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“Good” Inflation, “Bad” Inflation: Implications for Risky Asset Prices

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Abstract

Using inflation swap prices, we study how changes in expected inflation affect firm-level credit spreads and equity returns, and uncover evidence of a time-varying inflation sensitivity. In times of “good inflation,” when inflation news is perceived by investors to be more positively correlated with real economic growth, movements in 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 in an equilibrium asset pricing model with a time-varying inflation-growth relationship and persistent macroeconomic expectations.

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

JEL Classification: E31, E44, G12

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1 Introduction

The time-varying correlation between inflation and consumption growth is a robust feature of the U.S. economy. As the nature of inflation has varied over time, from the stagflationary era of the 1970s and early 1980s to the more demand-driven, procyclical inflation regime of the last two decades, it is natural that investors might change the way they incorporate revisions in inflation expectations into asset prices (e.g., David and Veronesi (2013) and Cieslak and Pflueger (2023), among others).

In this paper, we provide novel evidence that corporate credit spreads display a time-varying sensitivity to movements in inflation expectations that significantly depends on the market-perceived cyclicality of inflation. In times when inflation is perceived to be more positively related to real growth — a "good inflation" regime — credit default swap (CDS) spreads decline at greater rates following an upward revision in inflation expectations. Based on a matched sample, equity returns also display a qualitatively consistent pattern, suggesting a cohesive story across both asset classes.[1] We rationalize these findings through an equilibrium asset pricing model extended to price defaultable CDS. The model delivers a time-varying inflation sensitivity across both asset classes and highlights the importance of persistent growth expectations.

We design an empirical strategy centered around changes in expected inflation triggered by macroeconomic announcements as captured by daily and intraday movements of five-year inflation swaps. Because swaps are market-based contracts concerning longer-term inflation expectations, they allow us a better link to the long duration cash flows present in credit and equity secu-

[1] To the best of our knowledge, we are among the first to empirically explore the state-dependent response of corporate credit risk to revisions in inflation expectations. Boons, Duarte, de Roon, and Szymanowska (2020) provide evidence that the equity-implied inflation risk premium behaves in a time-varying fashion. Gil de Rubio Cruz, Osambela, Palazzo, Palomino, and Suarez (2023) show that the equity return response to CPI-based inflation surprises is also time-varying. Finally, Elenev, Law, Song, and Yaron (2023) study the time-varying response of equities with respect to macroeconomic announcements, focusing on growth-related news. We complement these studies by showing that the same is true on a high-frequency basis for the equity market response to expected inflation news.

rities. Furthermore, macroeconomic announcement days are relevant for our empirical strategy, as investors price in new information and inflation swaps display a greater degree of variation on these days.[2]

Using daily changes in five-year inflation swaps on announcement days, we first show that, on average, positive revisions in expected inflation reduce credit spreads and increase equity prices. Unconditionally, in our 2004 to 2023 sample, we find that a one standard deviation (1σ) movement in expected inflation reduces five-year credit default swap (CDS) spreads by roughly 1 basis point (b.p.) and increases equity returns by 40 b.p. over a one-day horizon.[3] These results are consistent with the prevalence of a good inflation regime that has characterized the U.S. economy since the start of this century.

That said, the market-perceived relationship between inflation news and future real growth can experience sudden changes due to rapidly evolving conditions. Macroeconomic quantities, which are observable at a lower frequency, cannot fully capture growth-inflation covariance changes in real-time. For this reason, we use an economically-motivated and well established proxy – the bond-stock return correlation – which we can conveniently track on a daily basis (e.g., Campbell, Pflueger, and Viceira (2020)). Within our inflation swap sample starting from 2004, the daily three-month bond-stock correlation averages -0.30, but we have several episodes where the correlation turns positive, and reaches the heights of the 1970s stagflationary period. For example, the correlation was roughly 0.50 toward the end of May 2021 and in December 2022, when, for brief periods of time, market participants were potentially associating higher expected inflation with lower future real economic growth.

Our analysis shows that high frequency changes in the bond-stock correlation matter for the response of financial markets to movements in inflation expectations. When we embed an interaction term in our baseline panel regres-

[2] We focus on macroeconomic announcements related to the Consumer Price Index (CPI), Producer Price Index (PPI), real Gross Domestic Product (GDP), and Nonfarm Payrolls. We choose this set of announcements as their survey-based surprises are significantly priced in intraday inflation swap markets.

[3] The magnitudes of the CDS and equity return responses are quantitatively sizable and comparable. They correspond to 10-15% of their respective standard deviations. Furthermore, these magnitudes are amplified if we look at riskier firms in the cross-section.

sion that combines the change in swap rates on macroeconomic announcement days and the lagged three-month stock-bond return correlation, 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 1σ movement in expected inflation is negative 2.1 b.p, while the equity return sensitivity is positive and equal to 0.81 percent. An analogous interpretation holds in the other direction.

We also provide novel results that better highlight the transmission channels of inflation news. Using a decomposition similar to the one in Berndt, Douglas, Duffie, and Ferguson (2018), we show that the majority of credit market effects operates through the risk premium channel. That said, even the expected losses (risk neutral) component of credit spreads, which highly correlates with pure default risk, displays time-variation in its inflation sensitivity. In the cross section, our findings are strongest for riskier firms, as there is a strong interaction between time variation and heterogeneity in inflation responsiveness. Finally, when we compare the bond-stock correlation with more direct, lower frequency measures of the inflation-growth relationship (as used in Boons et al. (2020)), it outperforms in many horse race tests.[4]

In the final part of our empirical analysis, we more precisely study movements in inflation expectations around announcements. Using high frequency, 60-minute changes in inflation swaps, we first provide evidence that swap rates significantly respond to macroeconomic surprises, lending credibility to the announcements we focus on. We next show that intraday swap movements significantly affect daily credit spreads and equity returns in a time-varying manner and, consistent with our findings using daily measures, movements in *intraday* expected inflation reduce credit risk and increase returns at a greater rate when the bond-stock correlation is lower.

[4]We also 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 inflation risk premia), and ensure that our results are not driven by liquidity issues in inflation swaps and CDS markets.

By definition, part of the change in inflation expectations occurs due to the headline macroeconomic surprise. However, there might exist an important residual component (i.e., non-headline news) as well that better describes the multidimensionality of macroeconomic announcement releases. To understand which of these two sources matter for the the market reaction, we decompose the intraday movements of inflation swaps using a heteroskedasticity-based approach (e.g., Rigobon and Sack (2004)). Following Gürkaynak, Kisacikoğlu, and Wright (2020), we leverage the greater variance in swap prices across all maturities on announcement days (versus non-announcement days), and identify a latent factor orthogonal to macroeconomic surprises. This latent factor captures the non-headline surprise component of macroeconomic announcements and accounts for over 60 percent of the total variation in the intraday five-year swap change. We show that this latent component significantly affects credit and equity markets above and beyond the headline component and helps to better capture their time-varying responsiveness.

In the last part of the paper, we rationalize our empirical analysis using an economic model that features a time-varying nominal-real covariance and persistent macroeconomic expectations (i.e., long-run risks). Building on Bansal and Yaron (2004) and Bansal and Shaliastovich (2013), this time-varying covariance between expected real growth and inflation shocks 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. To speak to credit spreads in the model, we also extend the long-run risks framework to price defaultable CDS, while accounting for the time-varying dynamics.

The calibrated model provides a number of implications consistent with the empirical analysis. First, the endogenous model-implied bond-stock return correlation behaves one-to-one with the real growth-inflation covariance. While this covariance ideally would be available on a real-time basis in the data, our framework shows that the bond-stock correlation serves as an excellent proxy. Second, when the covariance is significantly positive (i.e., a good inflation regime), the model displays credit spreads (equity returns) that negatively (positively) respond to expected inflation shocks. Finally, our model speaks to the importance of persistent expectations. When the long-run mechanism in expected growth is attenuated, the bond-stock correlation becomes less volatile, and expected inflation shocks are less relevant for asset prices on an absolute basis.[5]

Related Literature. Our paper relates to a broad set of economic research studying the asset prices' reaction to macroeconomic news, its state dependency, and structural models designed to examine how inflation news in particular affects equity and credit markets.

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., Bernanke and Kuttner (2005), Gürkaynak, Sack, and Swanson (2005)), more recent papers have focused on inflation surprises. Gil de Rubio Cruz et al. (2023) show that firm-level close-to-open equity returns react negatively to core CPI surprises, and that firm-level characteristics (e.g., market beta, leverage, and firm size) matter for the transmission.[6] 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 one-day movements in inflation swaps surrounding CPI announcements and show that increases in swap-implied inflation expectations increase equity prices. However, relative to Chaudhary and Marrow, our swap-based identification strategy focuses on multiple macroeconomic announcement days, we investigate corporate credit securities (credit default swaps), and focus on the time-variation and cross-sectional heterogeneity of inflation sensitivities.

Recent papers have also studied the state dependent pricing of macroeco-

[5]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 toward the volatility of the bond-stock correlation.

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

nomic risks. Elenev et al. (2023) use an array of macroeconomic announcements (capacity utilization, nonfarm payrolls, CPI, GDP, among others) to show that stock markets react more steeply when the output gap is higher and short-term rates are expected to increase. 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. 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. Relative to these works, we examine reactions in both equity and credit markets, and focus on the inflation-growth relation as the key state-dependent driver.

Boons et al. (2020), a more closely related paper to ours, show that the covariance between inflation and future consumption growth helps determine the equity-implied inflation risk premium. In states where the covariance is deeply negative, high inflation beta stocks serve as hedges and the inflation risk premium is lower, if not negative. Meanwhile in positive covariance states, the risk premium increases substantially. Our study differs from Boons et al. along several dimensions. First, our study explores the transmission of inflation expectation movements around macro announcements, as opposed to lower frequency inflation shocks, which requires a different testing environment. Second, our use of firm-level credit spread data is novel and leads to additional asset pricing insights related to inflation expectations and credit markets. Finally, we find that an alternative higher frequency measure of inflation-growth covariance, the stock-bond correlation, matters for the reaction of financial markets to inflation revisions, above and beyond lower frequency measures.[7]

[7] 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. A longer

Structural models of asset prices have also examined the effect of a time-varying nominal-real covariance. Building on Bansal and Shaliastovich (2013), Burkhardt and Hasseltoft (2012) and Song (2017), we embed a regime-switching relationship between shocks to expected growth and expected inflation in a long-run risks endowment economy, and provide evidence consistent with a real-nominal covariance shift in the early 2000's. The model we propose is conceptually similar to both of these works, however we additionally price credit securities (CDS) and derive time-varying inflation sensitivities for both credit spreads and equity returns. Bhamra, Dorion, Jeanneret, and Weber (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. Based on these assumptions, increases in expected inflation reduce credit spreads and equity valuation ratios.

A model 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) and price credit default swaps. 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) highlight 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.

In what follows, Section 2 provides details regarding the key data used in our study, while Section 3 focuses on our empirical tests. In Section 4, we discuss a model that rationalizes our empirical analysis.

sample at a lower frequency allows them to detect shifts in the covariance sign.

2 Data

This section describes the main data used to investigate the response of financial markets to changes in inflation expectations. The key objects of interest are inflation swap spreads, firm-level corporate CDS spreads and equity returns, and the time-varying correlation between aggregate stock and Treasury bond returns. All are available daily, from August 2004 to October 2023, with a focus on behavior around major macroeconomic announcements. We also use intraday inflation swap prices to confirm that daily patterns hold in a more precise setting.

Inflation Swaps. Inflation swaps are traded instruments that reflect expectations of future inflation. Each swap involves two cash flow components: a fixed payment set at the contract rate and a floating payment tied to the realized CPI inflation over the contract's term. By no-arbitrage, the contract rate represents "expected inflation;" however, as a traded security with future payoffs, it also includes a risk premium.[8]

Inflation swaps are useful for our study in a number of ways. As market contracts for longer-term inflation expectations, they link asset prices with longer-duration cash flows to the relevant views of market participants. This is different than looking at CPI inflation surprises, which are backward-looking, or inflation surveys like the Survey of Professional Forecasters or the Blue Chip Economic Indicators survey, which are only updated monthly or quarterly and do not capture immediate investor views. To this point, Diercks, Campbell, Sharpe, and Soques (2023) show that inflation swaps provide better forecasts of future inflation than survey-based measures. Moreover, breakeven inflation implied by TIPS offers a comparable measure of inflation expectations, but

[8] 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 Supplemental Appendix A using estimates from D'Amico, Kim, and Wei (2018), we show that the large majority of the time-varying sensitivity with respect to inflation compensation is driven by physical inflation expectations.

using swaps helps to avoid some of the liquidity issues prevalent in TIPS markets (see, e.g., Fleming and Sporn (2013), D'Amico et al. (2018)).

We use daily swap spreads from Bloomberg, focusing on the five-year horizon to align with the maturity of our CDS data. 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. As all of the key announcements occur at 8:30 AM ET, we compute intraday 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). Across all 622 macroeconomic releases, changes in five-year inflation swaps display a volatility of roughly 3.3 bps over the announcement window. This is fairly large considering that the daily counterpart displays a standard deviation of 4.9 bps.

Corporate CDS and Equity Returns. We include firm-level asset prices in credit and equity markets. For corporate credit risk, we use single-name CDS data at the five-year maturity from Markit[9], while daily equity returns are sourced from CRSP, matched to our CDS panel using 6-digit CUSIPs.[10] To control for outlier values in both CDS spreads and equity returns, we winsorize all data at the 0.5 percent level.

Relative to corporate bonds, there are multiple reasons why CDS data are ideal for our study. First, since 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

[9]Our approach closely follows Berndt et al. (2018), focusing on senior, unsecured bonds (tier category SNRFOR) with a no-restructuring (XR) clause, and excluding data from the *Financials, Utilities*, and *Government* sectors.

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

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

The average five-year CDS spread in our sample is 2.26 percent and exhibits a significant degree of skewness and kurtosis. The daily change in CDS spreads displays notable variation (8.4 basis points). 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. Our analysis focuses on time-variation in the inflation sensitivity of credit and equity markets and its connection to fundamental economic factors, particularly 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.

To approximate the inflation-growth relationship, we use the correlation between stock and U.S. Treasury bond returns. While not a "pure" indicator of inflation and growth, the bond-stock correlation serves as a good proxy. In Figure 1, we show rolling three-month (3M) and six-month (6M) correlations of daily aggregate stock returns (from Ken French's database) and daily U.S. Treasury bond returns (using zero-coupon 5-year yields). As is well documented in other studies, the stock-bond return correlation was strongly positive until the late 1990s, then shifted to a predominantly negative regime. This trend is clearly shown in the second panel of Figure 1, where we focus on data from July 2004 onward, overlapping with our inflation swap sample. Although there have been brief periods of positive correlation over the past 20 years (e.g., the mid-2000s and the past two years), the overall trend points to a shift from bad to good inflation regimes.

Despite the shift toward a good inflation regime, our data still show considerable variation in correlation measures. For instance, the average three-month correlation in the shorter sample ranges from -78 percent to 54 percent. In what follows, we exploit this variation to explore how the inflation-growth relationship amplifies effects on asset prices.

3 Empirical Results

Our empirical design relies on the information revealed by macroeconomic announcements. Specifically, we focus on days with data releases related to key price movements (CPI and PPI) or economic activity (nonfarm payroll and initial real GDP release). Market participants respond to surprises in these announcements by adjusting their inflation expectations. By a simple measure, the variance in swap movements is 2 to 3.5 times higher on announcement days compared to non-announcement days.[11]

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

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

where ΔY_{it} is either the one-day change in CDS spreads ($\Delta s_{it} \equiv s_{it} - s_{i,t-1}$) or excess equity returns ($R_{it} - R_{ft}$). $\Delta\pi^{swap}$ is the one-day change in five-year swap rates. Lagged variables ($X_{i,t-1}$) include CDS spreads and excess returns as these might also mechanically affect the daily change in spreads and returns. We control for firm fixed effects (β_i) and cluster standard error by firm-date, as there might be greater comovement of asset prices on event days.

The results for CDS and equity are reported in columns (1) and (4) of

[11] The degree of variance differences, between announcement and non-announcement days is dependent on the inflation swap maturity. Using swap prices in a narrow window around typical news release timings, we show that two- and three-year swaps display the highest degree of variance increases.

Table 1, respectively. We find that a positive change in inflation swaps significantly reduces CDS spreads – that is, higher expected inflation unconditionally reduces credit risk. A one standard deviation change in inflation swaps is associated with a 0.90 basis point reduction in CDS, while excess stock returns for the average firm increase by 38 basis points. Although the coefficient magnitude may seem small, such a change corresponds to about 12 (17) percent of the daily standard deviation in CDS rate changes (equity returns) during relevant macroeconomic announcement days.[12] The unconditional response of asset prices to expected inflation movements is qualitatively consistent across the two asset classes. 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.

This unconditional effect may mask time variation and potential reversals. Our hypothesis is that the market-perceived relationship between expected inflation and growth matters significantly for valuation purposes. To empirically test for this time variation, we add an interaction term between expected inflation changes and the stock-bond return correlation, which we use as a proxy for the inflation-growth relationship. We measure this correlation over a 3-month horizon, and for robustness, also over a 6-month horizon.[13] The baseline specification in Equation (1) becomes:

$$\Delta Y_{it} = \beta_i + \beta_\pi \Delta\pi_t^{swap} + \beta_\rho \tilde{\rho}_{t-1} + \beta_{\rho\pi}\left(\tilde{\rho}_{t-1} \times \Delta\pi_t^{swap}\right) + \beta_X' X_{i,t-1} + \varepsilon_{it}, \quad (2)$$

where $\tilde{\rho}$ is one of the correlation measures.[14] We standardize $\tilde{\rho}$ so that $\beta_{\rho\pi}$ indicates the additional sensitivity to changes in inflation swap when $\tilde{\rho}$ is one standard deviation (1σ) higher. Results from this test are displayed in Table 1. In column (2), we show that a standard deviation reduction in $\tilde{\rho}$ (a movement

[12]In unreported results we show that the effect further increases in the five-day window for both CDS and equity returns.

[13]In the Appendix, we replace the stock-bond correlation with a measure based on inflation swaps and market returns, which produces similar or stronger results.

[14]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.

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 use a slower-moving measurement of the stock-bond correlation.

Our results have an intuitive explanation. Because risk-free bonds yield negative real returns during inflationary periods, while stock returns align with longer-term growth expectations, the stock-bond return correlation serves as a negative proxy for the inflation-growth relationship. Lower values of $\tilde{\rho}$ suggest that inflation movements are seen as "good inflation," while higher, positive values—as observed in the mid-2000s, mid-2010s, and more recently—indicate "bad inflation." Consistently, when $\tilde{\rho}$ is very negative, the CDS response to inflation shocks is more pronounced downward. For example, with $\tilde{\rho} = -2$, the response to $\Delta\pi^{swap}$ becomes $-2.03 = -0.81 - 2 \times 0.61$. Conversely, when $\tilde{\rho}$ is positive, a strong stock-bond correlation can drive up credit risk following an inflation increase.

In the right-most columns of Table 1, we observe similar time-varying effects for equity returns. On average, a one-day response to a standard deviation increase in expected inflation is 38 basis points, but this impact grows in "good inflation" conditions. For example, when $\tilde{\rho} = -2$, the response reaches 0.79 percent $= 0.35 + 2 \times 0.22$ (column (5)), consistent with our hypothesis and results from CDS. These findings remain robust with the six-month measure (column (6)). Our equity results also align with Boons et al. (2020), which shows that the risk of inflation varies over time in the stock markets based on the degree of predictability of growth by inflation.

Overall, our analysis offers strong evidence that credit and equity markets respond in a time-varying manner to revisions in expected inflation. News of rising inflation expectations boosts valuations (i.e., lowers CDS spreads and raises equity returns) more significantly when these inflation movements signal future economic expansion. Conversely, positive inflation expectations raise valuations less—or may even harm them—when they signal potential economic slowdowns ahead.

3.1 Additional Results

In this subsection, we extend our analysis by exploring three main areas: the influence of credit risk premia versus expected losses toward the overall inflation sensitivity of CDS, the time-varying inflation response for firms with different risk profiles, and a comparison of the bond-stock correlation with alternative measures from the literature that reflect nominal-real covariance.

3.1.1 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 co-movement of investor marginal utility and losses in default. We decompose CDS spreads into these two components, by approximating the methodology in Berndt et al. (2018), which we describe in detail in the Appendix. Using this decomposition, we examine whether the inflation sensitivity of credit securities arises from expected losses (EL_{it}) or risk premia (RP_{it}). We do so by modifying Equation (2) using either ΔEL_{it} or ΔRP_{it} as the dependent variable and additionally controlling for the lagged expected loss component. Table 2 reports the results. Although the sample size is reduced by half due to the need of Moody's EDF data for expected losses, the average unconditional (column (1)) and conditional (column (4)) sensitivities of CDS changes to expected inflation remains close to the full-sample estimates.

Columns (2) and (3) suggest that the large majority of unconditional inflation sensitivity operates through the risk premium channel.[15] Close to two thirds of the overall sensitivity is attributable to ΔRP. More importantly, columns (5) and (6) show that risk premia drive most of the time-varying effect. Inflation-growth perceptions primarily influence inflation risk pricing through risk premia, however, the interaction term is also significant in the expected loss component, indicating a consistent change in default probabilities. Columns (7) through (9) confirm the robustness of these findings with a

[15] In theory, coefficients from the ΔEL and ΔRP should add up to those from the overall spread regression. The minor discrepancies in the table arise from winsorization of all firm-level dependent and independent variables.

longer stock-bond correlation window.

3.1.2 Time Variation in the Cross-Section

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 news (e.g., Palazzo and Yamarthy (2022)). We combine the cross-sectional heterogeneity with time variation to study potential interaction effects. We re-examine the results from Equation (2) by credit risk group, using a simple measure of risk – a quintile sort of CDS spreads on the day *prior* to the macroeconomic announcement. We report results in Table 3. CDS-based regressions are reported in columns (1) through (4). To facilitate comparisons to the average effect, the first column repeats an earlier result regarding the time-varying nature of inflation responsiveness, across all firms. Meanwhile, the next three columns focus on risk groups 1, 3, and 5 based on the ex-ante CDS values. 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. When combined with similar findings for equities (right four columns), we can conclude that there is an increased time-varying amplification of inflation responsiveness for riskier firms.

These findings clearly illustrate the need to jointly think about the cross-section and time-variation of inflation sensitivity. The baseline result in column (1) shows that CDS 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.).

3.1.3 Alternative Measures of Time Varying Inflation

Our baseline specification uses the stock-bond correlation as a proxy for the time-varying nominal-real covariance. While our model – discussed in detail later – establishes a direct link between the two, the bond-stock correlation may be a noisy proxy, as many factors beyond inflation and real growth could influence it. Here, we examine whether the monthly nominal-real covariance measure suggested by Boons et al. (2020) serves as a better proxy. Additionally, building on Elenev et al. (2023), we test whether capacity utilization, a measure of economic slack, is relevant for the time-varying inflation sensitivity of financial markets.

We follow the methodology of Boons et al., to construct the regression-based covariance measure. We use monthly nondurables and services consumption data from NIPA, deflate it with the PCE price index, and normalize it by population to create a real, per capita consumption series. We run the following predictive regression:

$$\Delta C_{s+1:s+12} = \alpha_t + \beta_t \Pi_s + e_{s+1:s+12}, \qquad \text{for } s = 1, \ldots, t-12 \tag{3}$$

where Π_s is the monthly PCE inflation rate, and $\Delta C_{s+1:s+12}$ is the future annual consumption growth rate. The baseline specification uses an expanding window, weighted least squares, with more weight on recent observations (exponentially decaying with a half-life of 60 months). We also test a rolling regression (OLS) over the past 60 months in our panel regression analysis.

In Table 4, we repeat our baseline tests from Equation 2, replacing the bond-stock correlation with the measures described above. All measures are standardized within the interaction effect term, using values available before the announcement day. The top panel focuses on CDS changes around macroeconomic announcements. Columns (2) and (3) show that the nominal-real covariance measures (expanding and rolling) yield expected coefficients: when covariance is more positive (indicating a good inflation environment), CDS spreads decrease further in response to swap movements. Although the capacity utilization coefficient sign is reasonable, implying that more economic slack leads to a better credit outcome, it is statistically insignificant. In columns (5) through (7), we compare the bond-stock correlation measure with the other three and show that the bond-stock correlation is a stronger driver of the time-varying inflation responsiveness. The bottom panel examines equities, where the bond-stock correlation outperforms most measures, with only the expanding window covariance marginally more important (0.19 versus 0.15). In summary, the bond-stock correlation serves as a strong indicator for good and bad inflation regimes, particularly so in credit markets.

3.2 Evidence from High Frequency Swap Prices

In this subsection, we address the question whether daily swap changes directly respond to news announcements, or whether they reflect the endogenous formation of inflation beliefs following economic news. We focus on the behavior of inflation swap prices in a narrower window surrounding macroeconomic news announcements. We show that asset prices respond in a meaningful manner to a more precisely measured change in inflation expectations. Towards the end of this subsection, we show that information beyond the headline macro surprise matters for asset prices.

3.2.1 Measuring Time-Variation Using Intraday Swaps

We focus on inflation swap changes in 60-minute window (8:15 AM to 9:15 AM EST) around our six macroeconomic announcement, which are all released at 8:30 AM EST on a monthly or quarterly basis. To avoid overlap with FOMC announcements, we exclude days when both macroeconomic and FOMC news are released. This results in 622 announcements from the merged sample of intraday inflation swap data, available starting from October 2007.[16]

We modify our baseline regression replacing daily movements in swap rates with high-frequency movements in swap rates ($\Delta\pi_t^{idswap}$). Table 5 reports the results. While the magnitudes are lower relative to the daily data, column (1) shows that intraday movements in swaps reduce credit risk. The effect of time-variation is strong, however. In column (2), we show that CDS spreads continue to display a time-varying sensitivity to intraday spread changes, as a function of the recent bond-stock correlation. In columns (5) and (6), we repeat the analysis and find that equity markets also respond in a time-varying

[16] In the Supplemental Appendix, we confirm that these announcements are of relevance for inflation swaps. To do so, we project 60-minute changes in inflation swaps onto standardized surprise measures and show that all of them significantly move inflation swap prices.

manner to intraday swap movements. Although the coefficient magnitudes are smaller generally, we interpret this as markets being slower to react; the response becomes clearer over the course of the trading day as inflation swaps incorporate economic information, influencing both credit and equity markets.

3.2.2 Latent Component in Inflation Swaps

High-frequency event studies usually focus solely on headline surprises from news releases. This narrow focus overlooks other valuable information in the announcements, making it challenging to fully explain asset price movements. We address this issue by applying Gürkaynak et al. (2020)'s heteroskedasticity-based approach to inflation swaps, using a Kalman filter one-step estimator to identify a latent factor orthogonal to macroeconomic news.[17] Using intraday inflation swap data from both announcement and non-announcement days, we estimate the following model :

$$y_t^i = \beta_i' s_t + \gamma_i d_t f_t + \eta_t^i, \tag{4}$$

where y_t^i is the vector of 60-minute window intraday changes in inflation swaps rate for various maturities i (1, 2, 3, 5, 7, and 10 years), and s_t is the vector of surprises. If an announcement occurs on a given day, d_t equals 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 maturities, with varying loadings (γ_i).[18] When estimating Model (4), 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. Next, we decompose intraday changes in inflation swaps

[17] Gürkaynak et al. methodology requires swap residuals to be heteroskedastic, with larger residual variance on announcement days compared to non-announcement days. We demonstrate this statistically in the Appendix.

[18] For more details regarding the estimation results, see Appendix A. 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.

into headline (surprises) and non-headline (latent factor) components,

$$\Delta\pi_t^{idswap,i} = \underbrace{\beta_i' s_t}_{\Delta\pi_t^{surp,i}} + \underbrace{\gamma_i d_t f_t}_{\Delta\pi_t^{latent,i}} + \eta_t^i, \tag{5}$$

for each maturity i. Focusing on the five-year maturity, we modify our baseline regression to include both components:

$$\begin{aligned} \Delta Y_{it} = \beta_i + \beta_{\pi_s}\Delta\pi_t^{surp} + \beta_{\pi_l}\Delta\pi_t^{latent} + \beta_\rho\tilde{\rho}_{t-1} + \\ \beta_{\rho\pi_s}\left(\tilde{\rho}_{t-1}\times\Delta\pi_t^{surp}\right) + \beta_{\rho\pi_l}\left(\tilde{\rho}_{t-1}\times\Delta\pi_t^{latent}\right) + \beta_X' X_{i,t-1} + \varepsilon_{it}. \end{aligned} \tag{6}$$

Table 5 presents the results. In column (3), we show the response of CDS spread changes to the surprise and latent factor components. Consistent with the estimation results, the latent factor has the largest effect and drives the negative reaction of CDS spreads unconditionallly. In column (4), we incorporate interaction effects with the lagged bond-stock return correlation and find significant time-varying sensitivities, for both the surprise and latent factor components. In columns (7) and (8), we repeat these tests using daily equity returns. Though the results are weaker than for CDS spreads, the latent factor matters unconditionally and in a time-varying manner. These findings provide additional evidence that information on inflation expectations, beyond headline surprises, are incorporated with significant time variation.

3.3 Robustness and Extensions

In this subsection, we briefly discuss some robustness exercises and extensions. Additional details regarding each analysis can be found in Appendix A. TIPS-implied breakeven inflation can serve as an alternative measure of expected inflation. We confirm that our main results hold when using five-year breakeven inflation in place of inflation swaps. Additionally, we find qualitatively consistent results when we replace our bond-stock correlation measure with a measure based on inflation swap movements and market returns.

To ensure that our results are driven by physical inflation expectations, as opposed to risk premia effects, we use data from D'Amico et al. (2018) based on a term structure model fitted to TIPS and nominal yields. While these results are specific to D'Amico et al.'s model estimate, they provide evidence that physical inflation expectations largely explain the time-varying responsiveness.

We also examine whether our results are driven by low liquidity periods in either inflation swap or CDS markets. Although we lack direct data on trading volume for the former, we use alternative measures. In a frictionless environment, inflation swaps and breakeven inflation should display prices that closely align with each other, while in a low liquidity environment the disagreement could be larger. We show that our results are driven by periods where the absolute difference in swap versus breakeven inflation is smaller.[19] For CDS, we use the number of dealers as a measure of liquidity. Our results are stronger for firms with more dealers (above the median) on announcement days, suggesting that more liquid CDS amplify our results.

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

4 Economic Model

In the second part of the paper, we present an equilibrium asset pricing model to study how inflation expectations are priced in credit and equity markets. Our model explicitly shows that the covariance of inflation and real growth is

[19] Additionally, we show similar results using the absolute difference between swap rates and the D'Amico et al. (2018) inflation compensation measure mentioned above.

one-to-one with the sign and magnitude of the endogenous bond-stock correlation.[20] Furthermore, the variation in this covariance determines the time-varying sensitivity of risky asset prices to expected inflation news. We conclude by discussing the role of persistent growth expectations.

4.1 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 expected inflation are crucial determinants of asset prices. Real and nominal fundamentals – that is, consumption growth and inflation – are partially determined by persistent components as follows:

$$\begin{aligned}
\Delta c_{t+1} &= \mu_c + x_{ct} + \sigma_c \varepsilon_{c,t+1}, \\
\pi_{t+1} &= \mu_\pi + x_{\pi t} + \sigma_\pi \varepsilon_{\pi,t+1}, \\
X_t \equiv \begin{pmatrix} x_{ct} \\ x_{\pi t} \end{pmatrix} &= \Pi X_{t-1} + \Sigma_{t-1}\eta_t, \\
\Sigma_t &= \begin{pmatrix} \sigma_{xc} & \sigma_{xc\pi}(s_t) \\ 0 & \sigma_{x\pi} \end{pmatrix},
\end{aligned} \tag{7}$$

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, with transition probability from state i to j denoted as p_{ij}. Naturally, $\sum_j p_{ij} = 1$ 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

[20] 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 et al. (2020) and Fang, Liu, and Roussanov (2023) attribute this change to the changing correlation between consumption growth and inflation – that is, the nominal channel.

shocks. 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 clear and parsimonious mechanism that works through the expected inflation channel.

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

$$V_t = \left[(1-\delta) C_t^{\frac{1-\gamma}{\theta}} + \delta \left(\mathbb{E}_t \left(V_{t+1}^{1-\gamma} \right) \right)^{\frac{1}{\theta}} \right]^{\frac{\theta}{1-\gamma}}, \tag{8}$$

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:

$$\begin{aligned} m_{t+1} &= \theta \log \delta - \frac{\theta}{\psi} \Delta c_{t+1} - (1-\theta) r_{c,t+1}, \\ r_{c,t+1} &= \kappa_0 + \kappa_1 pc_{t+1} - pc_t + \Delta c_{t+1}, \end{aligned} \tag{9}$$

where m is the stochastic discount factor, Δc is the log consumption growth, pc is the log price-to-consumption ratio, and r_c is the return on an asset that pays off the aggregate consumption tree as a dividend. Using the Campbell and Shiller (1988) log-linear return approximation, we write the log return in the linear form shown above, where κ_0 and κ_1 are constants that are a function of the average pc. Moreover, for any asset i, including the consumption-paying asset, the Euler condition holds: $E_t \left[\exp \left(m_{t+1} + r_{i,t+1} \right) \right] = 1$.

We focus on the consumption return as a proxy for aggregate equity returns. While the level and volatility of this asset return is less than the empirical counterparts for the aggregate stock market returns, we are mostly concerned about its cyclical properties. It is straightforward to extend the model to price a levered dividend claim, as done in Bansal and Yaron (2004).

4.1.1 Model Solution and Risk-Free Nominal Bonds

To solve the model, we first characterize the equilibrium price-consumption ratio. Based on the Euler equation 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. For a given set of fundamental parameters, A_1 can be solved directly while A_2 is solved numerically through a system of equations. For details regarding the model solution, see Appendix C.

To compute the bond-stock return correlation, we 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:

$$\exp\left(r_{f,t+1}^{\$,n}\right) = \frac{P_{f,t+1}^{\$,n-1}}{P_{f,t}^{\$,n}} = \exp\left(p_{f,t+1}^{\$,n-1} - p_{f,t}^{\$,n}\right), \tag{10}$$

where $P_{f,t}^{\$,n}$ is the price of a nominal risk-free bond at time t maturing at $t+n$, with lowercase indicating its log value. We 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 Ang and Piazzesi (2003), we first derive the coefficient values for a one-period risk-free bond and then show that maturity n coefficients can be written recursively. Based on these results, we compute nominal bond prices and corresponding bond returns. See Appendix C for details.

4.1.2 Pricing CDS

We also extend the model to price inflation risk in credit markets. While the long-run risks literature largely focuses on asset pricing implications for equity and risk free bond markets, less work has examined its implications for credit markets.[21] As given in Berndt et al. (2018), the CDS of maturity K periods

[21] Augustin (2018) is an exception and our model uses many elements from his work as a starting point, while embedding the time-varying covariance of real and nominal shocks.

is a rate C_t that satisfies:

$$\Delta C_t \sum_{k=1}^{K/\Delta} \mathbb{E}_t \left[\tilde{M}^{\$}_{t+k\Delta} \left(1 - D_{t,(k-1)\Delta}\right) \right] = \sum_{k=1}^{K/\Delta} \mathbb{E}_t \left[\tilde{M}^{\$}_{t+k\Delta} \times (1-R) \times D_{t+(k-1)\Delta,\Delta} \right], \quad (11)$$

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 $(1-R)$, and that default occurs shortly before the end of each period. Assuming quarterly payments ($\Delta = 1$), we can write the five-year CDS as:

$$C_t = \frac{\sum_{k=1}^{20} \mathbb{E}_t \left[\tilde{M}^{\$}_{t+k} \times (1-R) \times D_{t+k-1,1} \right]}{\sum_{k=1}^{20} \mathbb{E}_t \left[\tilde{M}^{\$}_{t+k} \left(1 - D_{t,k-1}\right) \right]} = (1-R) \times \left(1 - \frac{\sum_{k=1}^{20} \mathbb{E}_t \left[\tilde{M}^{\$}_{t+k} S_{t,t+k} \right]}{\sum_{k=1}^{20} \mathbb{E}_t \left[\tilde{M}^{\$}_{t+k} S_{t,t+k-1} \right]} \right), \quad (12)$$

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

Following Augustin (2018) and Doshi, Elkamhi, and Ornthanalai (2018), we assume that default dynamics are exogenous and related to key state variables. While 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:

$$D_{t,1} = \begin{cases} 0 & \text{w/probability } \exp\left(-\lambda_t\right), \\ 1 & 1 - \exp\left(-\lambda_t\right), \end{cases} \quad (13)$$

where the realization is conditionally independent of all other model variables. The ex-ante probability (hazard rate) is based on $\lambda_t = \beta_{\lambda 0}(s_t) + \beta'_{\lambda x} X_t$, which 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.[22]

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

To solve for CDS prices, we need to compute, for all k, $\mathbb{E}_t\left[\tilde{M}^{\$}_{t+k}S_{t,t+k}\right]$ and $\mathbb{E}_t\left[\tilde{M}^{\$}_{t+k}S_{t,t+k-1}\right]$, under the preference assumptions and model fundamentals. Using the Law of Iterated Expectations and conditional independence assumption of default, we show that there exist coefficients, B_1^k and $B_2^k(i)$, such that $\mathbb{E}_t\left[\tilde{M}^{\$}_{t+k}S_{t,t+k}\right] = \exp\left(B_1^{k\prime}X_t + B_2^k(s_t)\right)$. Similarly, coefficients C_1^k and $C_2^k(i)$ can be found for $\mathbb{E}_t\left[\tilde{M}^{\$}_{t+k}S_{t,t+k-1}\right]$. These coefficients 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:

$$C_t = (1-R)\times\left(1 - \frac{\sum_{k=1}^{20}\exp\left(B_1^{k\prime}X_t + B_2^k(s_t)\right)}{\sum_{k=1}^{20}\exp\left(C_1^{k\prime}X_t + C_2^k(s_t)\right)}\right), \tag{14}$$

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

4.2 Model Results

In this subsection, we describe the model's key mechanism, illustrate the baseline calibration, and discuss comparative statics. Finally, we show how persistent expectations interact with the time-varying real-nominal covariance.

4.2.1 Key Mechanism

We start by studying the covariance between expected inflation and growth shocks, which is directly affected by $\sigma_{xc\pi}$. We show that this parameter directly connects to the endogenous stock-bond correlation. In this exercise, we assume that $\sigma_{xc\pi}$ is constant and we vary it to examine the model's performance. As we change parameter values, we also ensure that the unconditional variance of expected growth does not change.[23] Fundamental model parameters are set to target values from the data.

Figure 2 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 the covariance parameter. Focusing on

[23]This is done by directly resizing the constant parameter, σ_{xc} in the growth equation.

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 real consumption growth ($\uparrow \sigma_{xc\pi}$), bond returns become more of a hedge. The reason being that potential shocks to expected inflation increase nominal yields (lead to negative bond returns) while increasing the payoffs of the consumption asset (positive stock returns). A similar interpretation holds in the opposite direction.

Furthermore, this exercise suggests that the model generates sizable movements in the bond-stock correlation. Hence, embeddding movements in $\sigma_{xc\pi}$ can generate plausible variation in this correlation and explain the patterns we see in the data. In what follows, we examine the implications of a time-varying $\sigma_{xc\pi}$.

4.2.2 Model Performance

In line with the long-run risks literature, we calibrate the model at a quarterly frequency and make two simplifying assumptions. First, the autoregressive matrix Π is set to be diagonal with no cross dependencies to allow for a clean interpretation of the covariance parameter as the sole source of the real-nominal interaction. Second, the number of regimes is $N = 2$ so that we have distinctive "good" and "bad" inflation regimes.

Many parameters are taken from the literature or calibrated directly to macroeconomic moments. Regarding the inflation-growth covariance parameter, $\sigma_{xc\pi}$, we calibrate it to be positive in the first regime indicating a good inflation regime, and its relative size such that the model unconditionally delivers a negative bond-stock return correlation. Credit-related parameters regarding recovery rates and the sensitivity of default rates to expected growth are also informed by the data. For more calibration details, see Appendix D.

Based on these parameter values, we solve the model and simulate $40,000$ quarters, including a burn-in period. The first column in Table 6 presents the asset pricing moments of the baseline model. The model does a reasonable job with the annualized nominal risk-free rate (4.63 percent), which is close to the average three-month Treasury bill rate over time. Similarly, the model produces a substantial annual equity premium (0.91 percent) that would be similar to the 5 percent value seen in the data if we employed a levered dividend claim. The average, annualized five-year CDS spread in the model is considerable (1.34 percent) with a reasonable volatility of credit spread movements (5.4 basis points).[24] In terms of risk-free bonds and stocks, the unconditional return correlation in the model is −15 percent as the dynamics from the "good inflation" regime dominate.[25] More specifically, the correlation is −45 percent in the good regime, and 28 percent within the bad regime. These values are reasonable in comparison with the ones documented in the empirical part.

To further understand the model, we use the simulated asset price data to run univariate regressions of spread changes and excess equity returns onto inflation expectation movements. These regressions test the model's ability to generate time-varying asset price sensitivities, similar to the data. In the first column of Table 6, we show that the model can generate differential inflation effects across the two regimes. On average, a standard deviation increase in $\Delta x_{\pi t}$ is associated with a 1.6 basis point decline in CDS spreads. In regime 1, the good regime, this coefficient more than doubles to a 6.3 basis point decline; while in the bad regime, a movement in expected inflation is associated with a 3.1 basis point increase. Similar results obtain for model-implied excess equity returns. A positive movement in inflation expectations increases equity prices. In good inflation regimes, this sensitivity is further amplified. Moreover, across both asset classes, the model displays qualitatively similar behavior as in the data.

4.2.3 Comparative Statics

To better understand the model mechanisms, we examine how the model performs under different parameter configurations and compare them to the base-

[24]The behavior of credit spreads in the model is particularly noteworthy given the parameter restrictions on the hazard rate ($\beta_{\lambda xc}$).

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

line.[26] We begin by looking at a calibration 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 second column of Table 6 ("Model 1"). We see that the absolute size of the bond-stock correlation has shrunk close to zero (0.09) and, similarly, the degree to which risky asset prices respond to inflation shocks is significantly reduced. Now, a standard deviation movement in expected inflation shocks only moves equity returns by about 1 basis point in absolute terms, compared to the 23 basis points in the baseline case. Similarly, CDS spreads move by roughly 0.01 basis points in response to the same shock.[27]

Next, we examine how the model performs under a symmetric calibration of the covariance parameter ("Model 2", $\sigma_{xc\pi}(s_1) = 6 \times 10^{-4}, \sigma_{xc\pi}(s_2) = -6 \times 10^{-4}$). Under this configuration, the model generates a greater absolute bond-stock correlation in the bad regime versus the good regime, thus determining an unconditional bias toward 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.

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 more for asset prices. Starting from the Baseline model, where $\Pi_{cc} = 0.95$, we lower this parameter to 0.85 and examine the model's performance in the final column of the table. We observe that the annualized risk premium reduces 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 correlations, CDS sensitivities, and equity sensitivities all shrink, suggesting a lower volatility of these quantities overall.

[26] Similar to the exercise in Figure 2, 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.

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

We can more directly see this result in Figure 2, which conveys the model-implied return correlation under a lower persistence of the expected growth component ($\Pi_{cc} = 0.85$, dashed red line). Similar to the baseline case, as $\sigma_{xc\pi}$ increases, the return correlation reduces. However, the bond-stock correlation is much less sensitive to movements in the covariance term. Because expected inflation shocks are embedded for a shorter duration of time, a movement in the covariance parameter governing the expected inflation shock has less impact on the correlation of assets that embed long-term cash flows. Due to a similar logic, the magnitude of the equity return and CDS responsiveness 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.

5 Conclusion

We study how changes in expected inflation affect 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, changes in expected inflation 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 nominal-real covariance..

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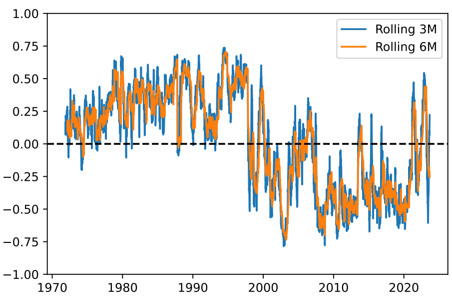
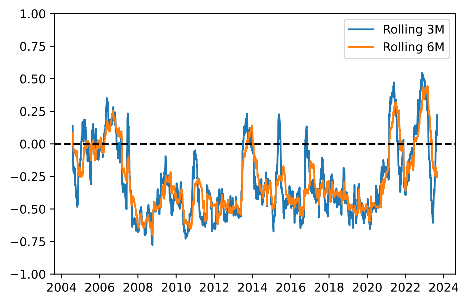
Figure 1: **Bond-Stock Return Correlation Over Time**

(a) Full Sample (Post 1970)

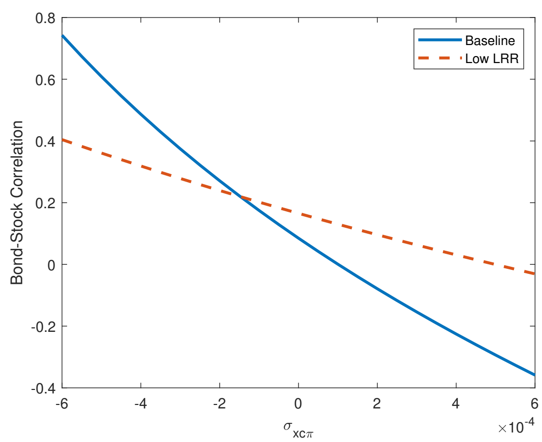


(b) Swap Sample (Post 2004)



The left 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 right figure displays the same measures over the period where inflation swaps are available (July 2004 and onwards).

Figure 2: **Model-Implied Bond-Stock 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.

Table 1: **Time-Varying Inflation Sensitivity of Financial Markets**

	(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 sensitivities of credit and equity markets to movements in inflation expectations. Columns (1) and (4) report the unconditional response, for CDS spreads and equities, respectively. Columns (2) and (5) report results where the inflation swap movements are interacted with the bond-stock correlation estimated using the 3-month rolling correlation, while columns (3) 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 spread or CDS spread 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 2: **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.)	ΔEL_i	ΔRP_i	Δs_i (b.p.)	ΔEL_i	ΔRP_i	Δs_i (b.p.)	ΔEL_i	ΔRP_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 sensitivity of CDS spreads, expected losses, and credit risk premia to movements in inflation expectations. Columns (1) - (3) report unconditional results. Columns (4) - (6) report time-varying sensitvities where inflation expectation movements are interacted with the bond-stock correlation estimated using the 3-month rolling correlation. Columns (7) - (9) report analogous results where inflation expectation movements are interacted with the inflation swap-stock correlation estimated using 6-month rolling correlation. Within each panel, from left to right, columns focus on movements in CDS spreads overall, the expected loss component, and credit risk premia. 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 3: **Time Varying Inflation Sensitivity 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 sensitivities of credit and equity markets to inflation expectation movements, across different risk groups. 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. Columns (1) - (4) focus on movements in CDS spreads overall, while columns (5) - (8) on equity returns. Within each panel, the left most column reports the unconditional result, and the right three columns focus on risk groups 1, 3, and 5. In all regressions, we include either the CDS spread or the CDS spread 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 4: **Time-Varying Inflation Sensitivity 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 time-varying sensitivities of credit and equity markets to inflation expectation movements, using alternative measures of the inflation-growth covariance. 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 bond-stock correlation and alternative measures. In all regressions, we include the CDS spread or CDS spread 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: **Intraday Swaps and Risky Asset Prices**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta\pi^{idswap,5Y}$	-0.22	-0.28*			0.14	0.19*		
	(-1.55)	(-1.79)			(1.45)	(1.65)		
$\Delta\pi^{surp,5Y}$			-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)
$\tilde{\rho}_{-1}^{bond-mkt,3M} \times \Delta\pi^{idswap,5Y}$		0.37***				-0.28***		
		(2.77)				(-2.95)		
$\tilde{\rho}_{-1}^{bond-mkt,3M} \times \Delta\pi^{surp,5Y}$				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)
$\tilde{\rho}_{-1}^{bond-mkt,3M}$		-0.04		-0.05		0.06		0.08
		(-0.39)		(-0.59)		(0.98)		(1.43)
$s_{i,-1}$	0.17**	0.18***	0.17***	0.18***	0.00	-0.00	0.00	0.00
	(2.58)	(2.67)	(2.62)	(2.71)	(0.13)	(-0.05)	(0.10)	(0.03)
$(R^i - R^f)_{-1}$					0.02	0.02	0.01	0.01
					(0.64)	(0.71)	(0.59)	(0.55)
Dependent Variable	Δs_i		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	350,067	358,035	350,067	172,046	170,166	172,046	170,166
Adj.R^2	0.011	0.012	0.012	0.015	0.004	0.019	0.005	0.020

This table reports sensitivities of credit and equity markets to intraday inflation expectation movements. The left (right) four columns report results where daily CDS spreads (equity returns) are the dependent variable. Columns (1) and (5) examine the unconditional sensitivity of asset prices with respect to the intraday swap change, while columns (2) and (6) additionally report time-varying results using the same intraday swap change interacted with the 3-month bond-stock return correlation. Columns (5) and (7) examine the unconditional sensitivity of asset prices with respect to the surprise and latent components of intraday inflation swap movements. Finally, columns (6) and (8) report time-varying results using the above surprise and latent components. 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 spread or CDS spread 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 6: **Model Performance and Comparative Statics**

	Baseline	Model 1 ($\sigma_{xc\pi} = 0$)	Model 2 (Symmetric $\sigma_{xc\pi}$)	Model 3 ($\Pi_{cc} = .85$)
$E[pc_t]$	7.607	7.311	7.312	8.521
$E[r_{ct}]$	2.011	1.971	2.001	1.732
$E\left[r_{ct}^{\$}\right]$	5.538	5.498	5.528	5.259
$E\left[r_{ft}^{\$}\right]$	4.629	4.641	4.653	4.89
$E[r_{ct} - r_{ft}]$	0.908	0.857	0.875	0.368
$E\left[r_{ft}^{5Y,\$}\right]$	3.466	4.284	4.273	4.499
$E\left[s_t^{5Y}\right]$	1.337	1.332	1.326	1.285
$\sigma\left[\Delta s_t^{5Y}\right]$ (b.p.)	5.371	5.095	5.009	4.611
$\rho(r_{ct}^{\$}, r_{ft}^{5Y,\$})$	-0.148	0.085	0.073	0.09
$\rho(r_{ct}^{\$}, r_{ft}^{5Y,\$})$ – Regime 1	-0.451	0.084	-0.289	-0.079
$\rho(r_{ct}^{\$}, r_{ft}^{5Y,\$})$ – Regime 2	0.284	0.086	0.501	0.28
$\beta(\Delta s_t^{5Y} \sim \Delta x_{\pi t})$ (b.p.)	-1.603	-0.005	-0.017	-0.817
$\beta(\Delta s_t^{5Y} \sim \Delta x_{\pi t})$ – Regime 1	-6.265	0.042	-4.673	-3.242
$\beta(\Delta s_t^{5Y} \sim \Delta x_{\pi t})$ – Regime 2	3.073	-0.052	4.641	1.612
$\beta(r_{ct} - r_{ft} \sim \Delta x_{\pi t})$	0.231	-0.009	-0.006	0.072
$\beta(r_{ct} - r_{ft} \sim \Delta x_{\pi t})$ – Regime 1	0.933	-0.015	0.692	0.306
$\beta(r_{ct} - r_{ft} \sim \Delta x_{\pi t})$ – Regime 2	-0.475	-0.003	-0.705	-0.162

This table reports model moments under different parameter sets. The first column reports the endogenous model asset prices, under the baseline calibration described in the text. Model 1 is a model where the covariance channel is non-existent in both regimes ($\sigma_{xc\pi} = 0$). Model 2 sets the covariance parameter to a symmetric value across regimes ($\sigma_{xc\pi}(s_1) = 6\times10^{-4}$ and $\sigma_{xc\pi}(s_2) = -6\times10^{-4}$). Model 3 sets the long-run risk parameter (Π_{cc}) to 0.85, which is less than the baseline parameter value of $\Pi_{cc} = 0.95$.

Supplemental Appendix

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 sensitivities, and replacing the bond-stock correlation measure with an alternative measure based on inflation swaps.

Intraday analysis In Section 3.2, we presented results based on intraday swap movements on announcement days. Appendix Table A2 details the macroeconomic announcements of interest, which include 622 announcements released monthly or quarterly at 8:30 AM ET. We also provide the number of announcements and the standard deviation of their surprises.

We use these macroeconomic announcements to examine whether swap residuals display heteroskedasticity across announcement and 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. These regression results are provided in Table A3. 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 A4 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 A2, TIPS-based inflation expectations (constant maturity five-year nominal yield minus constant maturity five-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 five-year breakeven inflation, $\Delta\pi^{be,5Y}$.

Appendix Table A5 shows that our main results are robust when we account for breakeven inflation. The first column shows that five-year CDS declines by 1.0 basis point, following a standard deviation movement in five-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 results using inflation swap changes, 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 also holds when looking at breakeven inflation. A more negative bond-stock correlation is associated with larger CDS declines and equity price appreciation, following an increase in inflation expectations as measured through TIPS breakeven inflation. 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 A6 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 significantly affects CDS spreads and equity returns in a time-varying manner, 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.

Inflation 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, inflation swap prices and inflation compensation measures 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 A4 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 past couple of years.

Appendix Table A7 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 percent most illiquid days based on the breakeven inflation based absolute differences while in columns (3) and (6) we remove the top 10 percent 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, Costello, and Shachar (2020)). Consequently, it is important to assess whether our results are affected by low liquidity in CDS markets. Appendix Table A8 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 is well documented, the bond-stock return correlation significantly changed sign in the late 1990s, turning from positive to negative. Because our sample focuses on the post-2004 period, it is difficult to detect discrete sign switches in inflation responsiveness. To understand whether sign switches are a possibility, we extend our equity panel back to the 1980s 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 in addition to the standardized correlation measure:

$$r_{it} - r_{ft} = \beta_i + \beta_\pi \Delta\pi_t^{InfComp} + \beta_{\rho\pi}\left(\mathbb{1}_{\{\rho_{t-1}>0\}} \times \Delta\pi_t^{InfComp}\right) + \beta_X' X_{i,t-1} + \varepsilon_{it} \quad \text{(A1)}$$

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 A9. 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 three-month or six-month 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 sensitivity 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 inflation swap prices to market returns. In Appendix Figure A5 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 1. Over the past 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 A10 displays these results. As shown through the CDS results (left three columns), regardless of the three-month or six-month 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 movement. 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.

B CDS Decomposition

CDS spreads at a given maturity is the annualized rate C_t, such that:

$$\Delta C_t \sum_{k=1}^{K/\Delta} \mathbb{E}_t \left[\tilde{M}^{\$}_{t+k\Delta} \left(1 - D_{t,(k-1)\Delta}\right) \right] = \sum_{k=1}^{K/\Delta} \mathbb{E}_t \left[\tilde{M}^{\$}_{t+k\Delta} \times L_{t+(k-1)\Delta,\Delta} \times D_{t+(k-1)\Delta,\Delta} \right] \tag{A2}$$

The only difference relative to Equation (11) 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:

$$ExpLoss_t = \frac{L_t \sum_{k=1}^{K/\Delta} d_{t,k\Delta} \mathbb{E}_t \left[D_{t+(k-1)\Delta,\Delta} \right]}{\Delta \sum_{k=1}^{K/\Delta} d_{t,k\Delta} \mathbb{E}_t \left[1 - D_{t,(k-1)\Delta} \right]} \tag{A3}$$

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 is 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, $RiskPrem_{it} = s_{it} - ExpLoss_{it}$.

C Model Solution

C.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:

$$pc_t = A_1' X_t + A_2(s_t) \tag{A4}$$

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:

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

$$(\Longleftrightarrow) \exp\left(\theta pc_t\right) = \mathbb{E}_t \left[\exp\left(\theta \log \delta + (1-\gamma)\Delta c_{t+1} + \theta\kappa_0 + \theta\kappa_1 pc_{t+1}\right)\right] \tag{A5}$$

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

$$
\begin{aligned}
\exp\left(\theta pc_t\right) &= \mathbb{E}_t\left[\exp\left(\theta\log\delta + (1-\gamma)\Delta c_{t+1} + \theta\kappa_0 + \theta\kappa_1 pc_{t+1}\right)\right] \\
&= \mathbb{E}_t\left[\exp\left\{(1-\gamma)\sigma_c\varepsilon_{c,t+1} + \theta\kappa_1 pc_{t+1}\right\}\right] \\
&\quad \times \exp\Big(\theta\log\delta + (1-\gamma)\mu_c + \theta\kappa_0 + (1-\gamma)e_1' X_t\Big) \\
&= \mathbb{E}_t\Big[\exp\Big(\theta\kappa_1 A_1'\Sigma_t\eta_{t+1}\Big)\Big] \times \mathbb{E}_t\left[\exp\left(\theta\kappa_1 A_2(s_{t+1})\right)\right] \\
&\quad \times \exp\left(\frac{1}{2}(1-\gamma)^2\sigma_c^2 + \theta\kappa_1 A_1'\Pi X_t\right) \\
&\quad \times \exp\Big(\theta\log\delta + (1-\gamma)\mu_c + \theta\kappa_0 + (1-\gamma)e_1' X_t\Big) \\
&= \underbrace{\exp\left(\frac{1}{2}\theta^2\kappa_1^2 A_1'\Sigma_t\Sigma_t' A_1\right) \times \exp\left(\log\left\{\sum_{j=1}^{2} p_{ij}\exp\left(\theta\kappa_1 A_2(s_j)\right)\right\}\right)}_{\text{Dependent on } s_t} \\
&\quad \times \exp\left(\frac{1}{2}(1-\gamma)^2\sigma_c^2 + \theta\kappa_1 A_1'\Pi X_t\right) \\
&\quad \times \exp\Big(\theta\log\delta + (1-\gamma)\mu_c + \theta\kappa_0 + (1-\gamma)e_1' X_t\Big)
\end{aligned}
\tag{A6}
$$

Matching coefficients on X_t we receive:

$$
\begin{aligned}
\theta A_1' &= (1-\gamma)e_1' + \theta\kappa_1 A_1'\Pi \\
A_1 &= (1-\frac{1}{\psi}) \times (I - \kappa_1\Pi')^{-1} e_1
\end{aligned}
\tag{A7}
$$

Matching coefficients on s_t we receive:

$$
\begin{aligned}
\theta A_2(s_t = i) &= \theta\log\delta + (1-\gamma)\mu_c + \theta\kappa_0 + \frac{1}{2}(1-\gamma)^2\sigma_c^2 \\
&\quad + \frac{1}{2}\theta^2\kappa_1^2 A_1'\Sigma_t\Sigma_t' A_1 + \log\left\{\sum_{j=1}^{N} p_{ij}\exp\left(\theta\kappa_1 A_2(s_j)\right)\right\} \\
&\text{for } i = 1, \ldots, N
\end{aligned}
\tag{A8}
$$

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

C.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:

$$\exp\left(r^{\$,n}_{f,t+1}\right) = \frac{P^{\$,n-1}_{f,t+1}}{P^{\$,n}_{f,t}} = \exp\left(p^{\$,n-1}_{f,t+1} - p^{\$,n}_{f,t}\right) \tag{A9}$$

where $P^{\$,n}_{f,t}$ 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:

$$p^{\$,n}_{f,t} = P^{n'}_1 X_t + P^n_2(s_t) \tag{A10}$$

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

$$\begin{aligned}
\exp\left(p^{\$,1}_{ft}\right) &= \mathbb{E}_t\left[\exp\left(m_{t+1} - \pi_{t+1}\right)\right] \\
&= \mathbb{E}_t\left[\exp\left(\theta\log\delta - \frac{\theta}{\psi}\Delta c_{t+1} - (1-\theta)r_{c,t+1} - \pi_{t+1}\right)\right] \\
&= \mathbb{E}_t\left[\exp\left(\theta\log\delta - (1-\theta+\frac{\theta}{\psi})\Delta c_{t+1} - (1-\theta)(\kappa_0 + \kappa_1 pc_{t+1} - pc_t) - \pi_{t+1}\right)\right] \\
&= \exp\left(\theta\log\delta - (1-\theta+\frac{\theta}{\psi})(\mu_c + e_1' X_t) - (1-\theta)(\kappa_0 + \kappa_1 A_1'\Pi X_t - pc_t) - (\mu_\pi + e_2' X_t)\right) \\
&\quad \times \mathbb{E}_t\left[\exp\left((1-\theta+\frac{\theta}{\psi})\sigma_c\varepsilon_{c,t+1} - (1-\theta)\left(\kappa_1 A_1'\Sigma_t\eta_{t+1} + \kappa_1 A_2(s_{t+1})\right) - \sigma_\pi\varepsilon_{\pi,t+1}\right)\right]
\end{aligned} \tag{A11}$$

Final price can be expressed as:

$$\begin{aligned}
p^{\$,1}_{ft} &= \theta\log\delta - (1-\theta+\frac{\theta}{\psi})\mu_c - (1-\theta)\kappa_0 - \mu_\pi + \frac{1}{2}(1-\theta+\frac{\theta}{\psi})^2\sigma_c^2 + \frac{1}{2}\sigma_\pi^2 \\
&\quad + (1-\theta)A_2(s_t) + \frac{1}{2}(1-\theta)^2\kappa_1^2 A_1'\Sigma_t\Sigma_t' A_1 + \log\left(\mathbb{E}_t\left[\exp\left((\theta-1)\kappa_1 A_2(s_{t+1})\right)\right]\right) \\
&\quad + \left[(\theta - 1 - \frac{\theta}{\psi})e_1' - (1-\theta)\kappa_1 A_1'\Pi + (1-\theta)A_1' - e_2'\right] X_t
\end{aligned} \tag{A12}$$

where $P^{1'}_1$ is indicated by the coefficient in the brackets in the third line, and $P^1_2(s_t)$ 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:

$$\exp\left(p_{ft}^{\$,n}\right) = \mathbb{E}_t\left[\exp\left(m_{t+1} - \pi_{t+1} + p_{f,t+1}^{\$,n-1}\right)\right] \tag{A13}$$

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

$$\begin{aligned}
\exp\left(p_{ft}^{\$,n}\right) &= \mathbb{E}_t\left[\exp\left(\theta\log\delta - (1-\theta+\frac{\theta}{\psi})\Delta c_{t+1} - (1-\theta)(\kappa_0+\kappa_1 pc_{t+1} - pc_t) - \pi_{t+1} + P_1^{n-1'}X_{t+1} + P_2^{n-1}(s_{t+1})\right)\right] \\
&= \exp\left(\theta\log\delta - (1-\theta+\frac{\theta}{\psi})(\mu_c + e_1' X_t) - (1-\theta)(\kappa_0 + \kappa_1 A_1'\Pi X_t - pc_t) - (\mu_\pi + e_2' X_t) + P_1^{n-1'}\Pi X_t\right) \\
&\quad\times \mathbb{E}_t\left[\exp\left((1-\theta+\frac{\theta}{\psi})\sigma_c\varepsilon_{c,t+1} - (1-\theta)\left(\kappa_1 A_1'\Sigma_t\eta_{t+1} + \kappa_1 A_2(s_{t+1})\right) + P_1^{n-1'}\Sigma_t\eta_{t+1} + P_2^{n-1}(s_{t+1}) - \sigma_\pi\varepsilon_{\pi,t+1}\right)\right]
\end{aligned} \tag{A14}$$

The final price can be written as:

$$\begin{aligned}
p_{ft}^{\$,n} &= \theta\log\delta - (1-\theta+\frac{\theta}{\psi})\mu_c - (1-\theta)\kappa_0 - \mu_\pi + \frac{1}{2}(1-\theta+\frac{\theta}{\psi})^2\sigma_c^2 + \frac{1}{2}\sigma_\pi^2 \\
&\quad + (1-\theta)A_2(s_t) + \frac{1}{2}\left(P_1^{n-1'} - (1-\theta)\kappa_1 A_1'\right)\Sigma_t\Sigma_t'\left(P_1^{n-1'} - (1-\theta)\kappa_1 A_1'\right)' \\
&\quad + \log\left(\mathbb{E}_t\left[\exp\left\{(\theta-1)\kappa_1 A_2(s_{t+1}) + P_2^{n-1}(s_{t+1})\right\}\right]\right) \\
&\quad + \left[(\theta - 1 - \frac{\theta}{\psi})e_1' - (1-\theta)\kappa_1 A_1'\Pi + (1-\theta)A_1' - e_2' + P_1^{n-1'}\Pi\right]X_t
\end{aligned} \tag{A15}$$

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.

C.3 CDS Spreads

As given in Equation (12) 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:

$$D_{t,1} = \begin{cases} 0 & \text{w/probability } \exp(-\lambda_t) \\ 1 & 1 - \exp(-\lambda_t) \end{cases} \tag{A16}$$

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

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:

$$\begin{aligned} \tilde{f}(s_t, x_t) &= \mathbb{E}_t\left[\tilde{M}^{\$}_{t+1} \times \exp\left(f_1' X_{t+1} + f_2(s_{t+1})\right)\right] \\ &= \mathbb{E}_t\left[\exp\left(m_{t+1} - \pi_{t+1} + f_1' X_{t+1} + f_2(s_{t+1})\right)\right] \\ &= \exp\left(\tilde{f}_1' X_t + \tilde{f}_2(s_t)\right) \end{aligned} \tag{A17}$$

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

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

$$\tilde{f}_1' = \left[(\theta - 1 - \frac{\theta}{\psi})e_1' - (1-\theta)\kappa_1 A_1'\Pi + (1-\theta)A_1' - e_2' + f_1'\Pi\right] \tag{A18}$$

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

$$\mathbb{E}_t\left[\tilde{M}^{\$}_{t+k}S_{t,t+k}\right] = \mathbb{E}_t\left[\tilde{M}^{\$}_{t+k}\Pi_{j=1}^k S_{t+j-1,1}\right] = \mathbb{E}_t\left[\tilde{M}^{\$}_{t+k}\exp\left(-\sum_{j=1}^k \lambda_{t+j-1}\right)\right] \tag{A19}$$

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

$$\begin{aligned}\mathbb{E}_t\left[\tilde{M}^{\$}_{t+1}S_{t,t+1}\right] = \exp(-\lambda_t)\times\mathbb{E}_t\left[\tilde{M}^{\$}_{t+1}\right] &= \exp\left(p^{\$,1}_{ft} - \beta_{\lambda x}'X_t - \beta_{\lambda 0}(s_t)\right) \\ &= \exp\left((P_1^1 - \beta_{\lambda x})'X_t + P_2^1(s_t) - \beta_{\lambda 0}(s_t)\right) \\ &= \exp\left(B_1^{1'}X_t + B_2^1(s_t)\right)\end{aligned} \tag{A20}$$

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

$$\begin{aligned}\mathbb{E}_t\left[\tilde{M}^{\$}_{t+k}\exp\left(-\sum_{j=1}^k\lambda_{t+j-1}\right)\right] &= \mathbb{E}_t\left[\tilde{M}^{\$}_{t+k-1}\exp\left(-\sum_{j=1}^k\lambda_{t+j-1}\right)\mathbb{E}_{t+k-1}\left[\exp\left(m_{t+k}-\pi_{t+k}\right)\right]\right] \\ &= \mathbb{E}_t\left[\tilde{M}^{\$}_{t+k-1}\exp\left(-\sum_{j=1}^k\lambda_{t+j-1}\right)\exp\left(p^{\$,1}_{f,t+k-1}\right)\right] \\ &= \mathbb{E}_t\left[\tilde{M}^{\$}_{t+k-1}\exp\left(-\sum_{j=1}^k\lambda_{t+j-1}\right)\exp\left(P_1^{1'}X_{t+k-1} + P_2^1(s_{t+k-1})\right)\right]\end{aligned} \tag{A21}$$

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:

$$
\begin{aligned}
&\mathbb{E}_t\left[\tilde{M}^{\$}_{t+k-1}\exp\left(-\sum_{j=1}^{k}\lambda_{t+j-1}\right)\exp\left(P_1^{1'}X_{t+k-1}+P_2^1(s_{t+k-1})\right)\right]=\\
&\mathbb{E}_t\left[\tilde{M}^{\$}_{t+k-2}\exp\left(-\sum_{j=1}^{k-1}\lambda_{t+j-1}\right)\mathbb{E}_{t+k-2}\left[M^{\$}_{t+k-1}\times\exp\left(P_1^{1'}X_{t+k-1}+P_2^1(s_{t+k-1})-\lambda_{t+k-1}\right)\right]\right]=\\
&\mathbb{E}_t\left[\tilde{M}^{\$}_{t+k-2}\exp\left(-\sum_{j=1}^{k-1}\lambda_{t+j-1}\right)\exp\left(\tilde{P}_1X_{t+k-2}+\tilde{P}_2(s_{t+k-2})\right)\right]=\\
&\mathbb{E}_t\left[\tilde{M}^{\$}_{t+k-3}\exp\left(-\sum_{j=1}^{k-2}\lambda_{t+j-1}\right)\mathbb{E}_{t+k-3}\left[M^{\$}_{t+k-2}\times\exp\left(\tilde{P}_1'X_{t+k-2}+\tilde{P}_2(s_{t+k-2})-\lambda_{t+k-2}\right)\right]\right]=\\
&\cdots=\exp\left(B_1^{k'}X_t+B_2^k(s_t)\right)
\end{aligned}
\tag{A22}
$$

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:

$$
\begin{aligned}
\mathbb{E}_t\left[\tilde{M}^{\$}_{t+k}S_{t,t+k-1}\right]&=\mathbb{E}_t\left[\tilde{M}^{\$}_{t+k}\Pi_{j=1}^{k-1}S_{t+j-1,1}\right]\\
&=\mathbb{E}_t\left[\tilde{M}^{\$}_{t+k}\exp\left(-\sum_{j=1}^{k-1}\lambda_{t+j-1}\right)\right]
\end{aligned}
\tag{A23}
$$

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

$$
\mathbb{E}_t\left[\tilde{M}^{\$}_{t+1}S_{t,t}\right]=\mathbb{E}_t\left[\tilde{M}^{\$}_{t+1}\right]=\exp\left(p^{\$,1}_{ft}\right)=\exp\left(C_1^{1'}X_t+C_2^1(s_t)\right)\tag{A24}
$$

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

$$\begin{aligned}\mathbb{E}_t\left[\tilde{M}^{\$}_{t+k}\exp\left(-\sum_{j=1}^{k-1}\lambda_{t+j-1}\right)\right] &= \mathbb{E}_t\left[\tilde{M}^{\$}_{t+k-2}\exp\left(-\sum_{j=1}^{k-1}\lambda_{t+j-1}\right)\mathbb{E}_{t+k-2}\left[M^{\$}_{t+k-1}\times M^{\$}_{t+k}\right]\right]\\ &= \mathbb{E}_t\left[\tilde{M}^{\$}_{t+k-2}\exp\left(-\sum_{j=1}^{k-1}\lambda_{t+j-1}\right)\exp\left(p^{\$,2}_{f,t+k-2}\right)\right]\\ &= \mathbb{E}_t\left[\tilde{M}^{\$}_{t+k-2}\exp\left(-\sum_{j=1}^{k-1}\lambda_{t+j-1}\right)\exp\left(P_1^{2'}X_{t+k-2}+P_2^2(s_{t+k-2})\right)\right]\end{aligned} \tag{A25}$$

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:

$$\mathbb{E}_t\left[\tilde{M}^{\$}_{t+k-2}\exp\left(-\sum_{j=1}^{k-1}\lambda_{t+j-1}\right)\exp\left(P_1^{2'}X_{t+k-2}+P_2^2(s_{t+k-2})\right)\right] = \exp\left(C_1^{k'}X_t + C_2^k(s_t)\right) \tag{A26}$$

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:

$$\begin{aligned}C_t &= (1-R)\times\left(1-\frac{\sum_{k=1}^{20}\mathbb{E}_t\left[\tilde{M}^{\$}_{t+k}S_{t,t+k}\right]}{\sum_{k=1}^{20}\mathbb{E}_t\left[\tilde{M}^{\$}_{t+k}S_{t,t+k-1}\right]}\right)\\ &= (1-R)\times\left(1-\frac{\sum_{k=1}^{20}\exp\left(B_1^{k'}X_t+B_2^k(s_t)\right)}{\sum_{k=1}^{20}\exp\left(C_1^{k'}X_t+C_2^k(s_t)\right)}\right)\end{aligned} \tag{A27}$$

D Calibration Details

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.

Appendix Table A11 lists the baseline parameter values (top panel). Some parameters are taken 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 1968:Q4 and 2019:Q4.[28] 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).

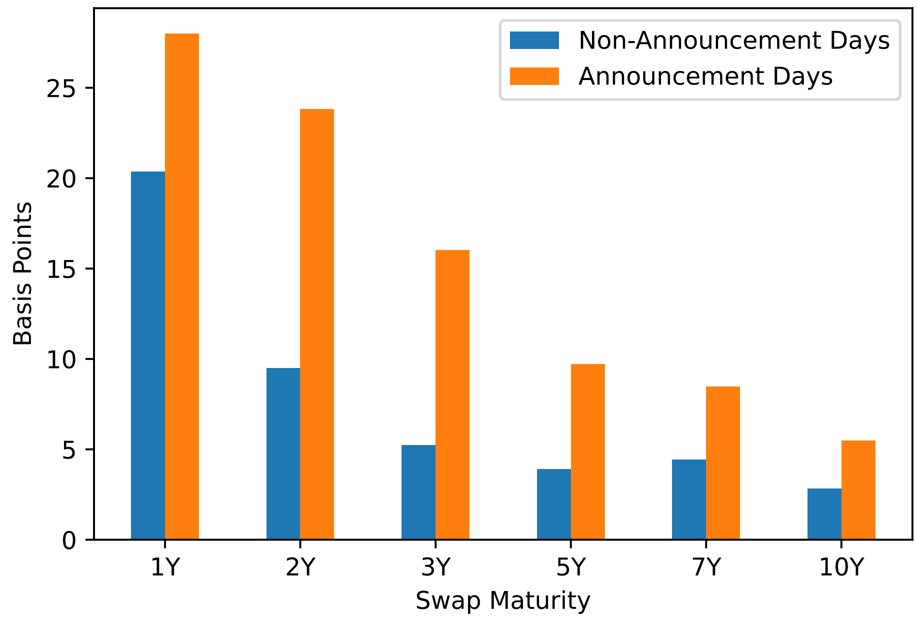
As shown in Figure 2, the "good inflation" regime with $\sigma_{xc\pi} > 0$ produces a negative stock-bond correlation, while the "bad inflation" regime produces the opposite. Because much of our data sample (post 2000s) lies in the former, we calibrate $|\sigma_{xc\pi}(s_1)| > |\sigma_{xc\pi}(s_2)|$, 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 probabilities on the regime (p_{11}, p_{22}) are chosen to be equal, with an average regime length of 8 to 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 $\beta_{\lambda 0} = 0.505$ percent across both regimes to target a 2 percent annual default rate, close to the empirical average.[29] 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.

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

[29] Based on Moody's EDF data, the average annualized five-year default probability is roughly 1.1 percent. We calibrate average default rates a bit higher to get closer to the CDS spread level in the data.

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

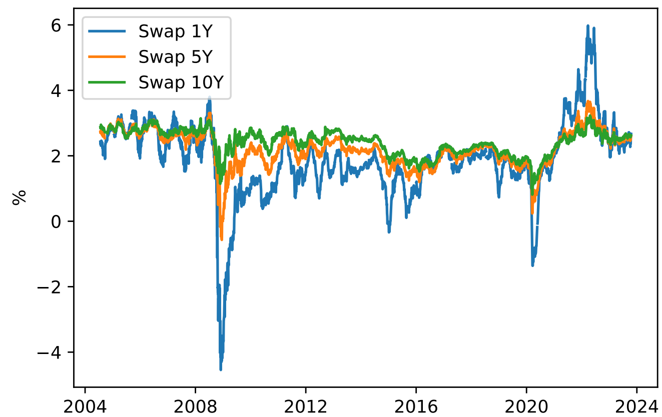


	1Y	2Y	3Y	5Y	7Y	10Y
var(η_t^A)	28.00	23.83	16.02	9.72	8.49	5.49
var(η_t^{NA})	20.37	9.50	5.23	3.90	4.44	2.84
F-test Statistic	1.37***	2.51***	3.06***	2.49***	1.91***	1.93***

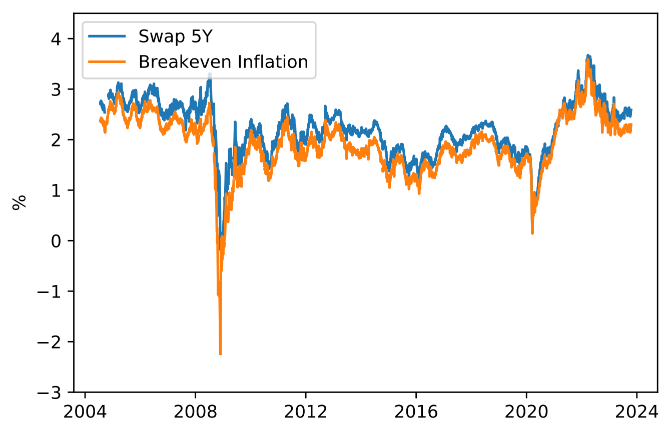
This figure display the maturity-specific variance of intraday inflation swap movements on announcement and non-announcement days. For announcement days, the variance is computed using the portion of intraday swap changes that is not related to macroeconomic surprises, via regression residuals. Meanwhile, 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: **CPI Inflation Swaps**

(a) Swaps Across Maturity



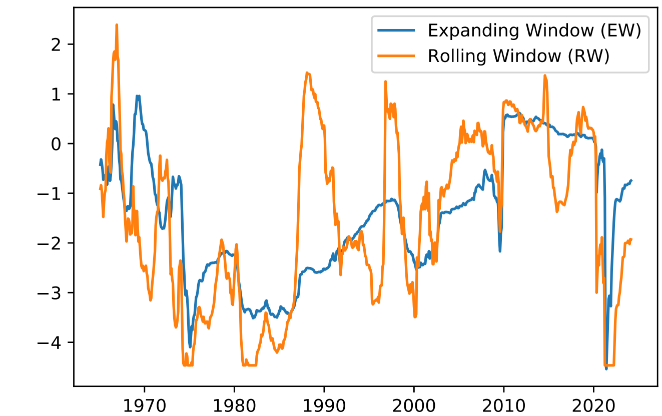
(b) Comparison to Breakeven Inflation (TIPS)



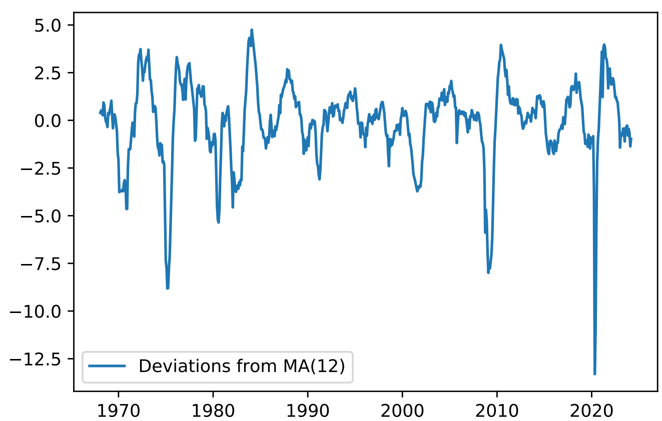
The top figure presents a time series plot of the 1-year (blue), 5-year (orange), and 10-year (green) inflation swap rates. The bottom figure displays a time series plot of the 5-year zero-coupon inflation swap rate (blue) and the 5-year TIPS implied zero-coupon break-even inflation yield (orange). Yields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

Figure A3: **Alternative Lower Frequency Measures**

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

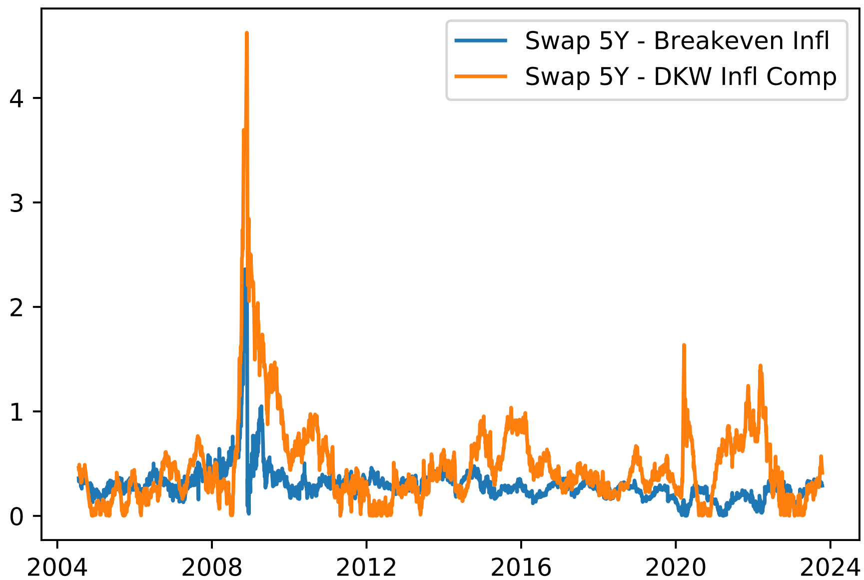


(b) Capacity Utilization (Adjusted)



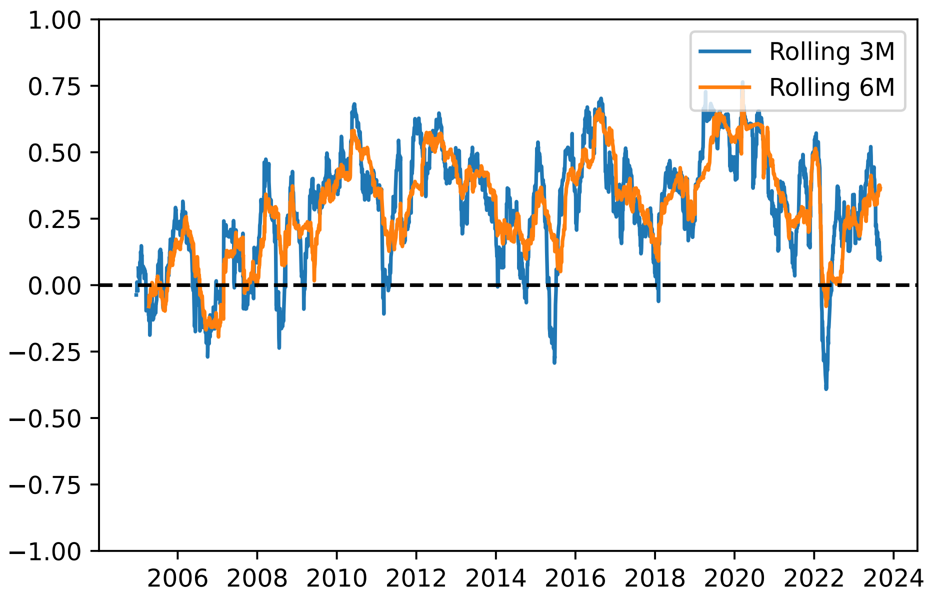
The top figure presents a monthly time series plot of the nominal real covariance computed on an expanding window through weighted least squares using exponential weights, identical to Boons et al. (2020) (blue) and a 60-month rolling window version of the same covariance (orange). The bottom figure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

Figure A4: **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 latter inflation compensation measure takes into account a liquidity premium adjustment.

Figure A5: **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: **Key Summary Statistics**

	Count	Mean	Std. Dev.	Min	Max
(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
(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
(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 A2: **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 A3: **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 Var.	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. 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 A4: **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 4. 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 A5: **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 A6: **Time-Varying Inflation Sensitivities 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 A7: **Time-Varying Inflation Sensitivities 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 A8: **Time-Varying Inflation Sensitivities 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 A9: **Time-Varying Inflation Sensitivities 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 A10: **Time-Varying Inflation Sensitivities 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 (2) in the main text. Columns (1) and (4) report the baseline, unconditional results as similarly reported in Table 1. 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.

Table A11: **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
$E\left[r_{ft}^{5Y,\$}\right]$	3.466	Nominal return on 5Y risk-free bond
$E\left[s_t^{5Y}\right]$	1.337	5Y CDS spread
$\sigma\left[\Delta s_t^{5Y}\right]$ (b.p.)	5.371	Volatility of spread changes
$\rho(r_{ct}^{\$}, r_{ft}^{5Y,\$})$	-0.148	Bond-stock correlation
$\rho(r_{ct}^{\$}, r_{ft}^{5Y,\$})$ – Regime 1	-0.451	–
$\rho(r_{ct}^{\$}, r_{ft}^{5Y,\$})$ – 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	
$\beta(\Delta s_t^{5Y} \sim \Delta x_{\pi t})$ (b.p.)	-1.603	Spread change regression coefficient
$\beta(\Delta s_t^{5Y} \sim \Delta x_{\pi t})$ – Regime 1	-6.265	
$\beta(\Delta s_t^{5Y} \sim \Delta x_{\pi t})$ – 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.