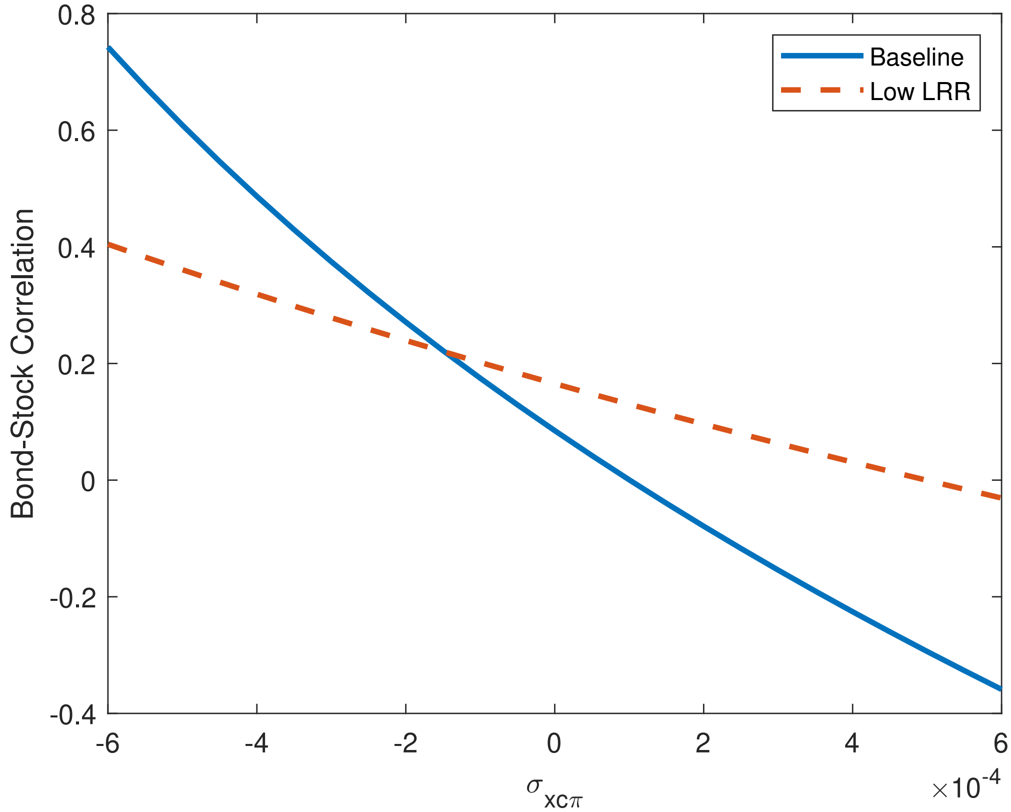
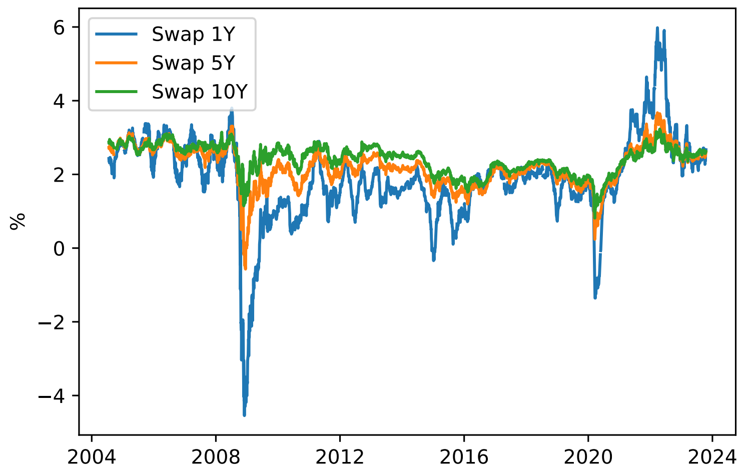
Figure 1: **Model-Implied Asset Correlation and the Inflation-Growth Covariance**



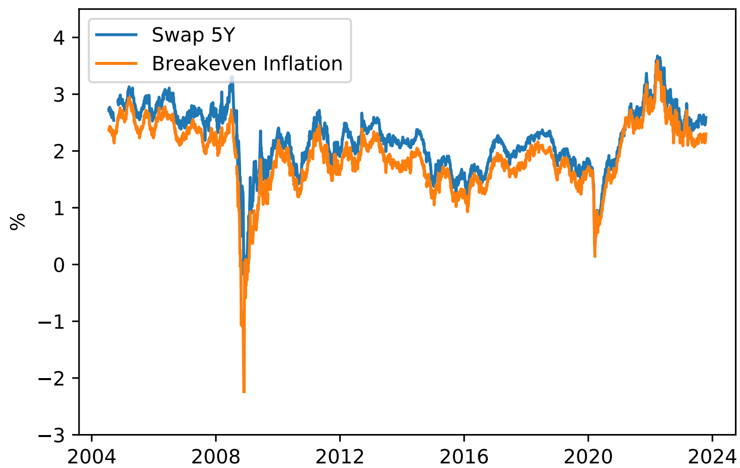
This figure shows the model-implied bond-stock correlation based on simulated nominal stock and 5-year bond return data. The y-axis shows the correlation while the x-axis denotes the covariance parameter ($\sigma_{xc\pi}$). The blue line represents the bond-stock correlation across different values of $\sigma_{xc\pi}$, fixing other baseline parameters and the overall volatility of the expected growth component. The dashed red line conveys the model-implied return correlation under a lower persistence of the expected growth component ($\Pi_{cc} = 0.85$). See main text for more details.

Figure 2: **CPI Inflation Swaps**

(a) Swaps Across Maturity



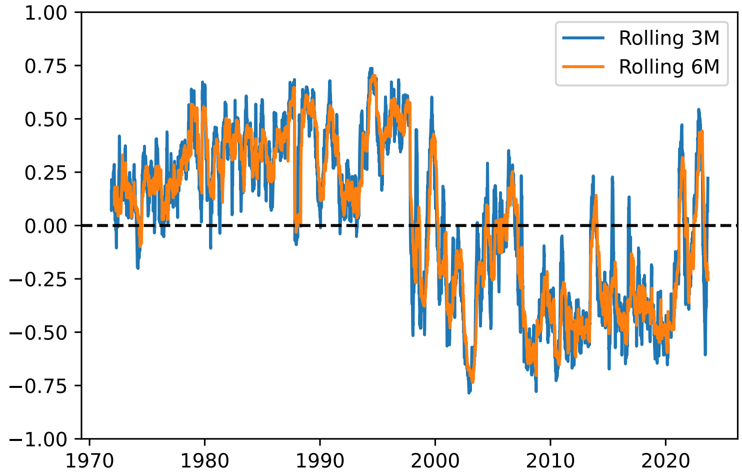
(b) Comparison to Breakeven Inflation (TIPS)



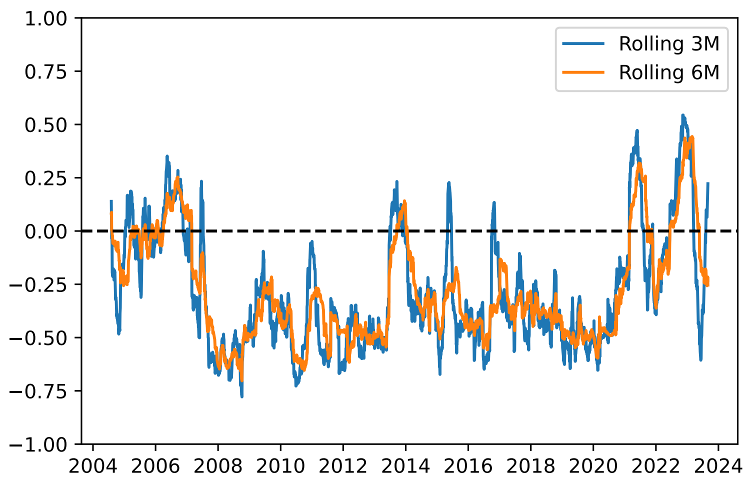
The top figure presents a time series plot of the 1-year (blue), 5-year (orange), and 10-year (green) inflation swap rates. The bottom figure displays a time series plot of the 5-year zero-coupon inflation swap rate (blue) and the 5-year TIPS implied zero-coupon break-even inflation yield (orange). Yields are expressed as annual percentages.

Figure 3: **Inflation-Growth Relationship Over Time**

(a) Stock-Bond Return Correlation



(b) Return Correlation over Swap Sample



The top figure presents a time series plot of the rolling 3-month (blue) and 6-month (orange) correlation between the daily bond (5-year US Treasury) and stock market returns. The bottom figure displays the same measures over the period where inflation swaps are available (July 2004 and onwards).

Table 1: **Baseline Model Calibration**

(a) Model Parameters

	Value	Notes
γ	20	Bansal and Shaliastovich (2013)
ψ	2.5	Target risk-free rate
δ	0.998	Bansal and Shaliastovich (2013)
μ_c	0.00474	Target consumption growth mean
μ_π	0.009	Bansal and Shaliastovich (2013)
Π_{cc}	0.95	Bansal and Yaron (2004)
$\Pi_{\pi\pi}$	0.988	Bansal and Shaliastovich (2013)
σ_{xc}	0.0000583	Target expected growth vol
$\sigma_{x\pi}$	0.000986	Target expected inflation vol
$\sigma_{xc\pi}(s_1)$	0.0008	"Good Inflation" regime
$\sigma_{xc\pi}(s_2)$	-0.0004	"Bad Inflation" regime
p_{11}	0.9	–
p_{22}	0.9	–
σ_c	0.00359	Target consumption growth vol
σ_π	0.00557	Target inflation vol
$\beta_{\lambda 0}$	0.00505	Target 2% annual default rate
$\beta_{\lambda xc}$	-0.5	Countercyclical default rates
R	0.4	Average recovery rate from Markit

(b) Model-Implied Values

	Value	Notes
$E\left[pc_t\right]$	7.607	Log price-consumption ratio
$E\left[r_{ct}\right]$	2.011	Real return on consumption
$E\left[r^{\$}_{ct}\right]$	5.538	Nominal return on consumption
$E\left[r^{\$}_{ft}\right]$	4.629	Nominal risk-free rate
$E\left[r_{ct} - r_{ft}\right]$	0.908	Risk premium
$E\left[r^{5Y,\$}_{ft}\right]$	3.466	Nominal return on 5Y risk-free bond
$E\left[s^{5Y}_t\right]$	1.337	5Y CDS spread
$\sigma\left[\Delta s^{5Y}_t\right]$ (b.p.)	5.371	Volatility of spread changes
$\rho(r^{\$}_{ct}, r^{5Y,\$}_{ft})$	-0.148	Bond-stock correlation
$\rho(r^{\$}_{ct}, r^{5Y,\$}_{ft})$ – Regime 1	-0.451	–
$\rho(r^{\$}_{ct}, r^{5Y,\$}_{ft})$ – Regime 2	0.284	–
$\beta(r_{ct} - r_{ft} \sim \Delta x_{\pi t})$	0.231	Excess return regression coefficient
$\beta(r_{ct} - r_{ft} \sim \Delta x_{\pi t})$ – Regime 1	0.933	
$\beta(r_{ct} - r_{ft} \sim \Delta x_{\pi t})$ – Regime 2	-0.475	
$\beta(\Delta s^{5Y}_t \sim \Delta x_{\pi t})$ (b.p.)	-1.603	Spread change regression coefficient
$\beta(\Delta s^{5Y}_t \sim \Delta x_{\pi t})$ – Regime 1	-6.265	
$\beta(\Delta s^{5Y}_t \sim \Delta x_{\pi t})$ – Regime 2	3.073	

This table presents parameters used to calibrate the model and the simulated model implied values. The top panel shows the baseline parameters. Some parameters come from the literature, while parameters related to consumption growth and inflation are calibrated using 1968Q4 to 2019Q4 data. The bottom panel displays the results of the model simulation, where we simulate 40,000 quarters, including a burn-in period.

Table 2: **Model Performance Under Alternative Parameters**

	(1) Model 1 ($\sigma_{xc\pi} = 0$)	(2) Model 2 (Symmetric $\sigma_{xc\pi}$)	(3) Model 3 ($\Pi_{cc} = 0.85$)	(4) Model 4 (Baseline)
$E\left[pc_t\right]$	7.311	7.312	8.737	7.607
$E\left[r_{ct}\right]$	1.971	2.001	1.733	2.011
$E\left[r_{ct}^{\$}\right]$	5.498	5.528	5.26	5.538
$E\left[r_{ft}^{\$}\right]$	4.641	4.653	4.891	4.629
$E\left[r_{ct} - r_{ft}\right]$	0.857	0.875	0.369	0.908
$E\left[r_{ft}^{5Y,\$}\right]$	4.284	4.273	4.687	3.466
$E\left[s_t^{5Y}\right]$	1.332	1.326	1.284	1.337
$\sigma\left[\Delta s_t^{5Y}\right]$ (b.p.)	5.095	5.009	4.601	5.371
$\rho(r_{ct}^{\$}, r_{ft}^{5Y,\$})$	0.085	0.073	0.162	-0.148
$\rho(r_{ct}^{\$}, r_{ft}^{5Y,\$})$ – Regime 1	0.084	-0.289	-0.007	-0.451
$\rho(r_{ct}^{\$}, r_{ft}^{5Y,\$})$ – Regime 2	0.086	0.501	0.349	0.284
$\beta(r_{ct} - r_{ft} \sim \Delta x_{\pi t})$	-0.009	-0.006	-0.007	0.231
$\beta(r_{ct} - r_{ft} \sim \Delta x_{\pi t})$ – Regime 1	-0.015	0.692	0.227	0.933
$\beta(r_{ct} - r_{ft} \sim \Delta x_{\pi t})$ – Regime 2	-0.003	-0.705	-0.241	-0.475
$\beta(\Delta s_t^{5Y} \sim \Delta x_{\pi t})$ (b.p.)	-0.005	-0.017	0.011	-1.603
$\beta(\Delta s_t^{5Y} \sim \Delta x_{\pi t})$ – Regime 1	0.042	-4.673	-2.417	-6.265
$\beta(\Delta s_t^{5Y} \sim \Delta x_{\pi t})$ – Regime 2	-0.052	4.641	2.439	3.073

This table compares model solutions under different parameter sets. Model 1 is a model where the covariance channel is non-existent in both regimes. Model 2 sets the covariance parameter to a symmetric value across regimes ($\sigma_{xc\pi}(s_1) = 6 \times 10^{-4}$ and $\sigma_{xc\pi}(s_2) = -6 \times 10^{-4}$). Model 3 modifies the setup in Model 2 and sets the long-run risk parameter (Π_{cc}) to 0.85, which is less than the baseline value of Π_{cc}. Model 4 is the baseline.

Table 3: **Key Summary Statistics**

	Count	Mean	Std. Dev.	Min	Max
Panel A: Aggregate Measures					
$\pi^{swap,1Y}$	730	1.903	1.168	-4.274	5.856
$\pi^{swap,5Y}$	730	2.222	0.533	-0.515	3.593
$\pi^{swap,10Y}$	734	2.423	0.379	0.992	3.190
$\Delta\pi^{swap,5Y}$	728	0.000	0.049	-0.285	0.191
$\rho\left(R_{bond}, R_{mkt}\right)^{3M}$	819	-0.293	0.280	-0.778	0.544
$\rho\left(R_{bond}, R_{mkt}\right)^{6M}$	819	-0.291	0.248	-0.733	0.433
$\rho\left(\Delta\pi^{swap}, R_{mkt}\right)^{3M}$	701	0.292	0.218	-0.348	0.746
$\rho\left(\Delta\pi^{swap}, R_{mkt}\right)^{6M}$	691	0.297	0.185	-0.167	0.704
Panel B: Firm-Level Data					
$Spread$	418911	2.257	3.767	0.101	33.054
$\Delta Spread$ (b.p.)	418808	0.139	8.359	-52.475	65.279
$ExpLoss$	204936	0.639	1.529	0.029	14.191
$RiskPrem$	204757	1.206	1.922	-2.686	16.365
R_i (%)	207853	0.032	2.276	-9.615	9.253
$R_i - R_f$ (%)	207853	0.027	2.276	-9.619	9.250
Panel C: Intraday Swaps					
$\Delta\pi^{idswap,5Y}$	622	0.116	3.364	-28.000	24.500
$\Delta\pi^{surp,5Y}$	622	0.052	1.208	-5.279	10.559
$\Delta\pi^{latent,5Y}$	622	0.097	2.703	-29.574	22.233

This table reports the aggregate measures and firm-level summary statistics for the variables used in the empirical analysis. Panel A reports aggregate measures on macroeconomic announcement days. Panel B reports summary statistics of firm-level CDS and equity returns on macroeconomic announcement days. Panel C reports summary statistics of intraday, 1-hour changes of 5Y inflation swaps surrounding macroeconomic announcements of interest. Subcomponents of the intraday changes are provided, based on the methodology from Gürkaynak et al. (2020). See main text for more details. CDS data come from Markit, and expected losses and risk premia are estimated using the conditional probability of default (EDF) and recovery rate estimates from Moody's Analytics and Markit, following Palazzo and Yamarthy (2022). Equity returns and excess returns come from CRSP. Intraday data are from Refinitiv TickHistory. All firm-level, daily data are winsorized at the 0.5% level.

Table 4: **Unconditional Response of Asset Prices to Inflation Risk**

	(1)	(2)	(3)	(4)
$\Delta\pi^{swap,5Y}$	-0.90***	-2.15***	0.38***	0.42**
	(-5.19)	(-3.85)	(3.91)	(2.31)
$s_{i,-1}$	0.18***	0.61**	-0.00	0.02
	(3.12)	(2.49)	(-0.10)	(0.50)
$(R_i - R_f)_{-1}$			0.00	0.00
			(0.22)	(0.09)
Dependent Variable	Δs_i (b.p.)		$R_i - R_f$ (%)	
Change Horizon	1D	5D	1D	5D
Firm FE	Y	Y	Y	Y
Clustering	Firm-Time		Firm-Time	
Obs	418,777	417,179	207,717	207,570
$Adj.R^2$	0.019	0.024	0.028	0.009

This table reports the average effect of inflation expectation movements on CDS and equity returns. For more details regarding the specification, see Equation (4) in the main text. Odd columns report results for the 1-day horizon, while even columns report results for the 5-day horizon. Columns (1) and (2), focus on movements in CDS spreads overall, and columns (3) and (4) focus on equity returns. In all regressions, we include the CDS rate or CDS rate and equity returns the day before the macroeconomic announcement, and firm fixed effects. Standard errors are clustered at the time and firm level. * Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

Table 5: **Pricing of Inflation Risk and the Inflation-Growth Correlation**

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\pi^{swap,5Y}$	-0.90***	-0.81***	-0.79***	0.38***	0.35***	0.35***
	(-5.19)	(-5.27)	(-5.27)	(3.91)	(3.82)	(3.92)
$\tilde{\rho}_{-1}^{bond-mkt,3M}$		-0.03			0.05	
		(-0.38)			(1.00)	
$\tilde{\rho}_{-1}^{bond-mkt,6M}$			-0.12			0.07
			(-1.57)			(1.59)
$\tilde{\rho}_{-1}^{bond-mkt,3M} \times \Delta\pi^{swap,5Y}$		0.61***			-0.22***	
		(5.05)			(-2.58)	
$\tilde{\rho}_{-1}^{bond-mkt,6M} \times \Delta\pi^{swap,5Y}$			0.52***			-0.16**
			(4.48)			(-2.02)
$s_{i,-1}$	0.18***	0.18***	0.18***	-0.00	-0.00	0.00
	(3.12)	(3.21)	(3.14)	(-0.10)	(-0.01)	(0.12)
$\left(R^i - R^f\right)_{-1}$				0.00	0.00	0.00
				(0.22)	(0.17)	(0.15)
Dependent Variable		Δs_i (b.p.)			$R^i - R^f$ (%)	
Correlation Horizon	–	3M	6M	–	3M	6M
Firm FE	Y	Y	Y	Y	Y	Y
Clustering		Firm-Time			Firm-Time	
Obs	418,777	410,129	410,129	207,717	205,837	205,837
$Adj.R^2$	0.019	0.024	0.023	0.028	0.036	0.034

This table reports the time-varying effects of inflation expectations movements on credit and equity markets. For more details regarding the specification, see Equation (6) in the main text. In this table, we interact the inflation expectation shocks with a proxy for the inflation-growth relationship. Columns (1) and (4) report the baseline unconditional results as in columns (1) and (3) in Table 4. Columns (2) and (5) report results where the inflation expectation movements are interacted with the bond-stock correlation estimated using the 3-month rolling correlation, while columns (4) and (6) use the 6-month rolling correlations. We standardize the correlation measures such that the interaction coefficient indicates the additional sensitivity to changes in inflation swap when the correlation is one standard deviation higher. In all regressions, we include the CDS rate or CDS rate and equity returns the day before the macroeconomic announcement, and firm fixed effects. Standard errors are clustered at the time and firm level. * Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

Table 6: **Risk Premia Effects and the Inflation-Growth Correlation**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta\pi^{swap,5Y}$	-0.89***	-0.27***	-0.58***	-0.82***	-0.25***	-0.53***	-0.79***	-0.25***	-0.51***
	(-5.16)	(-3.15)	(-3.89)	(-5.28)	(-3.07)	(-3.97)	(-5.24)	(-3.14)	(-3.93)
$\tilde{\rho}_{-1}^{bond-mkt,3M}$				-0.06	-0.02	-0.04			
				(-0.85)	(-0.67)	(-0.63)			
$\tilde{\rho}_{-1}^{bond-mkt,6M}$							-0.15**	-0.03	-0.12*
							(-1.97)	(-0.98)	(-1.90)
$\tilde{\rho}_{-1}^{bond-mkt,3M} \times \Delta\pi^{swap,5Y}$				0.63***	0.16**	0.44***			
				(5.15)	(2.48)	(4.16)			
$\tilde{\rho}_{-1}^{bond-mkt,6M} \times \Delta\pi^{swap,5Y}$							0.54***	0.13**	0.38***
							(4.56)	(2.01)	(3.85)
$s_{i,-1}$	0.10	0.05	0.00	0.11	0.05	0.01	0.10	0.05	-0.00
	(1.13)	(1.37)	(0.02)	(1.21)	(1.35)	(0.08)	(1.12)	(1.33)	(-0.01)
$ExpLoss_{i,-1}$	0.32***	-0.18***	0.54***	0.31***	-0.18***	0.53***	0.32***	-0.18***	0.54***
	(3.38)	(-3.22)	(5.18)	(3.26)	(-3.22)	(5.13)	(3.36)	(-3.19)	(5.25)
Dependent Variable	Δs_i (b.p.)	$\Delta ExpLoss_i$	$\Delta RiskPrem_i$	Δs_i (b.p.)	$\Delta ExpLoss_i$	$\Delta RiskPrem_i$	Δs_i (b.p.)	$\Delta ExpLoss_i$	$\Delta RiskPrem_i$
Correlation Horizon		–			3M			6M	
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Clustering		Firm-Time			Firm-Time			Firm-Time	
Obs	204,172	204,150	204,148	200,303	200,281	200,279	200,303	200,281	200,279
$Adj.R^2$	0.020	0.008	0.011	0.026	0.010	0.013	0.025	0.009	0.013

This table reports the time-varying effects of inflation expectation movements on changes in CDS spreads, expected losses, and credit risk premia. Columns (1) - (3) report unconditional results. Columns (4) - (6) report results where the inflation expectation shocks are interacted with the bond-stock correlation estimated using the 3-month rolling correlation. Columns (6) - (9) report results where the inflation expectation shocks are interacted with the inflation swap-stock correlation estimated using 6-month rolling correlation. Columns (1), (4) and (7), (2), (5) and (8), and (3), (6) and (9) focus on movements in CDS spreads overall, the expected loss component, and credit risk premia, respectively. We standardize the correlation measures such that the interaction coefficient indicates the additional sensitivity to changes in inflation swap when the correlation is one standard deviation higher. In all regressions, we include the CDS rate and expected loss the day before the macroeconomic announcement and firm fixed effects. Standard errors are clustered at the time and firm level. * Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

Table 7: **Time Varying Inflation Beta across Risk Groups**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta\pi^{swap,5Y}$	-0.81***	-0.18***	-0.62***	-1.99***	0.35***	0.26***	0.34***	0.42***
	(-5.27)	(-5.18)	(-5.35)	(-4.86)	(3.82)	(3.47)	(3.70)	(3.60)
$\tilde{\rho}_{-1}^{bond-mkt,3M}$	-0.03	-0.01	0.00	0.03	0.05	0.04	0.04	0.03
	(-0.38)	(-0.65)	(0.01)	(0.13)	(1.00)	(1.07)	(0.87)	(0.55)
$\tilde{\rho}_{-1}^{bond-mkt,3M} \times \Delta\pi^{swap,5Y}$	0.61***	0.13***	0.44***	1.45***	-0.22***	-0.18**	-0.21**	-0.29***
	(5.05)	(5.11)	(4.64)	(4.66)	(-2.58)	(-2.47)	(-2.55)	(-2.79)
$s_{i,-1}$	0.18***	0.17	0.48	0.22***	-0.00	0.17	0.07	-0.00
	(3.21)	(0.61)	(1.27)	(3.59)	(-0.01)	(0.52)	(0.31)	(-0.10)
$(R_i - R_f)_{-1}$					0.00	-0.02	-0.02	0.03
					(0.17)	(-0.73)	(-0.74)	(1.44)
Dependent Variable	Δs_i (b.p.)				$R_i - R_f$ (%)			
Which Risk Group	–	1	3	5	–	1	3	5
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Obs	410,129	82,300	82,007	81,701	205,837	41,453	41,166	40,862
$Adj.R^2$	0.024	0.048	0.048	0.032	0.036	0.044	0.043	0.029

This table reports time-varying effects of inflation expectation movements on CDS spreads and equity returns, across different risk groups as determined by past CDS spreads. Firms are sorted into CDS risk quintiles based on 5-year CDS spreads on the the day prior to macroeconomic announcements. We interact the inflation expectation movements with the bond-stock correlation estimated using the 3-month rolling correlation. Correlation measures are standardized such that the interaction coefficient indicates the additional sensitivity to changes in inflation swap when the correlation is one standard deviation higher. We report results for risk groups 1, 3, and 5 in columns (2) and (6), (3) and (7), and (4) and (8), respectively. Columns (1) - (4) focus on movements in CDS spreads overall, while columns (5) - (8) on equity returns. In all regressions, we include either the CDS rate or the CDS rate and equity return the day before the macroeconomic announcements, and firm fixed effects. Standard errors are clustered at the time and firm level. * Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

Table 8: **Time-Varying Inflation Beta using Alternative Measures**

(a) Credit Markets

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta\pi^{swap,5Y}$	-0.81***	-1.01***	-0.93***	-0.78***	-0.89***	-0.83***	-0.76***
	(-5.27)	(-5.92)	(-5.35)	(-5.56)	(-6.06)	(-5.32)	(-5.59)
$\tilde{\rho}_{-1}^{bond-mkt,3M} \times \Delta\pi^{swap,5Y}$	0.61***				0.53***	0.58***	0.60***
	(5.05)				(3.95)	(4.51)	(4.92)
$\widetilde{NRC}_{-1}^{EW} \times \Delta\pi^{swap,5Y}$		-0.41***			-0.20		
		(-3.59)			(-1.53)		
$\widetilde{NRC}_{-1}^{RW} \times \Delta\pi^{swap,5Y}$			-0.33***			-0.06	
			(-3.83)			(-0.63)	
$\widetilde{TCU}_{-1} \times \Delta\pi^{swap,5Y}$				0.17			0.09
				(1.34)			(0.77)
Firm FE	Y	Y	Y	Y	Y	Y	Y
Clustering		Firm-Time				Firm-Time	
Obs	410,129	418,777	418,777	418,777	410,129	410,129	410,129
$Adj.R^2$	0.024	0.021	0.021	0.021	0.024	0.024	0.025

(b) Equity Markets

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta\pi^{swap,5Y}$	0.35***	0.44***	0.38***	0.36***	0.41***	0.36***	0.35***
	(3.82)	(4.86)	(3.98)	(4.46)	(5.24)	(4.00)	(4.57)
$\tilde{\rho}_{-1}^{bond-mkt,3M} \times \Delta\pi^{swap,5Y}$	-0.22***				-0.15	-0.19**	-0.22***
	(-2.58)				(-1.48)	(-2.01)	(-2.77)
$\widetilde{NRC}_{-1}^{EW} \times \Delta\pi^{swap,5Y}$		0.25***			0.19**		
		(3.48)			(2.11)		
$\widetilde{NRC}_{-1}^{RW} \times \Delta\pi^{swap,5Y}$			0.15***			0.06	
			(2.73)			(1.04)	
$\widetilde{TCU}_{-1} \times \Delta\pi^{swap,5Y}$				-0.03			-0.00
				(-0.40)			(-0.03)
Firm FE	Y	Y	Y	Y	Y	Y	Y
Clustering		Firm-Time				Firm-Time	
Obs	205,837	207,717	207,717	207,717	205,837	205,837	205,837
$Adj.R^2$	0.036	0.037	0.032	0.028	0.041	0.037	0.036

This table reports the time-varying effects of inflation expectations movements on credit and equity markets using alternative measures of the inflation-growth correlation. In both tables, column (1) reports results using our baseline bond-stock correlation measure while column (2) reports results with an expanding window nominal real covariance measure, similar to Boons et al. (2020). Column (3) uses a 60-month rolling window version of the same covariance while column (4) reports results using an adjusted version of capacity utilization. In columns (5) to (7) we run a horse race between the stock-bond correlation and alternative measures. In all regressions, we include the CDS rate or CDS rate and equity returns the day before the macroeconomic announcement, and firm fixed effects. Standard errors are clustered at the time and firm level. * Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

Table 9: **Intraday Swap Prices and Macroeconomic Surprises**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\varepsilon^{corecpi}$	1.75***						0.91***
	(8.18)						(2.95)
ε^{cpi}		1.89***					1.28***
		(9.13)					(4.17)
$\varepsilon^{nonfarm}$			0.42**				0.45**
			(2.04)				(1.98)
ε^{gdp}				1.18			1.18***
				(1.47)			(2.71)
$\varepsilon^{coreppi}$					0.40**		0.13
					(2.00)		(0.45)
ε^{ppi}						0.54***	0.46
						(2.72)	(1.63)
Dependent Variable	Intraday $\Delta\pi^{swap,5y}$ (b.p.)						
Obs	184	184	196	54	188	188	622
$Adj.R^2$	0.265	0.310	0.016	0.022	0.016	0.033	0.120

This table reports the average effect of macroeconomic surprises on intraday inflation swap prices. Inflation swap data is collected daily from 8:15 AM to 9:15 AM ET, reflecting a 60-minute window. This table includes 622 announcements following October 2007. To ensure independence from monetary policy-related interest rate movements, days with FOMC announcements are excluded. For more details regarding the specification, see Equation (8) in the main text. Columns (1) - (6) report results of individual univariate regressions of intraday inflation swap movements onto macroeconomic surprises, while column (7) reports results of a multivariate regression including all macroeconomic surprises. Macroeconomic surprises are normalized by their respective standard deviations. * Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

Table 10: **Intraday Swaps and Risky Asset Prices**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta\pi^{swap,5Y}$	-1.00***		-0.85***		0.42***		0.37***	
	(-5.41)		(-5.12)		(3.91)		(3.78)	
$\Delta\pi^{idswap,5Y}$		-0.22		-0.28*		0.14		0.19*
		(-1.55)		(-1.79)		(1.45)		(1.65)
$\tilde{\rho}_{-1}^{bond-mkt,3M} \times \Delta\pi^{swap,5Y}$			0.59***				-0.21**	
			(4.34)				(-2.14)	
$\tilde{\rho}_{-1}^{bond-mkt,3M} \times \Delta\pi^{idswap,5Y}$				0.37***				-0.28***
				(2.77)				(-2.95)
$\tilde{\rho}_{-1}^{bond-mkt,3M}$			-0.02	-0.04			0.05	0.06
			(-0.28)	(-0.39)			(0.92)	(0.98)
$s_{i,-1}$	0.17***	0.17**	0.17***	0.18***	0.00	0.00	0.00	-0.00
	(2.67)	(2.58)	(2.75)	(2.67)	(0.22)	(0.13)	(0.21)	(-0.05)
$(R^i - R^f)_{-1}$					0.00	0.02	0.00	0.02
					(0.16)	(0.64)	(0.18)	(0.71)
Dependent Variable	Δs_i (b.p.)		Δs_i		$R^i - R^f$ (%)		$R^i - R^f$	
Firm FE	Y		Y		Y		Y	
Clustering	Firm-Time		Firm-Time		Firm-Time		Firm-Time	
Obs	358,035	358,035	350,067	350,067	172,046	172,046	170,166	170,166
Adj.R^2	0.024	0.011	0.028	0.012	0.035	0.004	0.042	0.019

This table reports average and time-varying effects of intraday inflation expectation movements on CDS spreads and equity returns. For more details regarding the specification, see Equation (9) in the main text. Columns (1) - (4) and (5) - (8) report results where the dependent variables are daily movements in CDS spreads and equity returns, respectively. Columns (1) and (5) report the baseline results using daily swap movements over the same sample as the intraday data. Similarly columns (3) and (7) report the time-varying results using daily swap changes. Columns (2) and (6) report the unconditional results using intraday inflation swaps. Columns (4) and (8) report results where the intraday inflation movements are interacted with the 3-month bond-stock return correlation. We standardize the correlation measures such that the interaction coefficient indicates the additional sensitivity to changes in inflation swap when the correlation is one standard deviation higher. In all regressions, we include the CDS rate or CDS rate and excess return the day before the macroeconomic announcement, and firm fixed effects. Standard errors are clustered at the time and firm level. * Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

Table 11: **Intraday Swap Decomposition and Risky Asset Prices**

	(1)	(2)	(3)	(4)
$\Delta\pi^{surp,5Y}$	-0.12	-0.20	-0.03	0.03
	(-0.89)	(-1.31)	(-0.36)	(0.38)
$\Delta\pi^{latent,5Y}$	-0.34***	-0.39***	0.16*	0.18*
	(-2.64)	(-2.76)	(1.76)	(1.80)
$\tilde{\rho}_{-1}^{bond-mkt,3M} \times \Delta\pi^{surp,5Y}$		0.23***		-0.18***
		(2.64)		(-3.59)
$\tilde{\rho}_{-1}^{bond-mkt,3M} \times \Delta\pi^{latent,5Y}$		0.33**		-0.15*
		(2.58)		(-1.93)
$\tilde{\rho}_{-1}^{bond-mkt,3M}$		-0.05		0.08
		(-0.59)		(1.43)
$s_{i,-1}$	0.17***	0.18***	0.00	0.00
	(2.62)	(2.71)	(0.10)	(0.03)
$(R^i - R^f)_{-1}$			0.01	0.01
			(0.59)	(0.55)
Dependent Variable	Δs_i (b.p.)		$R^i - R^f$ (%)	
Firm FE	Y		Y	
Clustering	Firm-Time		Firm-Time	
Obs	358,035	350,067	172,046	170,166
$Adj.R^2$	0.012	0.015	0.005	0.020

This table reports average and time-varying effects of surprise and latent factor components of intraday inflation swaps on CDS spreads and equity returns. For more details regarding the specification, see Equation (11) in the main text. Columns (1) - (2) and (3) - (4) report results where the dependent variables are CDS spread changes and daily equity returns, respectively. Columns (1) and (3) report the unconditional results decomposing intraday inflation swaps into surprise and latent factor components. Columns (2) and (4) report results where the inflation expectation movements are interacted with the bond-3-month bond-stock correlation. We standardize the correlation measures such that the interaction coefficient indicates the additional sensitivity to changes in inflation swap when the correlation is one standard deviation higher. In all regressions, we include the CDS rate or CDS rate and excess return the day before the macroeconomic announcement, and firm fixed effects. Standard errors are clustered at the time and firm level. * Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

A Robustness and Extensions

In this Appendix, we highlight additional robustness exercises and extensions. First, we provide more specific details regarding the intraday analysis and then we highlight other exercises supporting our main analysis. These exercises include testing alternative inflation expectations measures based on TIPS rates and measures from D'Amico et al. (2018), testing the robustness of the results to inflation swaps and CDS liquidity, using a longer equity sample to identify sign switches in inflation beta, and replacing the bond-stock correlation measure with an alternative.

Intraday analysis In Section 4.3, we presented results based on intraday swap movements on announcement days. Appendix Table A1 details the macroeconomic announcements of interest, which include 622 announcements released monthly or quarterly at 8:30 AM EST. We also provide the number of announcements and the standard deviation of their surprises.

We use these macroeconomic announcements to examine whether swap residuals show heteroskedasticity across announcement versus non-announcement days. This result is key to use the methodology of Gürkaynak et al. (2020). To do this, we compute the residual component of intraday swap movements on announcement days by regressing these movements on macroeconomic surprises. We then compare the variance of these residuals to the variance of intraday swap movements on non-announcement days. Appendix Figure A1 displays the variance specific to different maturities and the statistical significance of the differences.

After establishing the presence of heteroskedasticity, we follow the Gürkaynak et al. (2020) methodology to identify a latent factor that is orthogonal to macroeconomic news surprises. This is done using a one-step estimator via the Kalman filter. Appendix Table A2 presents the results of this latent factor estimation from intraday swaps, showing that the latent factor is significantly related to intraday swap movements and has strong explanatory power across all horizons.

Response to Breakeven Inflation As we show in the bottom panel of Figure 2, TIPS-based inflation expectations (constant maturity 5-year nominal yield minus constant maturity 5-year TIPS), broadly tracks well with our swap measure. To ensure that our results are not specific to the expected inflation measure we have chosen, we re-conduct our main analysis using 5-year breakeven inflation, $\Delta\pi^{be,5Y}$.

Appendix Table A3 shows that our main results are robust when we account for breakeven inflation. The first column shows that 5-year CDS decline by 1.0 basis point, following a standard deviation movement in 5-year breakeven inflation, surrounding macroeconomic announcements. Analogously, equity returns rise by 37 basis points following the movement in breakeven inflation. Columns (3) and (4) show, similar to earlier, that the large majority of the effect comes through risk premia effects. The final two columns suggest that the time-variation that was earlier documented (more negative bond-stock correlation $\Rightarrow$ inflation risk is further priced as a positive outcome) also holds when looking at breakeven inflation. Overall, these results confirm that our fundamental economic mechanism holds regardless of the expected inflation measure.

Inflation Expectations vs. Risk Premium Effects Movements in swap prices and breakeven inflation reflect real-time market expectations of inflation but they may also contain a risk premium component. We confirm that our empirical results are driven by physical expectations of inflation, in line with our model's predictions, using inflation expectations estimates derived in D'Amico et al. (2018). The authors use a term structure model fitted to TIPS and nominal yields, recovering physical inflation expectations and an inflation compensation measure cleaned from the illiquidity premium that affects TIPS markets.

Appendix Table A4 shows that our time-varying results are robust when using the inflation compensation measure. The first and third columns report results on CDS spreads and equity returns respectively, which are similar in magnitude to our baseline results. After showing that their daily inflation compensation measure is priced in a time-varying manner in CDS and equities, in columns (2) and (4) we show that estimates using inflation expectations alone are virtually identical. Overall, these results confirm that our fundamental economic mechanism works through physical expectations of inflation, in line with our model's predictions.

Swap and CDS Liquidity Inflation-linked products can suffer from low liquidity (e.g., Fleming and Sporn (2013), Diercks et al. (2023)). It is therefore important to confirm that our results are not driven by periods of greater turbulence and mispricing in the swap markets. Although we lack direct data on dealer trading volume, we use alternative measures of "disagreement" across similar inflation products. In an ideal market, swaps prices and inflation compensation should align closely, while in a low liquidity environment, the disagreement might be larger. We use two measures to think about swap market liquidity, the absolute difference between swap rates and breakeven inflation and the absolute difference between swap rates and D'Amico et al. (2018) inflation compensation. The reason we test the latter is that we try to control for TIPS illiquidity, which the inflation compensation measure of D'Amico et al. (2018) accounts for. In Appendix Figure A3 we report the difference between inflation swaps, the breakeven inflation, and the inflation compensation measure from D'Amico et al. (2018). As expected, the largest disagreement is during the

Global Financial Crisis for both measures. Additionally, when looking at the D'Amico et al. (2018) inflation compensation measure, it spikes around COVID and over the last couple of years.

Appendix Table A5 shows that our main results are robust when we account for swaps illiquidity. Columns (1) and (4) report our baseline results. In columns (2) and (5) we remove the top 10% most illiquid days based on the breakeven inflation based absolute differences while in columns (3) and (6) we remove the top 10% most illiquid days based on the D'Amico et al. (2018) compensation measure. Across all markets and measures, CDS and equity results are driven by the most liquid periods.

The Dodd-Frank Act and additional regulations have led to greater standardization and regulation of CDS trading, reducing the size of the single-name CDS market over time (e.g., Boyarchenko et al. (2020)). Consequently, it is important to assess whether our results are affected by low liquidity in CDS markets. Appendix Table A6 shows that our main results are robust in different CDS liquidity samples. We examine the number of participating dealers for a given reference entity, as a greater number of dealers might indicate higher liquidity. We compute the cross-sectional median number of dealers on each announcement date, and we report results across different groups (greater and less than the median number of dealers). Our results strengthen when focusing on firms with a larger number of dealers on each announcement day, while results also hold for firms with a low number of dealers CDS.

Overall, these findings confirm that our results remain robust when accounting for swap and CDS liquidity.

Inflation-Growth Regimes over a Long Sample As well documented, the bond-stock return correlation significantly changed sign in the late 1990's, turning from positive before to negative after. Because our sample focuses on the post-2004 period, it is difficult to detect discrete sign switches in inflation beta. To understand whether sign switches are a possibility, we extend our equity panel back to the 1980's and use the daily inflation measures from D'Amico et al. (2018) surrounding macroeconomic announcements.

In addition to the tests from our baseline analysis, we modify our interaction regression to include a dummy variable instead of the standardized correlation measure:

$$\Delta s_{it} = \beta_i + \beta_\pi \Delta\pi_t^{InfComp} + \beta_{\rho\pi}\left(\mathbb{1}_{\{\rho_{t-1}>0\}} \times \Delta\pi_t^{InfComp}\right) + \beta_X' X_{i,t-1} + \varepsilon_{it} \tag{12}$$

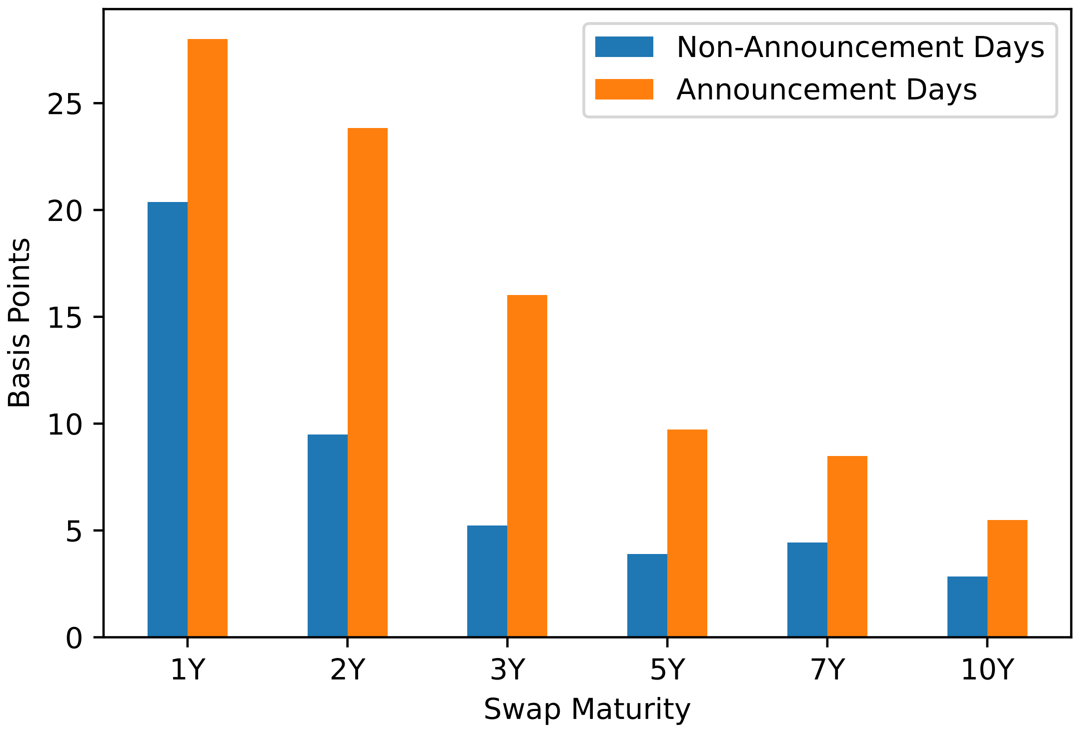
Using the correlation measure based on bond and stock returns, we interact the inflation measure change with a dummy variable ($\mathbb{1}_{\{\rho_{t-1}>0\}}$), which indicates whether the raw correlation (non-standardized) is positive, which is interpretable as a "bad inflation" state. Breaking up the regimes in this way will also tell us whether the bad inflation regime shows statistically different behavior than a good one.

We provide results for this test in Appendix Table A7. We first show that the time-varying results hold in the extended sample. Columns (1) and (2), and (5) and (6) report results using the bond-stock correlation at the 3M or 6M horizon. Using either total inflation compensation or physical inflation expectations, the time-varying coefficients are similar in magnitude to the ones in the baseline sample. Next, in columns (3) and (4), and (7) and (8) we report the results accounting for correlation regimes. It is evident that the bad inflation regime displays statistically *more negative* responses to inflation movements than in the good regime. Furthermore, the response to inflation news in the $\rho > 0$ regime is negative overall ($-0.536 + 0.341 < 0$). Both of these results validate our original hypothesis. We show that indeed in negative (positive) correlation regimes, the equity beta is positive (negative). While we are unable to extend the credit sample due to a lack of data, these results suggest the good and bad inflation pricing dynamics are present over a longer time span.

Swap-Based Correlation Measure Our results have focused on time-variation using the bond-stock return correlation as a key statistic. In this exercise we use an alternative measure which correlates daily changes in swap prices to market returns. In Appendix Figure A4 we display a plot of this measure over time. Because movements in swap rates positively correlate with inflation risk and yield movements, it is approximately the flipped image of the original bond-stock correlation measure displayed in the bottom of Figure 3. Over the last two decades it has remained mostly positive with short periods where it turns negative.

We replace our bond-based correlation measure with a swap-based one and re-examine our main regressions. Appendix Table A8 displays these results. As shown through the CDS results (left three columns), regardless of the 3M or 6M horizon, increases in the prior swap-market correlation (more of a good inflation environment) lead to a further reduction in spreads following an expected inflation shock. Equity markets provide a qualitatively similar result. All told, using the swap-based correlation measure does not affect our results and in some cases increases the statistical significance.

Figure A1: **Heteroskedasticty of Intraday Swap Residuals**

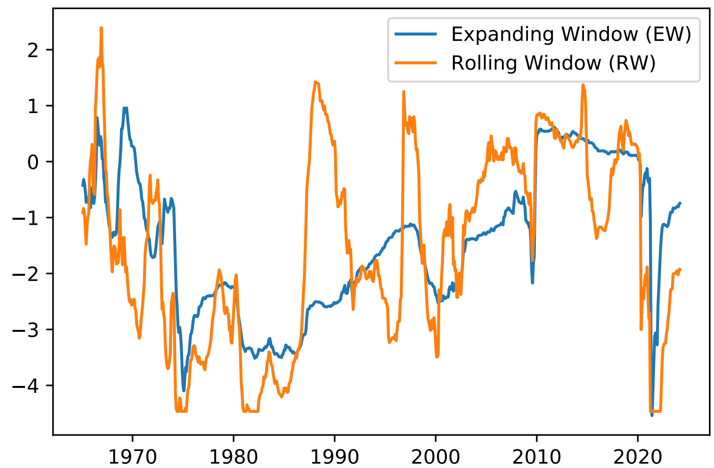


	1Y	2Y	3Y	5Y	7Y	10Y
var(η_t^A)	28.00	23.83	16.02	9.72	8.49	5.49
var(η_t^{NA})	20.37	9.50	5.23	3.90	4.44	2.84
F-test Statistic	1.37***	2.51***	3.06***	2.49***	1.91***	1.93***

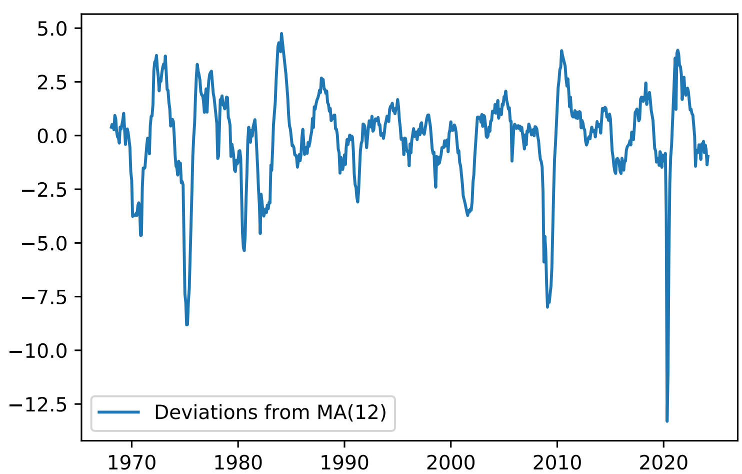
This figure display the maturity-specific variance of intraday inflation swap movements on announcement and non-announcement days. For announcement days, the variance is computed using the portion of intraday swap changes that is not related to macroeconomic surprises, via regression residuals. Meanwhile, for non-announcement days the raw swap change is used to compute the variance. Inflation swap data is collected daily from 8:15 AM to 9:15 AM ET, reflecting a 60-minute window. The table below reports the variance in basis points, and a F-test statistic regarding the significance of the difference.

Figure A2: **Alternative Lower Frequency Measures**

(a) Nominal-Real Covariance from Boons et al. (2020)

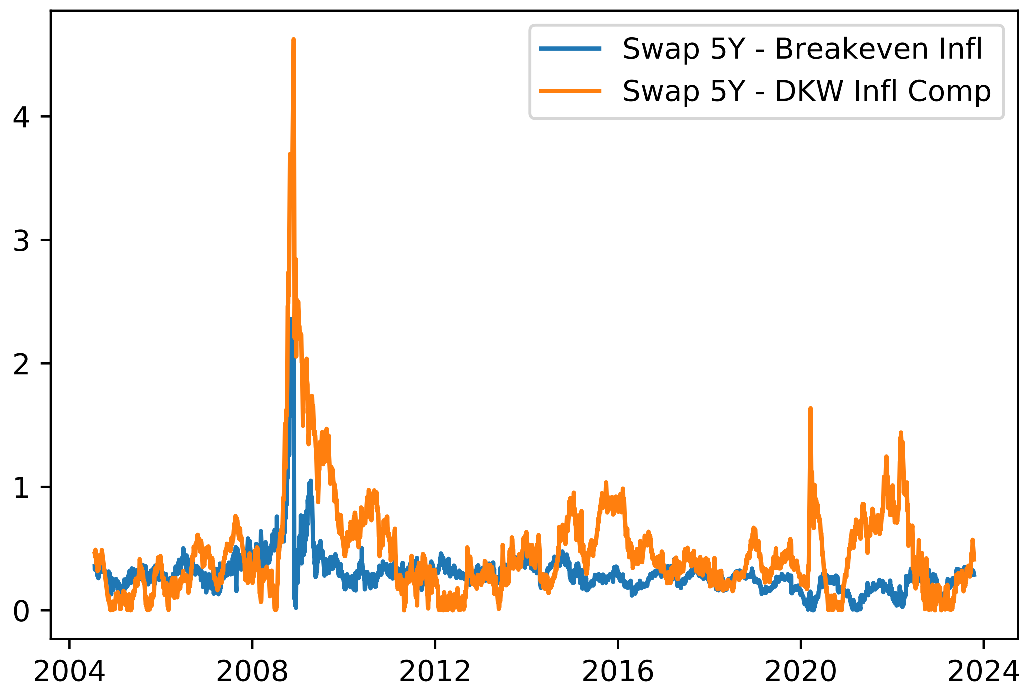


(b) Capacity Utilization (Adjusted)



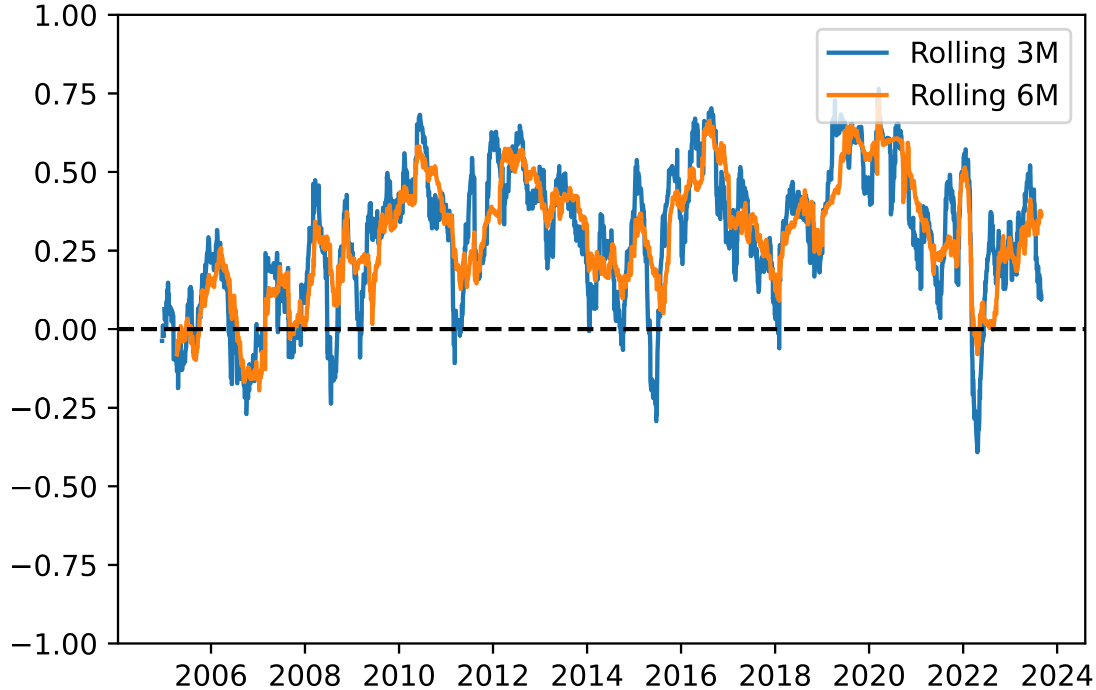
The top figure presents a monthly time series plot of the nominal real covariance computed on an expanding window through weighted least squares using exponential weights, identical to Boons et al. (2020) (blue) and a 60-month rolling window version of the same covariance (orange). The bottom figure displays an adjusted version of capacity utilization, constructed using deviations from a 12-month moving average.

Figure A3: **Comparison of Inflation Compensation Measures**



This figure presents a time series plot of the absolute difference between 5Y swap prices and 5Y TIPS breakeven rates (blue) and the absolute difference between 5Y swap prices and 5Y inflation compensation from D'Amico et al. (2018) (orange). The inflation compensation measure takes into account a liquidity premium adjustment.

Figure A4: **Inflation Swap and Market Return Correlation**



This figure presents a time series plot of the rolling 3-month (blue) and 6-month (orange) correlation between daily changes in 5-year inflation swap spreads and stock market returns.

Table A1: **Macroeconomic Announcements for Intraday Analysis**

Announcement	Time	Frequency	Observations	Unit	Std. Dev.
Core CPI	8:30	Monthly	184	% MoM	0.12
CPI	8:30	Monthly	184	% MoM	0.13
Nonfarm Payrolls	8:30	Monthly	196	Change	740.817k
GDP	8:30	Quaterly	54	% QoQ ann.	0.72
Core PPI	8:30	Monthly	188	% MoM	0.23
PPI	8:30	Monthly	188	% MoM	0.37

This table displays the selected macroeconomic announcements with their release times, frequencies, number of observations, units of measurement, and the conversion factor for a one standard deviation positive surprise to the original release unit. The data displays five major macroeconomic series examined throughout the paper, spanning from June 2007 to Oct 2023. “Frequency” denotes how often the data is released, while “Observations” refers to the total count of data points (surprises) for each macroeconomic series in the dataset. The term ”Unit” indicates the measurement unit in which the data is reported.

Table A2: **Latent Factor Estimation from Intraday Swaps**

	(1)	(2)	(3)	(4)	(5)	(6)
$\varepsilon^{corecpi}$	3.35***	2.79***	1.71***	0.90***	1.04***	0.65***
	(4.55)	(4.26)	(5.53)	(2.82)	(5.76)	(4.68)
ε^{cpi}	2.68***	2.41***	1.12***	1.30***	0.69***	0.79***
	(4.04)	(4.73)	(3.22)	(4.07)	(3.27)	(4.84)
$\varepsilon^{nonfarm}$	-0.11	0.01	0.06*	0.45***	0.38***	0.28***
	(-1.29)	(0.23)	(1.66)	(23.57)	(15.17)	(16.01)
ε^{gdp}	-0.19	-0.26	0.86	1.18***	-0.40	0.11
	(-0.23)	(-0.39)	(1.29)	(3.34)	(-1.08)	(0.42)
$\varepsilon^{coreppi}$	0.42	-0.71	0.73***	0.13	0.39***	-0.25
	(1.42)	(-0.98)	(2.78)	(1.19)	(2.61)	(-1.24)
ε^{ppi}	0.47**	0.41	0.48***	0.47***	0.44***	0.74***
	(2.34)	(1.42)	(2.92)	(3.56)	(3.27)	(3.28)
$\Delta\pi^{latent}$	2.56***	2.64***	3.46***	2.70***	2.33***	1.94***
	(4.09)	(6.32)	(21.15)	(29.57)	(17.21)	(16.23)
Dependent Variable			Intraday $\Delta\pi^{swap}$			
Horizon	1Y	2Y	3Y	5Y	7Y	10Y
Observations	622	622	622	622	622	622
R^2 without latent	0.235	0.208	0.119	0.120	0.091	0.096
R^2 with latent	0.410	0.434	0.769	0.771	0.665	0.709

This table reports the Kalman Filter estimates based on intraday data, as given in Equation 10. Inflation swap data is collected daily from 8:15 AM to 9:15 AM ET, reflecting a 60-minute window. This table includes 622 announcements or 6 relevant macroeconomic releases (corecpi, cpi, non-farm, gdp, coreppi and ppi) following October 2007. To ensure independence from monetary policy-related interest rate movements, days with FOMC announcements are excluded. Macroeconomic surprises are normalized by their respective standard deviations. The latent factor is estimated using changes in asset prices around macroeconomic releases similar to Gürkaynak et al. (2020). Each column reports results for a different maturity of intraday inflation swaps. The R^2 values are those of announcement day yields using (i) solely headline surprises vs. (ii) headline surprises and the latent factor. * Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

Table A3: **Asset Price Response to Breakeven Inflation**

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\pi^{be,5Y}$	-0.99***	0.37***	-0.30***	-0.65***	-0.94***	0.35***
	(-6.68)	(4.80)	(-4.07)	(-5.05)	(-7.07)	(4.73)
$\tilde{\rho}_{-1}^{bond-mkt,3M}$					0.02	0.04
					(0.29)	(0.83)
$\tilde{\rho}_{-1}^{bond-mkt,3M} \times \Delta\pi^{be,5Y}$					0.57***	-0.23***
					(4.99)	(-3.07)
$s_{i,-1}$	0.17***	-0.00	0.05	-0.00	0.17***	0.00
	(3.07)	(-0.14)	(1.42)	(-0.04)	(3.20)	(0.01)
$(R^i - R^f)_{-1}$		-0.00				-0.00
		(-0.01)				(-0.01)
$ExpLoss_{i,-1}$			-0.17***	0.55***		
			(-3.17)	(5.27)		
Dependent Variable	Δs_i	$R^i - R^f$	$\Delta ExpLoss_i$	$\Delta RiskPrem_i$	Δs_i	$R^i - R^f$
Firm FE	Y	Y	Y	Y	Y	Y
Clustering	Firm-Time		Firm-Time		Firm-Time	
Obs	440,133	223,199	210,332	210,330	432,551	221,319
$Adj.R^2$	0.020	0.028	0.009	0.012	0.025	0.038

This table reports the average and time-varying effects of inflation expectation movements, measured using 5-year TIPS breakeven inflation rates, on movements in CDS, expected losses, credit risk premia, and equity returns. Columns (1) - (4) report average effects, while columns (5) and (6), report the time-varying effects where we interact the inflation expectation shocks with the 3-month bond-stock correlation. We standardize the correlation measures such that the interaction coefficient indicates the additional sensitivity to changes in inflation swap when the correlation is one standard deviation higher. Columns (1) and (5) focus on movements in CDS spreads, columns (2), and (6) on equity returns, and columns (3) and (4) on the expected loss component and credit risk premia, respectively. In all regressions, we include either the CDS rate or the CDS rate and expected loss or the excess return the day before the macroeconomic announcement, and firm fixed effects. Standard errors are clustered at the time and firm level. * Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

Table A4: **Time-Varying Beta and Inflation Risk Premia Effects**

	(1)	(2)	(3)	(4)
$\Delta\pi^{InflComp}$	-0.64***		0.46***	
	(-4.69)		(7.59)	
$\Delta\pi^{ExpInfl}$		-0.65***		0.48***
		(-4.70)		(8.03)
$\tilde{\rho}_{-1}^{bond-mkt,3M}$	-0.02	-0.02	0.04	0.04
	(-0.31)	(-0.29)	(0.87)	(0.83)
$\tilde{\rho}_{-1}^{bond-mkt,3M} \times \Delta\pi^{InflComp}$	0.41***		-0.30***	
	(4.64)		(-5.52)	
$\tilde{\rho}_{-1}^{bond-mkt,3M} \times \Delta\pi^{ExpInfl}$		0.41***		-0.32***
		(4.58)		(-5.96)
$s_{i,-1}$	0.19***	0.19***	-0.01	-0.01
	(3.19)	(3.21)	(-0.48)	(-0.52)
$\left(R^i - R^f\right)_{-1}$			0.01	0.01
			(0.45)	(0.53)
Dependent Variable	Δs_i		$R^i - R^f$	
Firm FE	Y	Y	Y	Y
Clustering	Firm-Time		Firm-Time	
Obs	410,129	410,129	205,837	205,837
$Adj.R^2$	0.015	0.016	0.054	0.061

This table reports the time-varying effects of daily inflation compensation and inflation expectation movements. All inflation data come from D'Amico et al. (2018) where inflation compensation is defined as the sum of physical inflation expectation and inflation risk premia. Columns (1) - (2) focus on movements in CDS spreads. Columns (3) - (4) focus on equity returns. All columns report results where the inflation measure is interacted with the bond-stock correlation estimated using the 3-month rolling correlation. We standardize the correlation measures such that the interaction coefficient indicates the additional sensitivity to changes in inflation measures when the correlation is one standard deviation higher. In all regressions, we include the CDS rate and equity returns the day before the macroeconomic announcement and firm fixed effects. Standard errors are clustered at the time and firm level. * Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

Table A5: **Time-Varying Inflation Beta and Swap Market Liquidity**

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\pi^{swap,5Y}$	-0.81***	-0.89***	-0.65***	0.35***	0.38***	0.38***
	(-5.27)	(-6.85)	(-3.95)	(3.82)	(3.38)	(4.91)
$\tilde{\rho}_{-1}^{swap-mkt,3M}$	-0.03	0.05	0.04	0.05	0.00	0.03
	(-0.38)	(0.74)	(0.57)	(1.00)	(0.02)	(0.63)
$\tilde{\rho}_{-1}^{swap-mkt,3M} \times \Delta\pi^{swap,5Y}$	0.61***	0.66***	0.42***	-0.22***	-0.28***	-0.22***
	(5.05)	(6.29)	(3.91)	(-2.58)	(-3.03)	(-2.99)
$s_{i,-1}$	0.18***	0.08	-0.01	-0.00	0.02	0.00
	(3.21)	(1.56)	(-0.26)	(-0.01)	(1.24)	(0.28)
$\left(R^i - R^f\right)_{-1}$				0.00	-0.01	0.02
				(0.17)	(-0.50)	(0.91)
Dependent Variable		Δs_i			$R^i - R^f$	
Liquidity Statistic	–	BEI	DKW	–	BEI	DKW
Which Subsample	Full	High Liquidity ($\leq$ 90%)		Full	High Liquidity ($\leq$ 90%)	
Clustering		Firm-Time			Firm-Time	
Obs	410,129	356,338	365,801	205,837	178,820	184,069
$Adj.R^2$	0.024	0.021	0.011	0.036	0.035	0.034

This table reports the time-varying effects of inflation movements on CDS and equity returns controlling for swap market liquidity. Columns (1) and (4) report the baseline effect using the full sample, while columns (2) and (5) report the time-varying effects where we remove the top 10% illiquid days based on the absolute spread between swap prices and breakeven prices. Finally, columns (3) and (6) report the time-varying effects in which we remove the top 10% illiquid days based on the spread between swap prices and the inflation compensation measure of D'Amico et al. (2018). We standardize the correlation measures such that the interaction coefficient indicates the additional sensitivity to changes in inflation swap when the correlation is one standard deviation higher. Columns (1) to (3) focus on movements in CDS spreads, while columns (4) to (6) focus on equity returns. In all regressions, we include either the CDS rate or the CDS rate and excess return the day before the macroeconomic announcement, and firm fixed effects. Standard errors are clustered at the time and firm level. * Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

Table A6: **Time-Varying Inflation Risk and CDS Liquidity**

	(1)	(2)	(3)
$\Delta\pi^{swap,5Y}$	-0.81***	-1.11***	-0.42***
	(-5.27)	(-5.47)	(-4.18)
$\tilde{\rho}_{-1}^{swap-mkt,3M}$	-0.03	-0.02	-0.03
	(-0.38)	(-0.20)	(-0.51)
$\tilde{\rho}_{-1}^{swap-mkt,3M} \times \Delta\pi^{swap,5Y}$	0.61***	0.78***	0.38***
	(5.05)	(5.12)	(4.45)
$s_{i,-1}$	0.18***	0.22***	0.14***
	(3.21)	(2.62)	(2.65)
Number of Dealers	–	High ($\geq$ 50%)	Low (< 50%)
Firm FE	Y	Y	Y
Clustering		Firm-Time	
Obs	410,129	234,586	175,517
$Adj.R^2$	0.024	0.037	0.020

This table reports the time-varying effects of inflation movements on CDS, controlling for CDS market liquidity. Column (1) reports the baseline effect using the full sample, while column (2) reports the time-varying effects where we focus on CDS contracts traded by a number of dealers larger than the sample median on an announcement day, and in column (3) we focus on CDS contracts traded by a number of dealers lower than the sample median. We standardize the correlation measures such that the interaction coefficient indicates the additional sensitivity to changes in inflation swap when the correlation is one standard deviation higher. In all regressions, we include the CDS rate the day before the macroeconomic announcement, and firm fixed effects. Standard errors are clustered at the time and firm level. * Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

Table A7: **Time-Varying Inflation Risk over a Long Sample**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta\pi^{InflComp}$	0.063**		0.341***		0.051		0.275***	
	(2.073)		(5.541)		(1.599)		(4.974)	
$\Delta\pi^{ExpInfl}$		0.069**		0.352***		0.056*		0.284***
		(2.151)		(5.360)		(1.653)		(4.817)
$\Delta\pi^{InflComp} \times \tilde{\rho}_{-1}^{bond-mkt,3M}$	-0.281***							
	(-9.645)							
$\Delta\pi^{ExpInfl} \times \tilde{\rho}_{-1}^{bond-mkt,3M}$		-0.288***						
		(-9.577)						
$\Delta\pi^{InflComp} \times \tilde{\rho}_{-1}^{bond-mkt,6M}$					-0.246***			
					(-7.798)			
$\Delta\pi^{ExpInfl} \times \tilde{\rho}_{-1}^{bond-mkt,6M}$						-0.252***		
						(-7.683)		
$\mathbb{1}_{\rho_{-1}^{bond-mkt,3M}>0} \times \Delta\pi^{InflComp}$			-0.536***					
			(-8.023)					
$\mathbb{1}_{\rho_{-1}^{bond-mkt,3M}>0} \times \Delta\pi^{ExpInfl}$				-0.551***				
				(-7.835)				
$\mathbb{1}_{\rho_{-1}^{bond-mkt,6M}>0} \times \Delta\pi^{InflComp}$							-0.464***	
							(-7.523)	
$\mathbb{1}_{\rho_{-1}^{bond-mkt,6M}>0} \times \Delta\pi^{ExpInfl}$								-0.476***
								(-7.369)
Correlation Horizon	3 Months				6 Months			
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Clustering	Firm-Time				Firm-Time			
Obs	7,259,306	7,259,306	7,259,306	7,259,306	7,259,306	7,259,306	7,259,306	7,259,306
Adj.R^2	0.014	0.014	0.012	0.012	0.012	0.012	0.010	0.011

This table reports the time-varying effects of inflation compensation and expectations on equity returns from 1983 to 2023. All inflation measures come from D'Amico et al. (2018), where inflation compensation is defined as the sum of inflation expectations and inflation risk premia. Columns (1) - (4) report results where the inflation shocks are interacted with the bond-stock correlation estimated using the 3-month rolling correlation. Columns (5) - (8) report results where the inflation shocks are interacted with the bond-stock correlation estimated using 6-month rolling correlation. Columns (3) - (4) report results where the inflation expectation movements are interacted with a dummy variable, that indicates whether the 3-month bond-stock correlation (non-standardized) is positive. Columns (7) - (8) report results where the inflation expectation movements are interacted with a dummy variable, that indicates whether the 6-month bond-stock correlation (non-standardized) is positive. We standardize the correlation measures such that the interaction coefficient indicates the additional sensitivity to changes in inflation measures when the correlation is one standard deviation higher. In all regressions, we include the equity returns the day before the macroeconomic announcement and firm fixed effects. Standard errors are clustered at the time and firm level. * Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

Table A8: **Time-Varying Inflation Risk and the Inflation Swap-Market Correlation**

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\pi^{swap,5Y}$	-0.90***	-1.02***	-1.03***	0.38***	0.46***	0.47***
	(-5.19)	(-6.33)	(-6.04)	(3.91)	(4.97)	(4.92)
$\tilde{\rho}_{-1}^{swap-mkt,3M}$		-0.20**			0.02	
		(-2.58)			(0.55)	
$\tilde{\rho}_{-1}^{swap-mkt,6M}$			-0.20**			0.04
			(-2.55)			(0.84)
$\tilde{\rho}_{-1}^{swap-mkt,3M} \times \Delta\pi^{swap,5Y}$		-0.68***			0.38***	
		(-5.55)			(5.73)	
$\tilde{\rho}_{-1}^{swap-mkt,6M} \times \Delta\pi^{swap,5Y}$			-0.56***			0.34***
			(-4.56)			(4.91)
$s_{i,-1}$	0.18***	0.19***	0.19***	-0.00	0.00	-0.00
	(3.12)	(3.21)	(3.25)	(-0.10)	(0.07)	(-0.04)
$\left(R^i - R^f\right)_{-1}$				0.00	-0.01	-0.00
				(0.22)	(-0.33)	(-0.08)
Dependent Variable		Δs_i			$R^i - R^f$	
Correlation Horizon	–	3M	6M	–	3M	6M
Firm FE	Y	Y	Y	Y	Y	Y
Clustering		Firm-Time			Firm-Time	
Obs	418,777	405,195	400,641	207,717	202,603	199,661
$Adj.R^2$	0.019	0.026	0.024	0.028	0.056	0.049

This table reports the time-varying effects of inflation expectation movements on credit and equity markets, using a correlation measure based on daily movements of swap rates and aggregate equity returns. For more details regarding the specification, see Equation (6) in the main text. Columns (1) and (4) report the baseline results as in columns (1) and (3) in Table 4. Columns (2) and (5) report results where the inflation expectation movements are interacted with the 3-month swap-market correlation, while columns (3) and (6) use the 6-month rolling correlation. We standardize the correlation measures such that the interaction coefficient indicates the additional sensitivity to changes in inflation swap when the correlation is one standard deviation higher. In all regressions, we include the CDS rate or CDS rate and equity returns the day before the macroeconomic announcement, and firm fixed effects. Standard errors are clustered at the time and firm level. * Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

B Model Solution

B.1 Price-to-Consumption Ratio

Based on the Euler equation restriction and fundamental assumptions we can show that the price-consumption ratio takes the form:

$$pc_t = A_1' X_t + A_2(s_t)$$

where A_1 is a set of loadings on expected growth and inflation and A_2 is a regime switching component. To show this we start with the Euler Equation:

$$\mathbb{E}_t \left[\exp\left(m_{t+1} + r_{c,t+1}\right)\right] = \mathbb{E}_t \left[\exp\left(\theta \log \delta - \frac{\theta}{\psi}\Delta c_{t+1} + \theta r_{c,t+1}\right)\right] = \exp\left(0\right)$$

$$(\Longleftrightarrow) \exp\left(\theta pc_t\right) = \mathbb{E}_t \left[\exp\left(\theta \log \delta + (1-\gamma)\Delta c_{t+1} + \theta\kappa_0 + \theta\kappa_1 pc_{t+1}\right)\right]$$

We guess / verify the *pc* guess and simplify the right hand side:

$$\begin{aligned}
\exp\left(\theta pc_t\right) &= \mathbb{E}_t \left[\exp\left(\theta \log \delta + (1-\gamma)\Delta c_{t+1} + \theta\kappa_0 + \theta\kappa_1 pc_{t+1}\right)\right] \\
&= \mathbb{E}_t \left[\exp\left\{(1-\gamma)\sigma_c \varepsilon_{c,t+1} + \theta\kappa_1 pc_{t+1}\right\}\right] \times \exp\left(\theta \log \delta + (1-\gamma)\mu_c + \theta\kappa_0 + (1-\gamma)e_1' X_t\right) \\
&= \mathbb{E}_t \left[\exp\left(\theta\kappa_1 A_1' \Sigma_t \eta_{t+1}\right)\right] \times \mathbb{E}_t \left[\exp\left(\theta\kappa_1 A_2(s_{t+1})\right)\right] \times \exp\left(\frac{1}{2}(1-\gamma)^2\sigma_c^2 + \theta\kappa_1 A_1' \Pi X_t\right) \\
&\quad \times \exp\left(\theta \log \delta + (1-\gamma)\mu_c + \theta\kappa_0 + (1-\gamma)e_1' X_t\right) \\
&= \underbrace{\exp\left(\frac{1}{2}\theta^2\kappa_1^2 A_1' \Sigma_t \Sigma_t' A_1\right) \times \exp\left(\log\left\{\sum_{j=1}^{2} p_{ij} \exp\left(\theta\kappa_1 A_2(s_j)\right)\right\}\right)}_{\text{Dependent on } s_t} \\
&\quad \times \exp\left(\frac{1}{2}(1-\gamma)^2\sigma_c^2 + \theta\kappa_1 A_1' \Pi X_t\right) \\
&\quad \times \exp\left(\theta \log \delta + (1-\gamma)\mu_c + \theta\kappa_0 + (1-\gamma)e_1' X_t\right)
\end{aligned}$$

Matching coefficients on X_t we receive:

$$\begin{aligned}
\theta A_1' &= (1-\gamma)e_1' + \theta\kappa_1 A_1' \Pi \\
A_1 &= (1 - \frac{1}{\psi}) \times (I - \kappa_1 \Pi')^{-1} e_1
\end{aligned}$$

Matching coefficients on s_t we receive:

$$\theta A_2(s_t = i) = \theta \log \delta + (1-\gamma)\mu_c + \theta\kappa_0 + \frac{1}{2}(1-\gamma)^2\sigma_c^2 \\ + \frac{1}{2}\theta^2\kappa_1^2 A_1'\Sigma_t\Sigma_t' A_1 + \log\left\{\sum_{j=1}^{N} p_{ij}\exp\left(\theta\kappa_1 A_2(s_j)\right)\right\} \quad \text{for } i = 1,\ldots,N$$

This is a system of N equations and N unknowns that we can solve numerically.

B.2 Nominal Bond Returns

The return on an n-period zero-coupon bond return (purchase at t, sell at $t+1$) will be given by:

$$\exp\left(r_{f,t+1}^{\$,n}\right) = \frac{P_{f,t+1}^{\$,n-1}}{P_{f,t}^{\$,n}} = \exp\left(p_{f,t+1}^{\$,n-1} - p_{f,t}^{\$,n}\right)$$

where $P_{f,t}^{\$,n}$ indicates the price of a risk-free bond at time t that matures at $t+n$, and its lowercase is in log terms. We can show that the log price will take the form:

$$p_{f,t}^{\$,n} = P_1^{n'} X_t + P_2^n(s_t)$$

Starting with $n = 1$ (one period risk-free bond), we have:

$$\begin{aligned}
\exp\left(p_{ft}^{\$,1}\right) &= \mathbb{E}_t\left[\exp\left(m_{t+1} - \pi_{t+1}\right)\right] \\
&= \mathbb{E}_t\left[\exp\left(\theta\log\delta - \frac{\theta}{\psi}\Delta c_{t+1} - (1-\theta)r_{c,t+1} - \pi_{t+1}\right)\right] \\
&= \mathbb{E}_t\left[\exp\left(\theta\log\delta - (1-\theta+\frac{\theta}{\psi})\Delta c_{t+1} - (1-\theta)(\kappa_0 + \kappa_1 pc_{t+1} - pc_t) - \pi_{t+1}\right)\right] \\
&= \exp\left(\theta\log\delta - (1-\theta+\frac{\theta}{\psi})(\mu_c + e_1' X_t) - (1-\theta)(\kappa_0 + \kappa_1 A_1'\Pi X_t - pc_t) - (\mu_\pi + e_2' X_t)\right) \\
&\quad \times \mathbb{E}_t\left[\exp\left((1-\theta+\frac{\theta}{\psi})\sigma_c\varepsilon_{c,t+1} - (1-\theta)\left(\kappa_1 A_1'\Sigma_t\eta_{t+1} + \kappa_1 A_2(s_{t+1})\right) - \sigma_\pi\varepsilon_{\pi,t+1}\right)\right]
\end{aligned}$$

Final price can be expressed as:

$$\begin{aligned}
p_{ft}^{\$,1} = \theta\log\delta &- (1-\theta+\frac{\theta}{\psi})\mu_c - (1-\theta)\kappa_0 - \mu_\pi + \frac{1}{2}(1-\theta+\frac{\theta}{\psi})^2\sigma_c^2 + \frac{1}{2}\sigma_\pi^2 \\
&+ (1-\theta)A_2(s_t) + \frac{1}{2}(1-\theta)^2\kappa_1^2 A_1'\Sigma_t\Sigma_t' A_1 + \log\left(\mathbb{E}_t\left[\exp\left((\theta-1)\kappa_1 A_2(s_{t+1})\right)\right]\right) \\
&+ \left[(\theta-1-\frac{\theta}{\psi})e_1' - (1-\theta)\kappa_1 A_1'\Pi + (1-\theta)A_1' - e_2'\right] X_t
\end{aligned}$$

where $P_1^{1'}$ is indicated by the coefficient in the brackets in the third line, and $P_2^1(s_t)$ is indicated by the top two lines.

To solve for a maturity n, assume that the statement holds for $n-1$, i.e. that there exist coefficients such that $p_{ft}^{\$,n-1} = P_1^{n-1'} X_t + P_2^{n-1}(s_t)$. Due to the zero-coupon nature of these bonds:

$$\exp\left(p_{ft}^{\$,n}\right) = \mathbb{E}_t\left[\exp\left(m_{t+1} - \pi_{t+1} + p_{f,t+1}^{\$,n-1}\right)\right]$$

as the price will be the nominally discounted value of the future market value. We can further simplify:

$$\begin{aligned}\exp\left(p_{ft}^{\$,n}\right) &= \mathbb{E}_t\left[\exp\left(\theta\log\delta - (1-\theta+\frac{\theta}{\psi})\Delta c_{t+1} - (1-\theta)(\kappa_0 + \kappa_1 pc_{t+1} - pc_t) - \pi_{t+1} + P_1^{n-1'} X_{t+1} + P_2^{n-1}(s_{t+1})\right)\right] \\ &= \exp\left(\theta\log\delta - (1-\theta+\frac{\theta}{\psi})(\mu_c + e_1' X_t) - (1-\theta)(\kappa_0 + \kappa_1 A_1'\Pi X_t - pc_t) - (\mu_\pi + e_2' X_t) + P_1^{n-1'}\Pi X_t\right) \\ &\quad\times \mathbb{E}_t\left[\exp\left((1-\theta+\frac{\theta}{\psi})\sigma_c\varepsilon_{c,t+1} - (1-\theta)\left(\kappa_1 A_1'\Sigma_t\eta_{t+1} + \kappa_1 A_2(s_{t+1})\right) + P_1^{n-1'}\Sigma_t\eta_{t+1} + P_2^{n-1}(s_{t+1}) - \sigma_\pi\varepsilon_{\pi,t+1}\right)\right]\end{aligned}$$

The final price can be written as:

$$\begin{aligned}p_{ft}^{\$,n} &= \theta\log\delta - (1-\theta+\frac{\theta}{\psi})\mu_c - (1-\theta)\kappa_0 - \mu_\pi + \frac{1}{2}(1-\theta+\frac{\theta}{\psi})^2\sigma_c^2 + \frac{1}{2}\sigma_\pi^2 \\ &\quad + (1-\theta)A_2(s_t) + \frac{1}{2}\left(P_1^{n-1'} - (1-\theta)\kappa_1 A_1'\right)\Sigma_t\Sigma_t'\left(P_1^{n-1'} - (1-\theta)\kappa_1 A_1'\right)' \\ &\quad + \log\left(\mathbb{E}_t\left[\exp\left\{(\theta-1)\kappa_1 A_2(s_{t+1}) + P_2^{n-1}(s_{t+1})\right\}\right]\right) \\ &\quad + \left[(\theta - 1 - \frac{\theta}{\psi})e_1' - (1-\theta)\kappa_1 A_1'\Pi + (1-\theta)A_1' - e_2' + P_1^{n-1'}\Pi\right] X_t\end{aligned}$$

The coefficients for $\left\{P_1^{n'}, P_2^n(s_t)\right\}$ are a function of the maturity $n-1$ coefficients. Using these one can compute nominal bond prices and corresponding bond returns.

B.3 CDS Spreads

As given in Equation (2) of the main text, we need to compute two quantities to solve the model:

$$\underbrace{\mathbb{E}_t\left[\tilde{M}_{t+k}^{\$} S_{t,t+k}\right]}_{(*)}, \quad \underbrace{\mathbb{E}_t\left[\tilde{M}_{t+k}^{\$} S_{t,t+k-1}\right]}_{(**)}$$

taking into account the nominal SDF assumptions of the model, long-run risk fundamentals, and exogenous default dynamics:

$$D_{t,1} = \begin{cases} 0 & \text{w/probability } \exp(-\lambda_t) \\ 1 & 1 - \exp(-\lambda_t) \end{cases}$$

$$\lambda_t = \beta_{\lambda 0}(s_t) + \beta'_{\lambda x} X_t$$

Key Analytical Result Before simplifying the expectational terms, we mention a key analytical result. Suppose we have a generic function, $f_t = f_1' X_t + f_2(s_t)$, then we can show that there exists coefficients for $\tilde{f}_t$ such that:

$$\begin{aligned} \tilde{f}(s_t, x_t) &= \mathbb{E}_t \left[\tilde{M}^{\$}_{t+1} \times \exp\left(f_1' X_{t+1} + f_2(s_{t+1})\right) \right] \\ &= \mathbb{E}_t \left[\exp\left(m_{t+1} - \pi_{t+1} + f_1' X_{t+1} + f_2(s_{t+1})\right) \right] \\ &= \exp\left(\tilde{f}_1' X_t + \tilde{f}_2(s_t) \right) \end{aligned}$$

The coefficients for $\tilde{f}$ are given by:

$$\begin{aligned} \tilde{f}_2(s_t) = \theta \log \delta &- (1 - \theta + \frac{\theta}{\psi})\mu_c - (1-\theta)\kappa_0 - \mu_\pi + \frac{1}{2}(1 - \theta + \frac{\theta}{\psi})^2 \sigma_c^2 + \frac{1}{2}\sigma_\pi^2 \\ &+ (1-\theta) A_2(s_t) + \frac{1}{2} \left(f_1' - (1-\theta)\kappa_1 A_1' \right) \Sigma_t \Sigma_t' \left(f_1' - (1-\theta)\kappa_1 A_1' \right)' \\ &+ \log\left(\mathbb{E}_t \left[\exp\left\{ (\theta - 1)\kappa_1 A_2(s_{t+1}) + f_2(s_{t+1}) \right\} \right] \right) \end{aligned}$$

$$\tilde{f}_1' = \left[(\theta - 1 - \frac{\theta}{\psi}) e_1' - (1-\theta)\kappa_1 A_1' \Pi + (1-\theta) A_1' - e_2' + f_1' \Pi \right]$$

Solving for (*) We can rewrite the expression as:

$$\mathbb{E}_t \left[\tilde{M}^{\$}_{t+k} S_{t,t+k} \right] = \mathbb{E}_t \left[\tilde{M}^{\$}_{t+k} \Pi_{j=1}^{k} S_{t+j-1,1} \right] = \mathbb{E}_t \left[\tilde{M}^{\$}_{t+k} \exp\left(- \sum_{j=1}^{k} \lambda_{t+j-1} \right) \right]$$

where the right most term uses the conditional independence default assumption. For $k = 1$, this term simplifies to:

$$\begin{aligned}\mathbb{E}_t\left[\tilde{M}^{\$}_{t+1} S_{t,t+1}\right] = \exp\left(-\lambda_t\right) \times \mathbb{E}_t\left[\tilde{M}^{\$}_{t+1}\right] &= \exp\left(p^{\$,1}_{ft} - \beta'_{\lambda x} X_t - \beta_{\lambda 0}(s_t)\right) \\ &= \exp\left((P^1_1 - \beta_{\lambda x})' X_t + P^1_2(s_t) - \beta_{\lambda 0}(s_t)\right) \\ &= \exp\left(B^{1'}_1 X_t + B^1_2(s_t)\right)\end{aligned}$$

For $k > 1$, the right most term can be simplified to:

$$\begin{aligned}\mathbb{E}_t\left[\tilde{M}^{\$}_{t+k} \exp\left(-\sum_{j=1}^{k} \lambda_{t+j-1}\right)\right] &= \mathbb{E}_t\left[\tilde{M}^{\$}_{t+k-1} \exp\left(-\sum_{j=1}^{k} \lambda_{t+j-1}\right) \mathbb{E}_{t+k-1}\left[\exp\left(m_{t+k} - \pi_{t+k}\right)\right]\right] \\ &= \mathbb{E}_t\left[\tilde{M}^{\$}_{t+k-1} \exp\left(-\sum_{j=1}^{k} \lambda_{t+j-1}\right) \exp\left(p^{\$,1}_{f,t+k-1}\right)\right] \\ &= \mathbb{E}_t\left[\tilde{M}^{\$}_{t+k-1} \exp\left(-\sum_{j=1}^{k} \lambda_{t+j-1}\right) \exp\left(P^{1'}_1 X_{t+k-1} + P^1_2(s_{t+k-1})\right)\right]\end{aligned}$$

Given all terms on the RHS are at the $t + k - 1$ timestep we can apply the result from earlier. Sequentially, we compute the expectation:

$$\begin{aligned}&\mathbb{E}_t\left[\tilde{M}^{\$}_{t+k-1} \exp\left(-\sum_{j=1}^{k} \lambda_{t+j-1}\right) \exp\left(P^{1'}_1 X_{t+k-1} + P^1_2(s_{t+k-1})\right)\right] = \\ &\mathbb{E}_t\left[\tilde{M}^{\$}_{t+k-2} \exp\left(-\sum_{j=1}^{k-1} \lambda_{t+j-1}\right) \mathbb{E}_{t+k-2}\left[M^{\$}_{t+k-1} \times \exp\left(P^{1'}_1 X_{t+k-1} + P^1_2(s_{t+k-1}) - \lambda_{t+k-1}\right)\right]\right] = \\ &\mathbb{E}_t\left[\tilde{M}^{\$}_{t+k-2} \exp\left(-\sum_{j=1}^{k-1} \lambda_{t+j-1}\right) \exp\left(\tilde{P}_1 X_{t+k-2} + \tilde{P}_2(s_{t+k-2})\right)\right] = \\ &\mathbb{E}_t\left[\tilde{M}^{\$}_{t+k-3} \exp\left(-\sum_{j=1}^{k-2} \lambda_{t+j-1}\right) \mathbb{E}_{t+k-3}\left[M^{\$}_{t+k-2} \times \exp\left(\tilde{P}'_1 X_{t+k-2} + \tilde{P}_2(s_{t+k-2}) - \lambda_{t+k-2}\right)\right]\right] = \\ &\cdots = \exp\left(B^{k'}_1 X_t + B^k_2(s_t)\right)\end{aligned}$$

where to get from the second to third line, we use the earlier result. The final expression is exponential affine in the expected growth / inflation state and the Markov state.

Solving for (**) The proof will be similar to the solution for $(*)$. We can rewrite the expression as:

$$\mathbb{E}_t\left[\tilde{M}^{\$}_{t+k} S_{t,t+k-1}\right] = \mathbb{E}_t\left[\tilde{M}^{\$}_{t+k} \Pi^{k-1}_{j=1} S_{t+j-1,1}\right] = \mathbb{E}_t\left[\tilde{M}^{\$}_{t+k} \exp\left(-\sum_{j=1}^{k-1} \lambda_{t+j-1}\right)\right]$$

where the right most term uses the conditional independence default assumption. For $k = 1$, this term simplifies to:

$$\mathbb{E}_t\left[\tilde{M}^{\$}_{t+1} S_{t,t}\right] = \mathbb{E}_t\left[\tilde{M}^{\$}_{t+1}\right] = \exp\left(p^{\$,1}_{ft}\right) = \exp\left(C_1^{1'} X_t + C_2^1(s_t)\right)$$

For $k > 1$, the right most term can be simplified to:

$$\begin{aligned}
\mathbb{E}_t\left[\tilde{M}^{\$}_{t+k}\exp\left(-\sum_{j=1}^{k-1}\lambda_{t+j-1}\right)\right] &= \mathbb{E}_t\left[\tilde{M}^{\$}_{t+k-2}\exp\left(-\sum_{j=1}^{k-1}\lambda_{t+j-1}\right)\mathbb{E}_{t+k-2}\left[M^{\$}_{t+k-1}\times M^{\$}_{t+k}\right]\right] \\
&= \mathbb{E}_t\left[\tilde{M}^{\$}_{t+k-2}\exp\left(-\sum_{j=1}^{k-1}\lambda_{t+j-1}\right)\exp\left(p^{\$,2}_{f,t+k-2}\right)\right] \\
&= \mathbb{E}_t\left[\tilde{M}^{\$}_{t+k-2}\exp\left(-\sum_{j=1}^{k-1}\lambda_{t+j-1}\right)\exp\left(P_1^{2'} X_{t+k-2} + P_2^2(s_{t+k-2})\right)\right]
\end{aligned}$$

Given all terms on the RHS are at the $t + k - 2$ timestep we can apply the result from earlier. Sequentially, we compute the expectation and receive similar to earlier that:

$$\mathbb{E}_t\left[\tilde{M}^{\$}_{t+k-2}\exp\left(-\sum_{j=1}^{k-1}\lambda_{t+j-1}\right)\exp\left(P_1^{2'} X_{t+k-2} + P_2^2(s_{t+k-2})\right)\right] = \exp\left(C_1^{k'} X_t + C_2^k(s_t)\right)$$

The final expression is exponential affine in the expected growth / inflation state and the Markov state.

Overview Based on the solutions for $\left\{B_1^k, B_2^k(s_t), C_1^k, C_2^k(s_t)\right\}$ we can write the 5Y CDS as:

$$C_t = (1-R)\times\left(1 - \frac{\sum_{k=1}^{20}\mathbb{E}_t\left[\tilde{M}^{\$}_{t+k} S_{t,t+k}\right]}{\sum_{k=1}^{20}\mathbb{E}_t\left[\tilde{M}^{\$}_{t+k} S_{t,t+k-1}\right]}\right) = (1-R)\times\left(1 - \frac{\sum_{k=1}^{20}\exp\left(B_1^{k'} X_t + B_2^k(s_t)\right)}{\sum_{k=1}^{20}\exp\left(C_1^{k'} X_t + C_2^k(s_t)\right)}\right)$$