Innovation-Driven Contractions:

A Missing Link for Asset Pricing Puzzles

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Abstract

We provide a unified resolution for prominent conditional asset-pricing puzzles through "innovation-driven contractions." Empirically, we document two stylized facts: (1) technological innovations initially cause significant labor contractions and have negligible impact on capital, and (2) puzzling disconnections—between stock returns and either investment growth or hiring surprises—intensify under stickier prices. A two-sector New-Keynesian model quantitatively ties these facts, explaining the anomalous negative correlation between stock-returns and investment-returns, the negative market reactions to favorable labor market news, and the procyclical equity yield term-structure slope. Investment-based dividend yields filtered from our model strongly predict future returns, underscoring our mechanism's empirical applicability.

JEL Classification: G12, E32

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Existing asset pricing models, particularly those based on production, have been successful in explaining unconditional moments of asset prices and macroeconomic aggregates. These frameworks (e.g., Jermann, 1998; Kaltenbrunner and Lochstoer, 2010; Papanikolaou, 2011; Croce, 2014, among others) can jointly account for the average equity risk premium, the volatility of stock returns, and the long-run behavior of consumption and investment. However, many of the most persistent and challenging asset pricing puzzles today relate not to these unconditional features, but to the *conditional* comovement of macroeconomic variables with equity markets: existing frameworks largely struggle to address certain "disconnection puzzles," where short-term market valuations or risk premia appear to move counter to what standard economic intuition would suggest. This paper offers an integrated solution for such asset-pricing anomalies.

Specifically, three foundational puzzles—all related to correlations between financial markets and macroeconomic conditions—stand out. First, while expected stock returns and expected investment returns are positively correlated, the contemporaneous correlation between the two *realized* returns is close to zero and even negative in the data (see, e.g., Liu, Whited, and Zhang (2009)). The latter is quite puzzling, since under perfect competition or constant markups, both returns should perfectly comove, as occurs in extant production frameworks. Second, numerous studies show that deteriorating macro conditions, particularly in the labor market, often coincide with elevated stock valuations (see, e.g., Boyd, Hu, and Jagannathan (2005)), suggesting an ostensible disjunction between fundamentals and prices. Third, the slope of the equity yield term structure is positively correlated with the business cycle: it steepens in economic expansions and flattens in recessions (see, e.g., van Binsbergen, Brandt, and Koijen, 2012; Bansal, Miller, Song, and Yaron, 2021; Gormsen, 2021). This conditional behavior points to a systematic relationship between the business cycle and the market's expectation of long- versus short-horizon growth, a dynamic that canonical models fail to capture. Each of these puzzles highlights a conditional 'disconnection' that challenges our understanding of how financial markets reflect economic fundamentals.

At first glance, these big puzzles appear unrelated. We argue, however, that they share a common root: transient "innovation-driven contractions." Technological innovations—spanning from assembly lines to fiber optics, information technology, and artificial intelligence—are essential for sustained economic growth. While their long-term impact is unambiguously positive, prior macroeconomic research revealed that they can surprisingly lead initially to short-term production contractions (see, e.g., Basu, Fernald, and Kimball (2006)). Technological improvements often decrease firms' input usage in the near term, before subsequent recovery and growth. Despite robust documentation in macro literature, the quantitative implications of this phenomenon for asset pricing remain unexplored. The central thesis of our study is that the apparent macro disconnection between higher technological innovation and lower short-term input usage spills over into financial markets. It provides a unified explanation for the former puzzles, which initially suggest a financial disconnection but, upon closer examination, can be well understood under fair pricing.

We start the analysis by establishing two novel facts: (1) We uncover differences compared to the seminal findings of Basu et al. (2006): positive technological innovations initially reduce labor usage significantly; yet contrary to earlier findings, we find that their immediate effect on capital growth is small and statistically insignificant—an economically important distinction compared to prior literature. Novel analysis based on innovation metrics from Kogan, Papanikolaou, Seru, and Stoffman (2017) confirms these effects also at the firm-level. (2) We go beyond the macro domain into asset prices, and provide new evidence that disconnection puzzles intensify precisely when prices exhibit greater rigidity. Cross-sectional and time-series findings suggest that the contemporaneous correlation between stock returns and investment returns, and between stock returns and labor market surprises, becomes significantly more negative within firms or during periods characterized by higher price stickiness.

Motivated by these empirical findings, we develop a general equilibrium model designed to capture these macroeconomic dynamics and explore their financial market implications. It features two sectors: consumption and investment—each composed of monopolistically competitive firms facing nominal price rigidities. Importantly, our framework differs in its *scope* and *ingredients* from previous New-Keynesian models as well as existing asset pricing models: (1) In the New-Keynesian context, most prior frameworks such as Galí (2010) or Christiano, Eichenbaum, and Evans (2005), feature only a single sector, whereas we emphasize the role of splitting production into two sectors.[1] Even macro models that include multiple sectors, such as Basu, Fernald, and Liu (2013), overlook asset-pricing implications altogether. We further depart from existing macro setups by employing (i) recursive Epstein and Zin (1991) preferences instead of CRRA or habit formation and (ii) permanent technological shocks coupled with a long-run risk component, contrasting the transitory, mean-reverting shocks previously considered. These departures go a long way toward replicating asset-pricing facts that macro models fail to capture. In particular, (i) is important for obtaining the correct signs of conditional correlations while (ii) is important quantitatively.[2] (2) In the asset-pricing context, numerous studies feature two sectors (e.g., Papanikolaou, 2011; Garlappi and Song, 2017), but typically with flexible prices. It is the combination of price rigidity, our shock specification, *and* the two-sector structure, that is critical for the evidence.[3]

First, our model can quantitatively reconcile the negative correlation between investment returns and stock returns using a single type of capital good.[4] Technological innovations enhance firms' marginal productivities. Without sticky prices, this prompts immediate counterfactual expansions in capital growth and increases the relative price of investment goods. In contrast, empirically disciplined sticky prices introduce more subtle short-term effects of technological shocks. While firms still capitalize on higher productivity by increasing investment rates, price rigidity yields a temporary decline in the output and inflation gaps, which in equilibrium induce a short-lived but pronounced decline in the relative price of capital, thereby decreasing marginal production costs and raising markups.

These dynamics imply that technological shocks yield transient innovation-driven contractions in investment returns. Following a positive innovation, in our two-sector setup investment returns

[1] In such one-sector models, the negative effect of sticky prices is not limited to labor markets; it also leads to a contraction in capital and output growth, contrary to the data. In Section 1.1 we also empirically rule out models based on creative destruction for explaining the evidence.

[2] In Online Appendix Section OA.1 we provide a comprehensive discussion on the differences between our study and Basu et al. (2013). Importantly, their working paper did not explore any implications for asset prices. Nonetheless, we show that their study cannot fully explain the disconnection puzzles.

[3] In standard two-sector models—lacking sticky prices— aggregate (common) technology shocks have no contractionary effect: not only that they increase labor supply and investment rates but also elevate the relative price of capital, rendering a significantly positive impact on capital, contrasting with the data.

[4] In relation to this comovement puzzle, Belo, Deng, and Salomao (2024) show that traditional investment-based models with one type of physical capital fail to jointly match the time-series properties of stock returns along with cross-sectional patterns.

might rise due to increased investment rates, or they could drop because of a lower relative price of capital goods. Quantitatively, the latter dominates, leading to a drop in investment returns. At the same time, firm valuations and stock returns increase due to enhanced monopolistic rents — negatively comoving with investment returns. Importantly, the negative impact of nominal rigidity on capital prices is transitory, reversing eventually to suggest higher future investment returns. This mechanism explains the observed positive correlation between stock returns and *future* investment returns, as documented in the data.[5]

Second, our model explains the anomalous negative market reaction to positive labor market surprises. The common explanation for this inverse relationship often hinges on offsetting monetary or fiscal policies (see, e.g., Elenev, Law, Song, and Yaron, 2022; Xu and You, 2022). While such policies certainly contribute by softening the negative impact of adverse news on valuations, this rationale may not fully quantitatively explain, in general equilibrium, why these policies would overcompensate to the extent of reversing the sign of the market reaction.[6]

Furthermore, existing research typically interprets spikes in unexpected unemployment as inherently “bad" states. In contrast, we argue that unexpected employment changes are endogenous outcomes of innovation-driven contractions and should not be perceived as exogenous negative shocks. Specifically, our mechanism demonstrates that a positive technological shock, under price rigidity, initially reduces wages, leading to significantly higher firm markups. These elevated markups effectively act as higher implicit taxes, rationing short-term hiring. Thus, a single “good" technological innovation endogenously generates both higher firm valuations——driven by increased monopolistic rents——and simultaneous short-run reductions in employment. Moreover, by incorporating empirically-documented cyclicality in price rigidity, our model successfully replicates the time-varying nature of this correlation (which turns more negative in expansions).

Third, innovation-led contractions affect the term structure of equity yields. In the benchmark,

[5]The negative contemporaneous correlation between investment returns and stock returns highlighted by Liu et al. (2009) has previously been rationalized through mechanisms such as time-to-build investment structures (e.g., Kuehn, 2009). However, a neo-classical model featuring only a long time-to-build counterfactually produces a procyclical relative price of investment (as capital demand increases slowly in expansions). Our approach provides a complementary explanation, by integrating nominal rigidities within a two-sector framework. This approach leads to a short-term decline in the relative price of investment goods after positive shocks, aligning with the countercyclical nature of investment goods prices documented by Greenwood, Hercowitz, and Krusell (1997) and Christiano and Fisher (2003).

[6]See further theoretical discussion on this point in Online Appendix OA.2.

the slope of the term structure is procyclical, as in the data, whereas in the absence of sticky prices, the slope is countercyclical. Following a positive shock, input usage initially falls but is expected to revert and grow in the short-run. Thus, in good states, the expected dividend growth is larger in shorter-horizons relative to longer-horizons. This turns the equity yield term structure more upward-sloping in expansions, as there is an inverse relationship between equity yields and expected dividend growth rates.

Next, we show that the dynamics implied by innovation-driven contractions can be used for return predictability. We use our model along with observed paths of utilization-adjusted technological innovations to filter out empirical paths of investment returns and their associated investment-based dividend yields. In both the model and the data, investment-based dividend yields predict stock returns negatively. In a sample from 1964 to 2019, their R^2 exceeds those of the stock-market dividend yields or of the consumption-to-wealth ratio, reaching 35% at the five-year-ahead predictive horizon. These findings demonstrate the empirical applicability of our mechanism.

To rigorously validate our mechanism, we provide empirical and theoretical tests. First, we demonstrate that our model can quantitatively match the responses of inputs to technological shocks. Importantly, these are not targeted by our calibration, providing an over-identification test. In this context, the two-sector structure is critical for the insignificant response of capital growth: while investment quantity rises, its relative price declines, muting the overall impact. Second, we derive and empirically confirm two additional predictions of the model for labor markets: in the short-run, positive technological innovations lower wages and shift labor toward the consumption sector relative to the investment sector.

More broadly, our work contributes to an extensive literature exploring the relationship between production decisions and asset returns, complementing insights from numerous studies (e.g., Belo and Lin, 2012; Jones and Tuzel, 2013; Belo, Lin, and Bazdresch, 2014; Kuehn and Schmid, 2014; Belo, Li, Lin, and Zhao, 2017; Kilic, 2017; Ready, Roussanov, and Ward, 2017; Tuzel and Zhang, 2017; Belo, Lin, and Yang, 2018; Kilic and Wachter, 2018; Ai, Li, Li, and Schlag, 2019; Dou, Ji, Reibstein, and Wu, 2019; Bretscher, Hsu, and Tamoni, 2020; Gofman, Segal, and Wu, 2020; Corhay, Li, and Tong, 2022; Liu and Shaliastovich, 2022; Kogan, Li, Zhang, and Zhu, 2023; Anschukov, Bhamra, and Kuehn, 2024, among many others). While these studies primarily focus on long-term unconditional aggregate and cross-sectional risk premia, our work uniquely emphasizes short-term conditional dynamics arising from innovation-driven contractions. Under assumptions common to this prior literature—such as perfect competition or constant markups—the correlation between investment and stock returns is close to one, a key limitation our framework addresses.

While we do not exclude other potential explanations for the former puzzles, our core message is straightforward: seemingly unrelated stylized facts, previously viewed as distinct challenges, can be unified through the mechanism of innovation-driven contractions. Integrating these well-established (yet overlooked) macro dynamics into an asset pricing framework represents a crucial step forward — enhancing production-based asset-pricing models' ability to bridge between macro-fundamentals and financial markets.

1 Motivating Evidence

To motivate our theoretical analysis, we first lay out novel facts. We begin by revisiting and extending the seminal evidence on "innovation-driven contractions." We then present new model-free evidence that salient "disconnection" puzzles are governed by the degree of price stickiness. We tie these facts together in the subsequent model.

1.1 Innovation-Driven Contractions Revisited

Stylized Fact 1: Innovation-Driven Contractions. *The short-term effect of technological innovations on inputs' usage is: (a) negative for labor and (b) insignificant for capital.*

Aggregate Evidence. We follow the methodology of Basu et al. (2006) and project the growth rate of production inputs on contemporaneous and lagged values of technological innovations:

$$\Delta y_t = \text{const} + \sum_{i=0}^{4} b_i \cdot dz_{t-i} + \varepsilon_t, \tag{1}$$

where Δy_t denotes the log-growth rate of either hours per worker (*dhours*) or capital input (*dk*). We source the former from the Bureau of Labor Statistics (BLS), and the latter from the Bureau of Economic Analysis (BEA). The independent variable *dz* represents technological advancements

Table 1: **Hours and Capital Growth Response to Technological Advancements**

Period	1953 - 1996					1953 - 2019				
Annual	dz	dz(-1)	dz(-2)	dz(-3)	dz(-4)	dz	dz(-1)	dz(-2)	dz(-3)	dz(-4)
dhours	-0.72***					-0.76***				
	[-3.50]					[-3.99]				
	-0.60***	0.55**	0.51***	-0.06	-0.41**	-0.75***	0.46**	0.36***	-0.02	-0.48***
	[-4.42]	[2.03]	[4.34]	[-0.34]	[-2.21]	[-4.95]	[2.18]	[2.82]	[-0.11]	[-3.29]
dk	-0.17**					-0.02				
	[-2.12]					[-0.13]				
	-0.17*	-0.21***	0.06	0.09	0.02	-0.03	-0.08	0.12	0.11	-0.05
	[-1.84]	[-3.01]	[0.77]	[1.09]	[0.19]	[-0.22]	[-0.82]	[1.40]	[1.45]	[-0.60]
Quarterly	dz	dz(-1)	dz(-2)	dz(-3)	dz(-4)	dz	dz(-1)	dz(-2)	dz(-3)	dz(-4)
dhours	-0.40***					-0.38***				
	[-5.07]					[-5.52]				
	-0.40***	-0.24***	-0.08	0.07	0.02	-0.39***	-0.22***	-0.07	0.08	0.05
	[-5.36]	[-3.07]	[-0.85]	[0.85]	[0.32]	[-5.87]	[-3.39]	[-0.94]	[1.21]	[0.78]
dk	0.02					0.03				
	[0.73]					[1.41]				
	0.02	0.01	-0.02	-0.03	-0.03	0.03	0.03	0.01	0.00	-0.00
	[0.75]	[0.25]	[-0.78]	[-1.18]	[-1.50]	[1.44]	[1.17]	[0.33]	[0.10]	[-0.03]

This table reports slope coefficients and t-statistics from OLS regressions of input growth rates on current and lagged values of industry technology residuals (dz). The dependent variable is either the growth rate of hours per worker (*dhours*) or capital input (dk), as indicated in each row. The first row in each panel reports a simple projection on current dz_t only, while the second row includes dz_t and its four lags: $\Delta y_t = \text{const} + \sum_{i=0}^{4} b_i \cdot dz_{t-i} + \varepsilon_t$. The left panel uses data from 1953–1996; the right panel extends the sample to 2019. For 1953–1996, both dz and *dhours* are sourced from Basu, Fernald, and Kimball (2006). For 1997–2019 and for all quarterly regressions, we use utilization-adjusted TFP growth from Fernald (2014) as a proxy for dz, and the corresponding Fernald (2014) series for *dhours*. The capital input growth series (dk) is consistently from Fernald (2014). Heteroskedasticity- and autocorrelation-robust t-statistics (Newey and West, 1987) are shown in brackets.

and can be measured in two ways. First, dz could be directly sourced from Basu et al. (2006), who use Hall-style regressions to obtain industry-level technological innovations and then aggregate these to form macro-level purified technology shocks. The data are available at the annual frequency from 1953 to 1996. Second, dz could be sourced from Fernald (2014), who uses a similar methodology to Basu et al. (2006), but only utilizes aggregate-level data to estimate technological advancements, captured by utilization-adjusted TFP. The data are available until recent years, at both the annual and the quarterly frequency. Within the overlapping annual sample period of 1953–1996, the correlation between the measure of Basu et al. (2006) and Fernald (2014) is 0.7. Consequently, we employ both measures of dz: for annual projections from 1953 to 1996 we use data from Basu et al. (2006), while for the extended period of 1997—2019 or for quarterly regressions, we use data from Fernald (2014).

Table 1 reports results. We start by replicating the original evidence of Basu et al. (2006), using annual regressions from 1953 to 1996. In this sample, hours growth loads negatively both on the contemporaneous dz as well as its four lags. Importantly, Basu et al. (2006) do not consider the growth rate in capital directly. Rather, they consider changes in observed "inputs", capturing a cost-share-weighted growth in capital and labor jointly. For the purposes of the model analysis, we are interested in isolating capital, and we separate this margin in the same panel. Using the original sample of Basu et al. (2006), the growth of capital also loads negatively on contemporaneous dz, and its first lag. Overall, the evidence is broadly consistent with Basu et al. (2006) that technological advancements cause a short-term contraction in inputs' usage.

Next, we keep the analysis at the annual frequency but extend the sample to 2019. For hours growth, the loading on dz and its lagged values remain negative, and quantitatively similar to the slope coefficients obtained using the original sample period.[7] However, in the new updated sample, the response of capital growth to technological advancements is muted, with slope coefficients that are close to zero and statistically *insignificant*.

To examine which empirical pattern is more robust, the bottom panel of Table 1 refines the analysis by considering quarterly frequency regressions. The evidence is consistent with the updated annual data. In the quarterly samples ending either in 1996Q4 or 2019Q4, the contractionary effect of technological innovations is confined to the labor markets. For hours growth, the loadings on contemporaneous dz and its first two lags are negative, followed by a partial rebound in the subsequent period. For capital growth, on the other hand, the slope coefficients are statistically insignificant, close to zero and mostly positive. Lastly, the contemporaneous effect of dz on input growth rates remains robust across specifications, even when the lagged values of dz are excluded

[7] Anecdotally, and broadly related, a recent paper by Eisfeldt, Schubert, and Zhang (2023) shows that the introduction of generative AI has caused a general reduction in job postings for exposed firms.

Table 2: Innovation and Firm-Level Outcomes

	Panel A. Inputs		Panel B. Competitors and Markups	
	(1)	(2)	(3)	(4)
	Emp_Growth_{it}	Cap_Growth_{it}	$\text{Competitor\_Emp\_Growth}_{it}$	$\text{Markup\_Growth}_{it}$
$\text{Acw}_{i,t-1}$	-5.31***	-0.25	0.01	0.91***
	[-5.22]	[-0.21]	[0.43]	[2.37]
$\text{Size}_{i,t-1}$	-5.16***	-9.83***	0.05***	-2.29***
	[-15.14]	[-18.02]	[4.27]	[-14.60]
$\text{BM}_{i,t-1}$	-2.62***	-5.57***	0.01	-0.21
	[-5.39]	[-6.38]	[1.52]	[-1.44]
$\text{Lev}_{i,t-1}$	-22.35***	-30.28***	0.32***	4.18***
	[-19.37]	[-24.04]	[7.74]	[10.83]
Number of Observations	163,191	170,525	163,194	152,941
R-squared (incl. FE)	0.04	0.11	0.00	0.01
Fixed Effects				
Firm	Yes	Yes	Yes	Yes
Industry × Year	Yes	Yes	Yes	Yes

This table reports panel regressions where the dependent variables are (1) employment growth (EMP_Growth), (2) capital (asset) growth (Cap_Growth), (3) competitors' employment growth (Competitor_Emp_Growth), and (4) markup growth (Markup_Growth), all measured as log-differences. The key independent variable is lagged innovation intensity (Acw_{t-1}), constructed following Kogan et al. (2017). The construction of the independent variables and other control variables — including size, market ratio (BM), and leverage (Lev) — is described in Online Appendix Section OA.3. Coefficients are multiplied by 100. t-statistics (in brackets) are based on heteroskedasticity-robust standard errors clustered by firm and year. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

from the regressions.[8]

Firm-Level Evidence. Our main empirical results—which correspond to the model—pertain to aggregate technological shocks and follow the methodology of Basu et al. (2006) as discussed above. For robustness purposes only, we supplement the evidence using firm-level analysis. We conduct a series of panel regressions using data from 1953 to 2019. For brevity, we refer the reader to Section OA.3 of the Online Appendix for details about the panel regression specification and its controls. Our key independent variable is a firm's lagged innovation intensity ($Acw_{i,t-1}$), constructed following the citation-weighted patent value methodology of Kogan et al. (2017). Panel A

[8]In untabulated results, we repeat projection (1) using only for the most recent subsample from 1997 to 2019, at both annual and quarterly frequencies: for capital growth, the loading on dz remains positive but statistically insignificant. This indicates that the data do not show any deep structural change, pre- and post-1996. Rather, the negative slope coefficient for dk in the original sample of Basu et al. (2006) was a random in-sample artifact. Even within that sample, changing the frequency of the regression or including additional lags renders the slope on contemporaneous dz insignificant at the 5% level.

of Table 2 shows that a firm's innovation is associated with a statistically significant decline in its own employment growth (column (1)), consistent with Stylized Fact 1(a). By contrast, innovation features a muted relationship with capital growth (column (2)), consistent with Stylized Fact 1(b).

The evidence presented in Tables 1 and 2 poses a challenge for standard models: what economic mechanism causes a "good" technology shock to contract labor while leaving capital investment largely unchanged?

One candidate option is that the evidence is driven by creative destruction. A positive technological shock could be associated with displacement, leading to "winner" entrant firms and "loser" incumbent firms. If the mass of "losers" is greater, aggregate economic activity will be suppressed after a positive innovation.

However, an economic depression driven by creative destruction would be potentially pervasive, suppressing not only labor but also aggregate capital growth — in contrast to Table 1. Creative destruction would also typically lead to a negative risk price for displacing productivity shocks (see, e.g., Kogan, Papanikolaou, and Stoffman (2013)) — in contrast to the positive risk price for *aggregate* Hicks-Neutral technology.

Most importantly, the creative destruction hypothesis implies that innovators expand and displace their rivals, implying that employment losses should be concentrated *among competitor firms*, not on the innovators themselves. Panel B of Table 2 provides evidence which largely contradicts these effects. Whereas firms' technological innovation induces a negative impact on their own labor (column (1)), we find no statistically significant relationship between a firm's innovation and the subsequent employment growth of its competitors (column (3)); the coefficient is economically negligible (0.01) and statistically insignificant (t-stat = 0.43).

Another prominent option is that the evidence is explained by markup fluctuations, driven by nominal price rigidity. Smets and Wouters (2007), Galí (2010), among others, show that price stickiness can induce a rise in markups and a contraction in labor following a positive technology shock. Consistently, column (4) in Panel B of Table 2 shows that innovation leads to a significant increase in firms' own markups (coefficient = 0.91, t-stat = 2.37), suggesting that firms capitalize on innovation by increasing their margins instead of expanding production.

In the subsequent sections we argue, both empirically and theoretically, that price stickiness is useful in explaining not only the former macro-evidence, but also asset-pricing disconnection puzzles. However, as later explained in Section 2, the findings pertaining to capital growth's response also necessitate a two-sector structure.

1.2 Price Stickiness and Comovement Puzzles

Stylized Fact 2: Comovement puzzles and price rigidity. *The contemporaneous correlation between equity returns and either (a) investment growth or (b) hiring news is more negative when prices are stickier.*

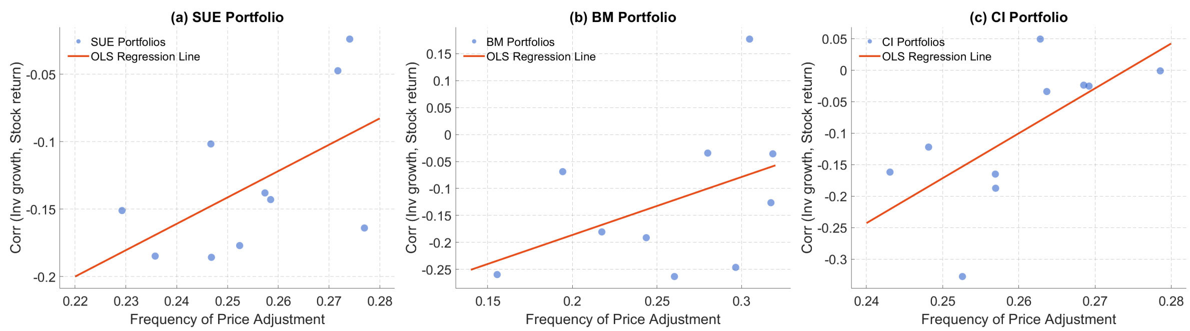
Investment. We first revisit the evidence pertaining to the comovement puzzle between investment and stock returns, as documented by Liu et al. (2009). Liu et al. (2009) form decile portfolios sorted on three characteristics: standardized unexpected earnings (SUE), book-to-market (BM) and corporate investment (CI). They show that for each of these portfolios, the contemporaneous correlation between stock returns and either investment returns or investment growth rates is negative, or at a minimum, indistinguishable from zero, contrasting with neo-classical theory.

To materially replicate Liu et al. (2009), we use their original sample and the methodology to create decile portfolios based on the former characteristics. Portfolios sorted on BM and CI are rebalanced annually, while portfolios sorted on SUE are rebalanced monthly. For each of the 30 portfolios, we compute time-series correlation between its value-weighted stock returns and its investment growth. The latter is highly correlated with portfolio-level investment returns, but does not rely on a specific functional form for capital adjustment costs. Portfolio-level investment growth is defined as the value-weighted average of firm-level investment growth rates.[9]

We then extend the analysis of Liu et al. (2009) by considering the nexus to price rigidity. We obtain cross-sectional data on price stickiness from Pasten, Schoenle, and Weber (2021), who measure the frequency of price adjustment at the 4-digit NAICS industry level. We assign each firm a price adjustment frequency based on its granular industry classification. For each of the former 30

[9] A specific challenge arises for the monthly-rebalanced SUE portfolios; to align their investment growth with an annual horizon, we form 12 monthly portfolios for each decile from July of year t to June of year $t+1$, calculate the investment growth for each, and then average these 12 figures to obtain a single annual investment growth measure for each decile.

Figure 1: **Correlations and Frequency of Price Adjustment (Portfolio Level)**



The figure presents the relationship between the portfolio-level correlation between investment growth and stock returns, $\left(\frac{I_{\text{Port},t+1}}{I_{\text{Port},t}}, R^S_{\text{Port},t+1}\right)$, and the frequency of price adjustment. Panels (a), (b), and (c) correspond to ten portfolios sorted on standardized unexpected earnings (SUE), book-to-market (BM), and corporate investment (CI), respectively. The correlation for each portfolio is computed from the time series of its investment growth and its contemporaneous stock return. Investment growth, $\frac{I_{\text{Port},t+1}}{I_{\text{Port},t}}$, is calculated as the market value-weighted average of firm-level investment growth rates. $R^S_{\text{Port},t+1}$ is the value-weighted stock return for firms in each portfolio. The frequency of price adjustment is taken from Pasten, Schoenle, and Weber (2021), defined at the 4-digit NAICS industry level. Portfolio-level frequencies are computed as the market value-weighted average across firms within each portfolio, using market capitalization at the time of portfolio formation. Each panel shows an OLS regression of the portfolio-level correlation on the frequency of price adjustment. Red lines represent fitted regression lines, and the corresponding Newey-West t-statistics are reported. Data for the SUE portfolios in panel (a) are from 1972 to 2005, while data for the BM and CI portfolios in panels (b) and (c) are from 1963 to 2005, following Liu, Whited, and Zhang (2009).

portfolios, the portfolio-level metric of price adjustment is defined as the value-weighted average of its underlying constituent firms' frequencies.

Figure 1 shows a scatter plot of portfolio-level stock return-investment growth correlations against portfolio-level frequency of price adjustment, along the three dimensions of BM, CI and SUE. First, consistent with Liu et al. (2009), for almost all portfolios the time-series correlation between stock returns and investment growth rates is negative, as shown on the y-axes of the scatter plots. Second, across all three sorting dimensions, a visual pattern clearly emerges: the lower (higher) the price-adjustment frequency is, the more (less) negative the stock return-investment correlation is. Notably, a lower frequency for price adjustment is equivalent to a higher degree of price stickiness. This pattern is statistically significant: The red lines in each panel represent the best linear fit for each scatter plot. For SUE-, BM- and CI- sorted portfolios the lines' slope coefficients are 1.85 ($t-stat = 2.49$), 1.08 ($t-stat = 2.31$) and 7.13 ($t-stat = 3.42$), respectively.[10]

[10] In the interest of space, we confirm that these results hold for alternative specifications, including the use of different weighting schemes, investment return definitions, industry classifications, and an extension of the sample period through 2019.

Labor. Boyd et al. (2005) and subsequent studies show that at the aggregate level, equity valuations typically rise in response to bad labor-market unemployment news. We re-establish a similar finding in an expanded sample, and examine its connection to business-cycle fluctuations in the degree of price stickiness.

We first obtain quarterly time series on the aggregate frequency of price adjustment from Vavra (2014) and apply a Hodrick-Prescott (HP) filter to isolate its cyclical component. Figure OA.4 in the Online Appendix shows this time series, which exhibits countercyclicality, typically peaking during recessions.

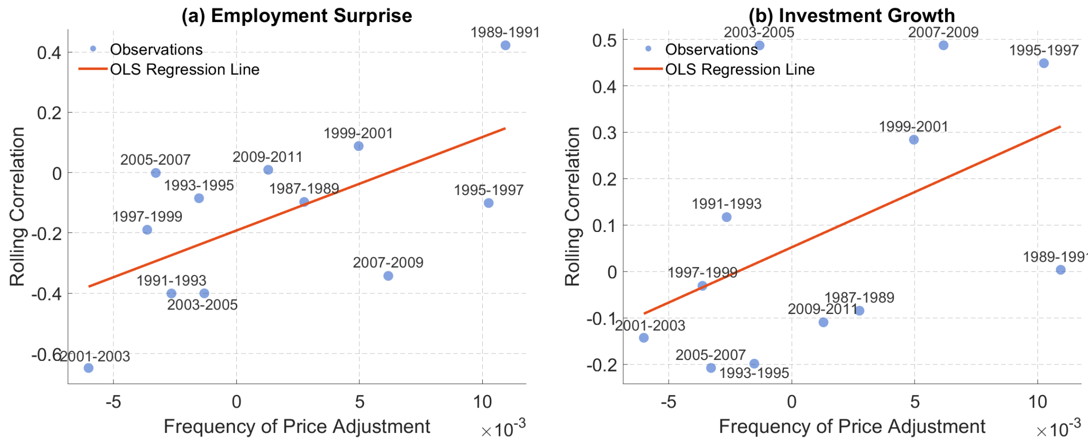
Next, we construct labor market surprises using a methodology similar to Boyd et al. (2005). To measure the surprise in quarter t, we project the quarterly change in the unemployment rate on a set of predictors from the previous quarter ($t-1$): its own past change, quarterly industrial production growth, the change in the 3-month T-bill rate, and the change in the National Financial Conditions Index (NFCI) compiled by the Chicago Fed. The inclusion of the last predictor is motivated by a broad literature linking financial conditions with labor market dynamics (see Bauer, Bernanke, and Milstein, 2023; Beaudry, Galizia, and Portier, 2020).

This predictive regression is estimated via a recursive, expanding window.[11] The fitted value from this regression serves as the out-of-sample forecast for the change in the unemployment rate in quarter t. The unexpected change in unemployment is defined as the difference between its realized value in quarter t and its forecasted value. Following the convention in the literature, the time-t employment surprise is then defined as the negative of this unemployment forecast error.

We partition the full sample period into equal-length, non-overlapping windows of eight quarters each. Within each window, we compute the correlation between employment surprises and contemporaneous stock market returns. Panel (a) of Figure 2 presents a scatter plot of these rolling-window correlations against the corresponding frequency of price adjustments over the same window. For ease of interpreting the slope coefficient of the best linear fit, the values on both the horizontal and vertical axes are standardized.

[11]Following Boyd et al. (2005), we require an initial training period of at least five years. Constrained by the availability of the National Financial Conditions Index (NFCI), which begins in 1971, the estimation window for a forecast for quarter t uses all available data from 1971Q1 up to quarter $t-1$.

Figure 2: **Rolling Correlations and Frequency of Price Adjustment**



The figure presents scatter plots of two standardized rolling correlations—employment surprise with stock returns, and investment growth with stock returns—against the standardized frequency of price adjustment. The left panel (a) plots $\text{Corr}(EMP^{\text{surprise}}_{t+1}, R^S_{M,t+1})$ and the right panel (b) plots $\text{Corr}(\frac{I_{t+1}}{I_t}, R^S_{M,t+1})$. The solid red line in each panel is the OLS regression line. The rolling correlations are computed using an 8-quarter window. To ensure non-overlapping samples, each data point corresponds to a two-year period, sampled every 8 quarters from 1989Q1 to 2011Q1. The employment surprise, $EMP^{\text{surprise}}_{t+1}$, is derived from the unemployment surprise methodology of Boyd et al. (2005), with our refinements as detailed in the text. The investment growth rate, $\frac{I_{t+1}}{I_t}$, is computed as the market value-weighted average of firm-level investment growth rates from Compustat. $R^S_{M,t+1}$ is the S&P 500 return from Goyal et al. (2024). The frequency of price adjustment is from Vavra (2014), and we apply a Hodrick-Prescott (HP) filter to retain its cyclical component. All variables are standardized by computing their z-scores.

Panel (a) shows that when the frequency of price adjustments is higher — usually in recessions — the correlations between employment surprises and stock returns rise (less negative or even positive). The converse happens in expansions, when prices are more rigid: the correlation between employment surprises and stock returns drops (more negative). The correlation between the two dimensions shown in the scatter plot, captured by the slope coefficient of the best linear fit, is 0.62 ($t-stat = 2.03$).

In panel (b) of Figure 2, we perform a similar exercise for aggregate investment growth. The panel confirms a similar positive relationship — in this case — using the correlation between market returns and aggregate investment growth, which is constructed as the value-weighted average of firm-level investment growth rates. The correlation coefficient between the two series, represented by the slope of the best linear fit, is 0.49 ($t-stat = 2.00$), and the economic message echoes the former cross-sectional analysis: when prices are stickier, the inverse relation between stock returns and investment returns intensifies.

Taken together, the conditional "disconnection" between stock valuations and real economic activity — pertaining to either investment or hiring — is systematically related to the degree of price stickiness.

2 Model

We present a model to explain prominent asset pricing disconnection puzzles via the phenomenon of innovation-driven contractions — connecting Stylized Facts 1 and 2. The model features two sectors, consumption and investment. Intermediate good producers in each sector face monopolistic competition and nominal price rigidity. While these New Keynesian ingredients seem superficially similar to a working paper by Basu et al. (2013), our approach to modeling risk premia is markedly different and leads to distinct outcomes, as shown in Section 4. In particular, our setup features two notable departures: (1) the *preference* of household follow Epstein and Zin (1991) — instead of Habit formation, and (2) *technology* shocks have a permanent effect (unit root), accompanied by a long-run risk component — instead of having a pure transitory effect.

Economically, these differences go a long way in differentiating the implications of our model, particularly in the asset-pricing domain. In Online Appendix OA.1 we replicate Basu et al. (2013): Regarding stylized fact 1, the model of Basu et al. (2013) generates a strict counterfactual decline in capital growth in response to technological changes. Regarding stylized fact 2, Basu et al. (2013) do not explore any unconditional or conditional asset-pricing moments. Nonetheless, our replication uncovers that their setup cannot fully explain key aspects of disconnection puzzles. It produces: (i) a counterfactual sign for the correlation between stock returns and *future* investment returns, (ii) a counterfactual sign for the correlation between stock returns and labor market surprises during expansions and recessions (when interest rates are high and low), and (iii) a countercyclical to acyclical slope for the term structure of equity yields. The Appendix traces these failures of their model to departure points (1) and (2) above.

2.1 Aggregation

The aggregator in each sector turns intermediate goods into final consumption and investment goods, denoted by $Y_{c,t}$ and $Y_{i,t}$, respectively. $Y_{c,t}$ is used for consumption by the household, while $Y_{i,t}$ equals aggregate investment goods in the economy. Production of final consumption (investment) goods requires a continuum of differentiated intermediate goods as inputs, denoted by $\{y_{c,t}(n)\}_{\{n\in[0,1]\}}$ $\left(\{y_{i,t}(n)\}_{\{n\in[0,1]\}}\right)$. The production of the composite good $Y_{j,t}$, in sector $j \in \{c,i\}$, converts the sector's intermediate goods into a final good using a constant elasticity of substitution (CES) aggregator:

$$Y_{j,t} = \left[\int_0^1 \left(y_{j,t}(n)\right)^{\frac{\mu_j - 1}{\mu_j}} dn\right]^{\frac{\mu_j}{\mu_j - 1}}, \quad j \in \{c,i\}. \tag{2}$$

The parameter μ_j, $\quad j \in \{c,i\}$, controls the substitutability among the intermediate goods. Perfect competition between intermediate good producers implies that $\mu_j \to \infty$. When μ_j is finite, the intermediate goods in sector j are not perfect substitutes, and thus each intermediate good producer has some degree of monopolistic power. The final good producer in sector j sells its output $Y_{j,t}$ at nominal price $P_{j,t}$. Each intermediate good producer sells its intermediate good to the aggregator at a nominal price $p_{j,t}(n)$. The aggregator in each sector $j \in \{c,i\}$ faces a perfectly competitive market, thus solving:

$$\max_{\{y_{j,t}(n)\}} P_{j,t}Y_{j,t} - \int_0^1 p_{j,t}(n) y_{j,t}(n) dn, \quad j \in \{c,i\}, \tag{3}$$

where $Y_{j,t}$ is given by equation (2). The first-order condition of equation (3) yields the demand schedule for differentiated intermediate goods of type n in the sector j:

$$y_{j,t}(n) = \left[\frac{p_{j,t}(n)}{P_{j,t}}\right]^{-\mu_j} Y_{j,t}, \quad j \in \{c,i\}. \tag{4}$$

As the market for final goods is perfectly competitive, the aggregator in sector j earns zero profits in equilibrium. This condition, along with equations (3) and (4), yields the aggregate price index in sector j, given by $P_{j,t} = \left[\int_0^1 \left(p_{j,t}(n)\right)^{1-\mu_j} dn\right]^{\frac{1}{1-\mu_j}}, \quad j \in \{c,i\}$.

2.2 Intermediate good production

2.2.1 Sectoral intermediate good producers

Intermediate goods in sector $j \in \{c,i\}$ are differentiated, and each type is denoted by $n \in [0,1]$. Each intermediate good producer n in sector j rents labor $n_{j,t}(n)$ from the household and owns a capital stock $k_{j,t}(n)$. The intermediate good producer n in sector j produces an intermediate good $y_{j,t}(n)$, using a constant returns-to-scale Cobb-Douglas production function over capital and labor subject to technology shocks $Z_{j,t}$:

$$y_{j,t}(n) = Z_{j,t} k_{j,t}(n)^{\alpha_j} n_{j,t}(n)^{1-\alpha_j}, \quad j \in \{c,i\}, \tag{5}$$

where α_j is the capital share of output. An intermediate good producer who wishes to invest an amount $i_{j,t}(n)$ must purchase $\Phi_{j,k}\left(i_{j,t}(n), k_{j,t}(n)\right) k_{j,t}(n)$ units of capital goods under an equilibrium price of investment goods $P_{i,t}$. The convex adjustment cost function $\Phi_{j,k}(.)$ is:

$$\Phi_{j,k}\left(i_{j,t}(n), k_{j,t}(n)\right) = \frac{i_{j,t}(n)}{k_{j,t}(n)} + \frac{\phi_{k,j}}{2}\left(\frac{i_{j,t}(n)}{k_{j,t}(n)} - \delta\right)^2 \tag{6}$$

where $\phi_{k,j}$ governs the degree of adjustment costs and δ is the depreciation rate for capital. Capital of each producer of type n in sector j evolves as:

$$k_{j,t+1}(n) = (1-\delta)\, k_{j,t}(n) + i_{j,t}(n). \tag{7}$$

Intermediate good producers in both sectors are monopolistic competitors in the product market and price takers in the input market. They face a quadratic cost when changing their nominal output price $p_{j,t}(n)$ each period, similar to Rotemberg (1982), given by:

$$\Phi_{P,j}\left(p_{j,t}(n), p_{j,t-1}(n)\right) = \frac{\phi_{P,j}}{2}\left[\frac{p_{j,t}(n)}{\Pi_j p_{j,t-1}(n)} - 1\right]^2 p_{j,t}(n) Y_{j,t}, \quad j \in \{c,i\}, \tag{8}$$

where $Y_{j,t}$ is the final composite good in sector j, Π_j is the steady-state inflation in the j sector, and $\phi_{P,j}$ governs the degree of price rigidity in sector j. In all, the nominal dividend of the good producer of type n in sector j, in terms of nominal consumption goods, is given by:

$$d^{\$}_{j,t}(n) = p_{j,t}(n) y_{j,t}(n) - W_t n_{j,t}(n) - P_{i,t}\Phi_{j,k}\left(\frac{i_{j,t}(n)}{k_{j,t}(n)}\right) k_{j,t}(n) - \Phi_{P,j}\left(p_{j,t}(n), p_{j,t-1}(n)\right). \tag{9}$$

Each intermediate good producer n chooses optimal hiring, investment, and nominal output price to maximize the firm's market value, taking as given nominal wages W_t, the nominal price of investment goods $P_{i,t}$, the demand for differentiated intermediate good n in sector j given by equation (4), and the nominal stochastic discount factor of the household $M^{\$}_{t,t+1}$. Specifically, the intermediate good producers maximize:

$$V^{\$}_{j,t}(n) = \max_{\{n_{j,s}(n),k_{j,s}(n),p_{j,s}(n)\}} E_t \Sigma_{s=t}^{\infty} M^{\$}_{t,t+s} d^{\$}_{j,t+s}(n), \tag{10}$$

subject to equation (7), equation (9), and the demand constraint:

$$\left[\frac{p_{j,t}(n)}{P_{j,t}}\right]^{-\mu_j} Y_{j,t} \leq Z_{j,t} k_{j,t}(n)^{\alpha_j} n_{j,t}(n)^{1-\alpha_j}, \quad j \in \{c,i\}. \tag{11}$$

Note that $V^{\$}_{j,t}(n)$ is in nominal consumption units. The real firm value $V_{j,t}(n)$ and real dividend $d_{j,t}(n)$ are defined as:

$$V_{j,t}(n) = V^{\$}_{j,t}(n)/P_{c,t}; \quad d_{j,t}(n) = d^{\$}_{j,t}(n)/P_{c,t}. \tag{12}$$

Lastly, define the real growth rate of aggregate investment expenditures (in terms of real consumption goods) as $\triangle I_t = \frac{(P_{i,t}/P_{c,t})Y_{i,t}}{(P_{i,t-1}/P_{c,t-1})Y_{i,t-1}}$ and the growth rate in the relative price of investment goods by $\triangle P_{i,t} = \frac{P_{i,t}/P_{c,t}}{P_{i,t-1}/P_{c,t-1}}$.

2.2.2 Technology

Production in the investment (consumption) sector is subject to a technology shock, denoted $Z_{i,t}$ ($Z_{c,t}$). The technological growth rate is characterized as follows:

$$\frac{Z_{j,t}}{Z_{j,t-1}} = g_z + x_{j,t} + \sigma_{z,j}\varepsilon_{z,t}, \quad j \in \{c,i\} \tag{13}$$

$$x_{j,t} = \rho_x x_{j,t-1} + \sigma_{x,j}\varepsilon_{x,t}, \tag{14}$$

where $\rho_x \in (-1,1)$ measures the persistence of long-term technology growth, similar to Croce (2014), and $\sigma_{x,j}$ denotes long-run shocks' standard deviation. The shocks $\varepsilon_{z,t}$ and $\varepsilon_{x,t}$ are standard normal and independent over time. Equations (13) and (14) have two key implications: (i) The innovations $\varepsilon_{z,t}$ and $\varepsilon_{x,t}$ are common across sectors, rather than sector-specific. This implies that technological changes in the investment and consumption sectors are perfectly correlated—each responds to the same aggregate technological growth—scaled by sector-specific volatilities $\sigma_{z,j}$ and $\sigma_{x,j}$. This assumption ensures that the model captures a single, economy-wide technological change (dz) driving both sectors, consistent with the empirical evidence in Section 1.1, which pertains to the effects of aggregate technological changes rather than sectoral ones. (ii) Despite sharing the same innovation source, the sectors differ in how strongly they react to it, as reflected in the distinct volatility parameters $\sigma_{z,j}$ and $\sigma_{x,j}$. This allows for heterogeneous sensitivity to aggregate technology shocks—a salient feature observed in the data (see Fernald (2014)).[12]

2.3 Household

The economy is populated by a representative household that supplies total labor N_t, which flows into both sectors. It derives utility from an Epstein and Zin (1991) and Weil (1989) utility over a stream of consumption goods C_t and disutility from labor N_t:[13]

$$U_t = \left\{ (1-\beta)\left[C_t\left(1-\xi N_t^{\eta}\right)\right]^{1-1/\psi} + \beta\left(E_t U_{t+1}^{1-\gamma}\right)^{\frac{1-1/\psi}{1-\gamma}} \right\}^{\frac{1}{1-1/\psi}} \tag{15}$$

where β is the time discount rate[14], γ is the relative risk aversion, ψ is the inter-temporal elasticity of substitution (IES), ξ is the amount of disutility from labor, and η is the sensitivity of disutility to working hours. When $\gamma > (<) \frac{1}{\psi}$, the household has preferences exhibiting early (late) resolution of uncertainty. The household derives income from labor and from the dividends of intermediate consumption and investment goods producers. She chooses labor supply and consumption to maximize her lifetime utility, subject to the budget constraint:

$$\max_{\{C_s, N_s\}} U_t, \qquad \text{s.t. } P_{c,t}C_t = W_t N_t + \int_0^1 d_{c,t}^{\$}(n)dn + \int_0^1 d_{i,t}^{\$}(n)dn \tag{16}$$

where $P_{c,t}$ is the nominal price of final consumption goods, and W_t is the nominal market wage. The household problem yields the nominal SDF used to discount the nominal dividend of intermediate good producing firms in both sectors:

$$M_{t+1}^{\$} = \beta\left(\frac{C_{t+1}}{C_t}\right)^{-1/\psi}\left(\frac{1-\xi N_{t+1}^{\eta}}{1-\xi N_t^{\eta}}\right)^{1-1/\psi}\left(\frac{U_{t+1}}{\left(E_t U_{t+1}^{1-\gamma}\right)^{\frac{1}{1-\gamma}}}\right)^{1/\psi-\gamma}\frac{P_{c,t}}{P_{c,t+1}} \tag{17}$$

[12] In-line with the modeling choice of Papanikolaou (2011) and Garlappi and Song (2017), Z_c and Z_i are not co-integrated. Balanced growth is achieved as consumption and investment expenditures (i.e., investment quantity times its price) grow at the same rate. This also implies that valuations in both sectors–denominated in consumption units–grow at the same rate.

[13] In the current specification, we adopt King–Plosser–Rebelo (1988) preferences, in which consumption and leisure are multiplicative. For robustness, we have experimented with Jaimovich–Rebelo preferences (2009), in which the wealth effect on labor supply is muted. Despite having a small quantitative effect, this departure does not change the sign of any of our results.

[14] We assume the time-discount rate is non-stochastic, and abstract from demand shocks despite their importance in the macro literature, in order to focus on the key stylized facts related to supply shocks.

Closing the model. To conserve space, Appendix A discusses the monetary authority in the model – needed to obtain endogenous inflation, while Appendix B formalizes an equilibrium[15] along with the market clearing conditions.

2.4 Returns

2.4.1 Stock Returns

The real realized stock return for each sector $j \in \{c,i\}$ is:

$$R_{j,t+1}^{S(unlevered)} = \frac{d_{j,t+1} + V_{j,t+1}}{V_{j,t}} = \frac{d_{j,t+1}^{\$}/P_{c,t+1} + V_{j,t+1}^{\$}/P_{c,t+1}}{V_{j,t}^{\$}/P_{c,t}},$$

where the dividend $d_{j,t+1}^{\$}$ and firm value $V_{j,t+1}^{\$}$ are defined in equations (9) and (10).

Define the unlevered market return as the value-weighted return of both sectors, i.e.,

$$R_{M,t}^{S(unlevered)} = \frac{V_{c,t-1}}{V_{c,t-1} + V_{i,t-1}} R_{c,t}^{S(unlevered)} + \frac{V_{i,t-1}}{V_{c,t-1} + V_{i,t-1}} R_{i,t}^{S(unlevered)}. \tag{18}$$

Our model does not feature financial debt, operating leverage, or nonsystematic payouts. We therefore define the observed excess returns as follows:

$$R_{j,t}^{e} = \phi_{lev}(R_{j,t}^{S(unlevered)} - R_t^f) + \sigma_d \varepsilon_{j,d,t} \quad j \in \{c,i,m\}, \tag{19}$$

where ϕ_{lev} is the degree of total financial and operating leverage, and σ_d captures the volatility of idiosyncratic dividend shocks. Importantly, the leverage parameter does not affect the cyclicality of the market return, and the shocks, $\varepsilon_{j,d,t}$, do not covary with the SDF. The implied levered market gross return $R_{j,t}^S$ is defined as the sum of the market excess return and the risk-free rate. Lastly, the real risk-free rate satisfies: $\frac{1}{R_t^f} = E_t\left[M_{t+1}\right]$.

2.4.2 Investment Returns

The first-order conditions of each sector are detailed in Appendix C. Let $q_{j,t}$ be the price of a marginal unit of installed capital in sector j:

$$q_{j,t} = P_{i,t} \frac{\partial \Phi_{j,k}(i_{j,t}, k_{j,t})}{\partial i_{j,t}} k_{j,t}, \tag{20}$$

which depends on the relative price of capital goods, $P_{i,t}$, and on capital installation costs $\partial \Phi_{j,t}/\partial i_{j,t}$, and let $\theta_{j,t}$ be the marginal cost of producing an additional unit of intermediate good in sector j

[15] In what follows, we suppress the variety type (n) from the model's state and control variables, as equilibrium is symmetric.

(i.e., inverse of the markup). Investment returns in sector j are given by:

$$R^I_{j,t+1} = \frac{\partial V_j / \partial k_{j,t+1}}{q_{j,t}} =$$

$$\frac{\overbrace{\alpha_j \theta_{j,t+1} Z_{j,t+1} k_{j,t+1}^{\alpha_j - 1} n_{j,t+1}^{1-\alpha_j} - P_{i,t+1}\left(\Phi_{j,k}(i_{j,t+1}, k_{j,t+1}) + \frac{\partial \Phi_{j,k}\left(i_{j,t+1}, k_{j,t+1}\right)}{\partial k_{j,t+1}} k_{j,t+1}\right) - \delta q_{j,t+1}}^{\text{Dividend Gain}} + \overbrace{q_{j,t+1}}^{\text{Capital Gain}}}{\underbrace{q_{j,t}}_{\text{Cost}}}, \tag{21}$$

aligning with traditional decompositions of investment return. The market investment return is defined as:

$$R^I_{M,t} = \frac{V_{c,t-1}}{V_{c,t-1} + V_{i,t-1}} R^I_{c,t} + \frac{V_{i,t-1}}{V_{c,t-1} + V_{i,t-1}} R^I_{i,t}. \tag{22}$$

In the investment return equation (21), the first term is the dividend (cash-flow) component: marginal product scaled by marginal cost, $\theta_{j,t+1}$, less capital installation expenses. The second term is the capital–gain component $q_{j,t+1}/q_{j,t}$, where $q_{j,t+1}$ depends on $P_{i,t+1}$ (see equation (20)). The key wedge is that sticky prices move θ and P_i jointly, so investment–returns' dividend and capital gains can fall even as stock valuations rise, as we show in section 4.1.

3 Quantification

3.1 Calibration

The model is calibrated at the quarterly frequency. The parameters are detailed in Table 3. We divide these into several categories.

Technology. We set the technological drift of both sectors, g_z, to match the mean of per-capita real consumption growth of about 2%. The parameters $\sigma_{z,i}$ and $\sigma_{z,c}$, which govern the volatility of short-term sectoral technology growth, are jointly set to target the standard deviation of total output growth and the ratio of consumption growth volatility to output growth volatility. In particular, short-term technology shocks in the investment sector are about 30% more volatile than consumption sector shocks, consistent with Fernald (2014). The long-run technological growth parameters follow Croce (2014). Specifically, we set the persistence of long-run technology, ρ_x, at 0.975 to match the first-order autocorrelation of output growth. The standard deviations of long-

Table 3: **Model Parametrization**

Symbol	Parameter	Value
A. Technology		
g_z	Technological drift	1.0032
$\sigma_{z,i}$	Volatility of short-run growth - investment sector(%)	1.65
$\sigma_{z,c}$	Volatility of short-run growth - consumption sector (%)	1.23
ρ_x	Persistence of long-run growth	0.975
$\sigma_{x,i}$	Volatility of long-run growth - investment sector (%)	$0.1*\sigma_{z,i}$
$\sigma_{x,c}$	Volatility of long-run growth - consumption sector (%)	$0.1*\sigma_{z,c}$
B. Production		
α_i	Capital share of output - investment sector	0.33
α_c	Capital share of output - consumption sector	0.33
δ	Capital depreciation rate	0.02
$\phi_{k,i}$	Capital adjustment cost - investment sector	2.9
$\phi_{k,c}$	Capital adjustment cost - consumption sector	2.9
μ_i	Elasticity of good substitution - investment sector	4
μ_c	Elasticity of good substitution - consumption sector	2.4
$\phi_{p,i}$	Rotemberg adjustment cost - investment sector	25
$\phi_{p,c}$	Rotemberg adjustment cost - consumption sector	25
C. Preferences and Rates		
γ	Relative risk aversion	5
ψ	Intertemporal elasticity of substitution	1.4
ξ	Disutility from labor	2
η	Sensitivity of disutility to working hours	4
β	Time discount factor	0.9955
ϕ_{lev}	Combined Financial and Operating Leverage	1.3
D. Monetary Policy		
π_{ss}	Steady state inflation	0.005
ρ_r	Smoothing coefficient of Taylor rule	0.5
ρ_π	Weight on inflation gap	1.5
ρ_y	Weight on output gap	0.5

The table presents the parameter choice of the model (in quarterly frequency) in the benchmark case.

run technology shocks is 10% of the volatility of short-run technology shocks, consistent with Croce (2014), which helps to pin down the unconditional level of the equity premium.

Production. Capital's share of output in both sectors, $\alpha_c = \alpha_i$, is 33%, as in the data. The capital depreciation rate is 2%, implying an annual depreciation of 8.2%. Capital adjustment costs in both sectors, $\phi_{k,c} = \phi_{k,i}$, are set at 2.9, to match the ratio of investment growth volatility to output growth volatility. These values are also consistent with estimates by Basu and Bundick (2017). We set μ_i and μ_c to 4 and 2.4, respectively. The first implies that the average markup in the investment sector is 33%, close to the value estimated by Bilbiie, Ghironi, and Melitz (2012) and close to Garlappi and Song (2017), while the latter implies that the average ratio of investment sector markup to consumption sector markup is 46%, consistent with De Loecker, Eeckhout, and Mongey (2021).[16] The Rotemberg adjustment costs, $\phi_{p,c} = \phi_{p,i} \equiv \phi_p$, are calibrated to match the data on average price duration, as estimated by Galı, Gertler, and Lopez-Salido (2001) and Sbordone (2002). We set ϕ_p to 25, close to Kung (2015), corresponding to a price duration of approximately four quarters.[17] This degree of price rigidity is conservative compared to the literature (see, e.g., Basu and Bundick (2017), who set ϕ_p to 100), and implies a very small output loss of about 0.28%.

Preferences and rates. We adopt a standard preference parameter configuration in the production-based asset pricing literature. Specifically, γ is set to a conservative value of 5, while the IES, ψ, is calibrated to 1.4, in line with Croce, Nguyen, Raymond, and Schmid (2019), suggesting an early resolution of uncertainty. The degree of disutility to working hours ξ is chosen such that in the deterministic steady state, the household works roughly 20% of its time. η, the Frisch elasticity of the labor supply is 4, consistent with Keane and Neal (2023). The time discount factor β is 0.9955, targeting a low real risk-free rate. Consistent with the total degree of leverage (joint operating and financial leverage) estimated in García-Feijóo and Jorgensen (2010), we set ϕ_{lev} to 1.3, a conservative value compared to Bansal and Yaron (2004) and Croce (2014).

Monetary Policy. The monetary policy parameters are identical to Basu and Bundick (2017). π_{ss} implies an annual inflation rate of 2%. The weights on the inflation gap and the output gap are 1.5 and 0.5, respectively. The smoothing parameter of the nominal policy rule, ρ_r, is 0.5. We solve the model using a third-order perturbation method.[18]

[16] While the specific values of μ_c and μ_i are disciplined by recent data, the forces at play in Section 4 do not qualitatively depend on the average level of markups. So long as the ratio between the consumption-sector markup to investment-sector markup is maintained, changing μ_c and μ_i only induces a small quantitative effect on the results to follow.

[17] See Online Appendix section OA.4 for details on this mapping.

[18] We verify that usage of higher orders induces a minimal impact on the quantitative results, and that model-simulated paths are well-defined even without pruning.

Table 4: **Model-Implied Aggregate Moments**

	Data	Benchmark	No-LRR	No-LRR & No-Sticky	No-LRR & Perfect-Comp
$E(\Delta C)(\%)$	1.80	1.85	1.83	1.83	1.83
$\sigma(\Delta Y)(\%)$	3.05	3.14	2.37	2.64	2.84
$AC(\Delta Y)$	0.54	0.40	0.11	0.00	-0.01
$\rho(\Delta Y, \Delta C)$	0.88	0.80	0.99	1.00	0.99
$\sigma(\Delta C)/\sigma(\Delta Y)$	0.88	0.88	0.79	0.82	0.70
$\sigma(\Delta I)/\sigma(\Delta Y)$	3.02	2.85	2.12	1.87	1.72
$\sigma(\Delta N)/\sigma(\Delta Y)$	0.73	0.41	0.39	0.05	0.06
$E(R^e_M)(\%)$	4.71	3.97	0.46	0.59	0.14
$\sigma(R^e_M)(\%)$	20.89	19.31	2.67	3.34	0.78
$E(r^f)(\%)$	0.65	1.24	2.89	2.80	2.82
$\sigma(r^f)(\%)$	1.86	1.23	0.51	0.23	0.23

The table presents annual moments from the data and the model simulation. We report four alternative calibrations: (I) The benchmark model with parameters from Table 3, referred to as 'Benchmark', (II) A model excluding long-term productivity shocks, with $\sigma_{x,c} = \sigma_{x,i} = 0$, labeled as 'No-LRR', (III) A model void of long-term risk shocks and price stickiness, where $\phi_{p,c} = \phi_{p,i} = 0$, termed as 'No-LRR & No-Sticky', (IV) A model devoid of long-term risk shocks, sticky prices, and markups, signifying perfect competition where $\mu_c = \mu_i \to \infty$, designated as 'No-LRR & Perfect-Comp'. The model-implied moments are based on the average across a thousand finite paths simulations, each of 160 quarters (after dropping the first 400 quarters). Quarterly model observations are aggregated to form annual paths.

3.2 Unconditional Aggregate Moments

Table 4 reports annual moments in the data and the model. The model-implied moments are based on the average across a thousand simulations for 560 quarters. We drop the first 400 quarters to neutralize the impact of the initial condition. The remaining paths match the length of the empirical path used for projection (1). Quarterly model paths are converted into annual non-overlapping observations by compounding the last four quarters.

We distinguish four cases: (I) the benchmark model (henceforth 'Benchmark'), (II) a model without long-run technology shocks, where $\sigma_{x,c} = \sigma_{x,i} = 0$ (henceforth 'No-LRR'), (III) a model without long-run risk and no sticky prices, $\phi_{p,c} = \phi_{p,i} = 0$ (henceforth 'No-LRR & No-Sticky'), (IV) a model without long-run risk, no sticky prices, and no markups, $\mu_c = \mu_i \to \infty$, suggesting perfect competition (henceforth 'No-LRR & Perfect-Comp').

In the benchmark framework, both the model and data exhibit an output growth volatility of approximately 3%. The first-order autocorrelation of output growth is around 0.40, while the correlation between consumption growth and output growth is 0.80, closely matching the data. The proportion of consumption growth volatility to output growth volatility is 0.88, and for investment growth to output growth volatility it is 2.85. The model produces a more subdued volatility in hours' growth relative to the data. Empirically, the hour-to-output growth volatility ratio is 0.73, whereas in the model it is 0.41. However, we verify that, in finite-sample simulations, the model-implied upper bound of this ratio overlaps with the empirical counterpart. The asset pricing moments implied by the benchmark model align closely with empirical observations. The model generates an equity premium of 3.97% and a modest risk-free rate of 1.24%. Consistent with the data, the model excess market return has a volatility of 19.31%, and the risk-free rate shows a volatility of about 1%.

The 'No-LRR' configuration and the 'Benchmark' configuration feature similar unconditional aggregate macroeconomic moments. Yet in the absence of long-run risks, the equity premium contracts to only 0.46%. Importantly, these shocks play a key quantitative role in explaining the magnitudes of conditional price dynamics, as explained in the next section. The moments implied by both 'No-LRR & No-Sticky' and 'No-LRR & Perfect-Comp' configurations exhibit marked similarity. The presence of sticky prices is important in generating sizable business-cycle fluctuations of input variables. In both configurations, the volatility of investment and hours is notably lower compared to the data.

4 Resolution of Asset-Pricing Correlation Puzzles

In this section we show that the two-sector New-Keynesian model can explain several disconnection puzzles, pertaining to the co-movement of equity markets with cyclical macroeconomic quantities. We show that the reconciliation of the puzzles can be jointly attributed to the motivating evidence — the transitory contractionary effect of technological innovations (Stylized Fact 1), which are endogenously generated by the model, and the degree of sticky prices (Stylized Fact 2).

4.1 Puzzle I: The comovement of investment and stock returns

We examine the ability of the model to tackle the co-movement puzzle of Liu et al. (2009), whereby stock returns and contemporaneous (future) investment returns are weakly negatively

Table 5: **Investment and Stock Returns Correlations**

	Data	Benchmark	No-LRR	No-LRR & No-Sticky	No-LRR &Perfect-Comp
$\text{Corr}(R^I_{M,t}, R^S_{M,t})$	-0.10	-0.17	-0.09	0.90	1.00
$\text{Corr}(R^I_{M,t+1}, R^S_{M,t})$	0.20	0.08	0.67	0.09	0.11
$\text{Corr}(\frac{I_t}{I_{t-1}}, R^S_{M,t})$	-0.20	-0.22	-0.01	0.98	0.95
$\text{Corr}(\frac{I_{t+1}}{I_t}, R^S_{M,t})$	0.10	0.14	0.10	0.04	-0.01

The table shows correlations in the data (obtained from Liu et al. (2009)) and in the simulated model. We report the simultaneous correlation between investment returns (R^I) and stock returns (R^S), and the correlation between equity returns and subsequent investment returns. We also report the correlation between current or future investment growth and stock returns. For each moment, we compare four alternative calibrations: (I) The benchmark model with parameters from Table 3, referred to as 'Benchmark', (II) A model excluding long-term productivity shocks, with $\sigma_{x,c} = \sigma_{x,i} = 0$, labeled as 'No-LRR', (III) A model devoid of long-term risk shocks and price stickiness, where $\phi_{p,c} = \phi_{p,i} = 0$, termed as 'No-LRR & No-Sticky', (IV) A model devoid of long-term risk shocks, sticky prices, and markups, signifying perfect competition where $\mu_c = \mu_i \to \infty$, labeled as 'No-LRR & Perfect-Comp'. The model-implied moments are based on the average across annualized finite sample paths.

(positively) correlated. Table 5 lists the correlation between stock returns and measures of investment, as implied by the model.

The benchmark case of the model quantitatively replicates the comovement anomaly — without being targeted by the calibration. As shown in the first row of Table 5, the 'Benchmark' configuration produces a negative contemporaneous correlation between market stock returns and investment returns. The correlation is -0.1 in the data from Liu et al. (2009), compared to -0.17 in the model. Moreover, the second row of the table shows that the correlation between market returns and one-year-ahead investment returns is positive, at around 0.1, mirroring the empirical pattern.

As noted in Cochrane (1991), investment returns are closely linked to a model-free time series of investment growth. Rows 3 and 4 of Table 5 report the model-implied correlations between market returns and either contemporaneous or future investment growth, respectively. Under the benchmark, the former correlation is negative (consistent with row 1) while the latter is positive (consistent with row 2).

Long-run productivity risks help quantitatively: in their absence ('No-LRR'), the signs of the correlations in rows 1–4 are maintained, but the magnitudes are off. Specifically, the correlation between current market returns and contemporaneous investment growth (future investment return) is too low (high) — in absolute value — compared to the data.[19]

Conversely, as shown in rows 1 and 3, in configurations without sticky prices — having either constant markup or perfect competition — investment measures and stock returns are (almost) perfectly positively correlated, counterfactually so. The fact that the contemporaneous correlation between stock- and investment- return/growth is less negative (and even positive) in the absence of sticky prices is consistent with Stylized Fact 2(a). This counterfactual sign is prevalent in the literature (see, e.g., Jermann, 1998; Zhang, 2005; Kaltenbrunner and Lochstoer, 2010; Croce, 2014; Garlappi and Song, 2017, among many others).

Importantly, our benchmark model addresses the comovement puzzle with a single type of capital goods. While introducing other types of capital could potentially decrease the contemporaneous correlation between stock- and investment- returns, by creating an additional wedge, the model-implied investment returns would not correspond to the empirical evidence of Liu et al. (2009), who only rely on physical capital.[20]

4.1.1 Inspecting the Mechanism

To explain the core mechanism for the anomaly's resolution, we shut down long-run risks and plot impulse response functions from technological innovations to macro variables, market stock returns, and investment returns, contrasting the case with sticky prices (represented in blue) against those devoid of such rigidity (in red), as shown in Figure 3.

Underlying Macro Dynamics. Without sticky prices, a technological innovation increases firms' contemporaneous and future marginal productivity of capital. This prompts firms to immediately raise their investment, as shown by the red line in panel (b) of Figure 3. The demand for capital raises the relative price of capital goods (red line in panel (c)), and thereby increases firms'

[19] In Online Appendix Section OA.1 we explain why long-run risks help in this context, by contrasting our setup to Basu et al. (2013) which features habit formation, and consequently, fails to obtain a positive correlation between current stock returns and future investment returns.

[20] A Recent study by Gonçalves, Xue, and Zhang (2020) suggests that when accounting for multiple types of capital goods, including working capital, the correlation between fundamental returns and stock returns could be mildly positive (around 0.1). Despite the fact that our model features a single type of capital, consistent with Liu et al. (2009), this close-to-zero estimate falls within the model's confidence interval implied by finite sample simulations.

marginal production costs in panel (d). Notably, higher investment combined with a higher relative price of capital implies that capital growth strictly increases following the technological innovation, in contrast to Stylized Fact 1(b). We elaborate more on this tension in Section 6.1.

Nominal rigidities change the implications of technological innovations on the relative price of investment, from expansionary to contractionary. After a positive technological innovation, output underreacts to the supply shock, compared to the scenario with flexible prices (panel (a) of Figure 3). This more muted output response occurs as price levels are unable to fully react to the shock because of nominal rigidities, resulting in a contraction in the output gap. The decreased output gap, in turn, implies a decrease in the inflation gap, according to the New-Keynesian Phillips curve (equation (A.10)). Within the New-Keynesian framework, inflation is proportional to the expected discounted value of future marginal costs, which depend on the relative price of investment. Thus, the decline in the inflation gap under sticky prices, in turn, implies a downward pressure on the relative price of investment goods.

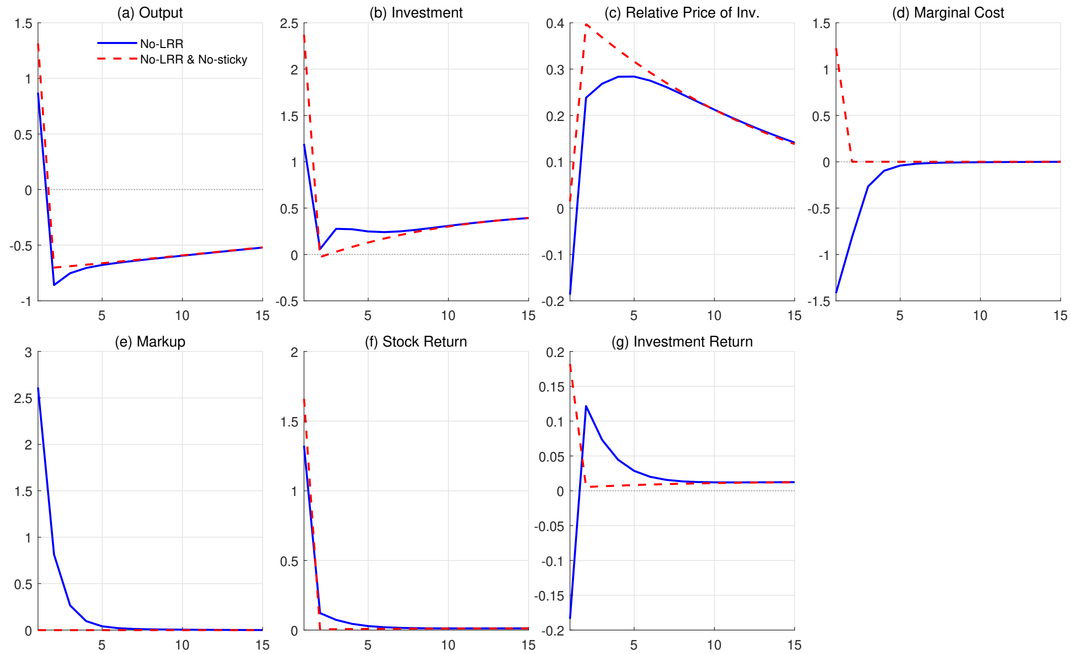
If the degree of price stickiness is sufficiently large — yet, empirically disciplined — the price of capital goods declines after a positive innovation, as illustrated by the blue line in panel (c). As explained later, this is instrumental in reconciling Stylized Fact 1(b). The countercyclical behavior of capital goods' prices is also consistent with the empirical findings of Greenwood et al. (1997) and Christiano and Fisher (2003). Furthermore, the decrease in the price of capital goods drops the marginal production costs (panel (d)), in sharp contrast to the flexible price case.[21]

Returns. Under both the flexible and sticky price cases, positive technological shocks raise firms' valuations and stock returns, as shown in panel (f) of Figure 3. In the sticky-price case, the higher valuation arises due to elevated monopolistic rents: The drop in firms' marginal costs raises markups (see panel (e)), as output prices are rigid in the short run .

At the same time, the former dynamics imply that technological shocks yield transient innovation-driven contractions in investment returns. Specifically, within a two-sector New-Keynesian framework featuring monopolistic power, stock returns and investment returns are not equal state-by-

[21]The IRFs plot the average marginal cost between the two sectors, each is proportional to $W_t^{1-\alpha_j} R_{K,j,t}^{\alpha_j}$, where W_t denotes the wage—the price of one unit of labor services—and $R_{K,j,t}$ denotes the rental rate (user cost) of one unit of installed capital services in sector j.

Figure 3: **Model-Implied Impulse-Responses of Macro Variables and Returns**



The figure shows impulse responses of model-detrended real output, investment expenditures, the relative price of investment, marginal cost, markup, stock return and investment return to one standard deviation shock of aggregate technology. The solid blue line shows impulse responses from the 'No-LRR' model. The dash-dotted red line shows impulse responses from a 'No-LRR & No-Sticky', which is identical to the former calibration but without price stickiness ($\phi_{p,c} = \phi_{p,i} = 0$). The horizontal axis represents quarters. The vertical axis represents percent deviations from the steady state.

state. Two dominant, yet opposing forces affect investment returns:

On the one hand, technological shocks increase the expected marginal productivity of capital, thereby increasing investment rates, as evidenced in panels (b) of Figure 3. In the presence of capital frictions (i.e., adjustment costs), heightened investment rates should also increase the shadow price of capital (see equation (20)), and consequently, the return on investment. This dynamic, featured in the conventional flexible-price case, operates to induce a counterfactual strong positive correlation between stock and investment returns, as depicted by the red line in panel (g).

On the other hand, as previously discussed, technological shocks can decrease the relative price of capital when prices exhibit sufficient rigidity. Ceteris paribus, this decreases the shadow price of capital in the short term (see equation (20)), and thereby also investment returns. When the degree of price rigidity is empirically disciplined, this force dominates, as indicated by the blue line in panel (g) — resulting in a negative comovement between investment returns and stock returns, consistent with the empirical findings of Liu et al. (2009), as well as Stylized Fact 2(a).

Lastly, the negative impact of sticky prices on the relative price of investment is transient. In subsequent periods, the relative price spikes, converging to its dynamics under the flexible price case (see panel (c)). This renders higher future investment returns (see panel (g)) and explains the positive lead-lag relationship between market and investment returns, in both the model and the data.

4.1.2 Alternative Construction of Investment Returns

Table 5 shows that the benchmark model generates a negative comovement between stock returns and either investment growth or investment returns, when the latter are defined using equations (21) and (22). In Table 6 we demonstrate that this negative correlation is not contingent on our model's specific functional form of investment returns.

We consider an alternative definition of sectoral investment returns — which generalizes the functional form employed empirically by Liu et al. (2009), and is consistent with one-sector perfect-competition setups:

$$R^{I,(\text{Alt})}_{j,t+1} = \frac{\alpha_j \widetilde{YK}_{j,t+1} + \frac{\phi_{k,j}}{2}\left(\widetilde{IK}^2_{j,t+1} - \tilde{\delta}^2\right)}{1+\phi_{k,j}\left(\widetilde{IK}_{j,t} - \tilde{\delta}\right)} + (1-\delta)\frac{1+\phi_{k,j}\left(\widetilde{IK}_{j,t+1} - \tilde{\delta}\right)}{1+\phi_{k,j}\left(\widetilde{IK}_{j,t} - \tilde{\delta}\right)}, \; j \in \{c, i\}, \tag{23}$$

where $\widetilde{YK}_{j,t}$ represents an empirical equivalent for the marginal product of capital in sector j, and $\widetilde{IK}_{j,t}$ represents observed paths of sectoral investment rates. The rate $\tilde{\delta}$ is equal to δ, if the quadratic adjustment costs are defined over net investment (as in our model) or 0, if the adjustment costs are defined over gross investment (as in Liu et al. (2009)).[22] The market-wide return on investment is identical to equation (22) when replacing R^I_j by $R^{I,(\text{Alt})}_j$.

To be consistent with the empirical construction of $\widetilde{YK}$ by Liu et al. (2009), we simulate detrended model paths and divide firms' sales revenue by their capital stock, expressed in dollar amounts (i.e., in consumption units).[23] Similarly, to measure $\widetilde{IK}$, we use the same simulations of detrended model paths and divide firms' investment expenditures by the lagged value of their

[22] That is, definition (23) is identical to equation (3) in Liu et al. (2009), when $\tilde{\delta} = 0$, and the tax rate, τ, is also set to 0.

[23] Firms' sales revenue is equal to the amount produced Y_j times the sell-price P_j. Firms' end-of-period capital stock in dollar amount equals the amount of their machines K_j multiplied by the machines' market price P_I.

end-of-period capital stock, also expressed in dollar amounts.

We examine four different configurations for the parameter values, suggesting four different time series of investment returns: (i) $R^{I,(\text{Alt i})}$: Setting $\tilde{\delta} = 0$, and where the values of α and ϕ_k are identical to those of Table 3; (ii) $R^{I,(\text{Alt ii})}$: Setting $\tilde{\delta} = \delta$, and where the values of α and ϕ_k are identical to those of Table 3; (iii) $R^{I,(\text{Alt iii})}$: Setting $\tilde{\delta} = 0$, and where the values of α and ϕ_k are identical to their average estimates from Liu et al. (2009), amounting to 0.33 and 10.3, respectively. (iv) $R^{I,(\text{Alt iv})}$: Setting $\tilde{\delta} = \delta$, where the values of α and ϕ_k are taken from Liu et al. (2009). Columns (1)—(4) of Table 6 show that the population correlation between stock returns and the alternative investment returns remains negative, and even closer to the point estimate reported by Liu et al. (2009).

Table 6: **Investment and Stock Returns Correlation: Alternative Measures**

	(1) $R^{I,(\text{Alt i})}$	(2) $R^{I,(\text{Alt ii})}$	(3) $R^{I,(\text{Alt iii})}$	(4) $R^{I,(\text{Alt iv})}$
$\text{Corr}(R^{I,(\text{Alt})}_{M,t}, R^S_{M,t})$	-0.08	-0.08	-0.16	-0.16

The table report the simultaneous correlation between investment returns (R^I) and stock returns (R^S) in the simulated model. We show four alternative specifications of investment returns: (1) $R^{I,(\text{Alt i})}$: Setting $\tilde{\delta} = 0$ in equation (23), and where the values of α and ϕ_k are identical to those of Table 3; (2) $R^{I,(\text{Alt ii})}$: Setting $\tilde{\delta} = \delta$ in equation (23), and where the values of α and ϕ_k are identical to those of Table 3; (3) $R^{I,(\text{Alt iii})}$: Setting $\tilde{\delta} = 0$ in equation (23), and where the values of α and ϕ_k are taken from Liu et al. (2009), amounting to 0.33 and 10.3, respectively; (4) $R^{I,(\text{Alt iv})}$: Setting $\tilde{\delta} = \delta$ in equation (23), where the values of α and ϕ_k are taken from Liu et al. (2009).

4.2 Puzzle II: Labor markets surprises and stock valuations

We explore the ability of the model to resolve the puzzle of Boyd et al. (2005) among others, whereby equity valuations often rise in response to announcements of heightened unemployment. The underlying premise posited by these papers is that greater unemployment signals an expected decrease in interest rates (see, e.g., Elenev et al. (2022)). Xu and You (2022) provide similar empirical evidence during the COVID period and argue that following increased unemployment, investors anticipate greater fiscal interventions by the Federal Government, resulting in elevated stock valuations.

In all of the aforementioned studies, the resolution of this anomaly is predominantly attributed to offsetting (monetary or fiscal) policy. We argue that while such channels can certainly play an important role,[24] the foundational empirical observations might not inherently be as "anomalous" if technological innovations raise stock prices while simultaneously leading to transient contractions in the labor market.

Table 7 shows that our model explains this puzzle without resorting to aggressive exogenous policy shocks. We derive labor surprises within the model by subtracting expected hiring from realized hiring. Under the 'Benchmark' configuration, the correlations between labor surprises and either market stock returns or the risk-free rate are negative, and both are close to the data. This mirrors the average empirical case documented by Boyd et al. (2005).

As in the former subsection, long run risk shocks do not alter the sign of the correlation, but they help quantitatively. In their absence, the stock market-labor surprise correlation is almost perfectly negative, overshooting the data. Furthermore, in cases where sticky prices are shut down, the correlation inverts to a positive value. While unconditionally this is a counterfactual, obtaining a positive correlation when prices are flexible is consistent with Stylized Fact 2(b) (i.e., at times of lower rigidity the correlation increases).

Indeed, the correlation between labor market surprises and the stock market exhibits time variation. In particular, Boyd et al. (2005) find that rising unemployment is good news for equities, particularly during economic expansions, when nominal interest rates are high. Our framework is able to replicate this finding when accounting for the findings of Vavra (2014) that the frequency of price changes is countercyclical in the data. In the Online Appendix we incorporate this insight by augmenting the 'No-LRR' model configuration with a procyclical degree of price rigidity. The results are reported in Table OA.5. During expansions, the nominal interest rate and the nominal price rigidity are both high, leading to a negative correlation between labor surprises and the market. During recessions, when the nominal interest rate is low, the degree of price stickiness falls, decreasing the role of the monetary authority and attenuating markup fluctuations. As in the perfect competition case, the correlation between the stock market and labor market surprises turns

[24]In Online Appendix OA.2 we corroborate that changes to the conduct of monetary policy can decrease the correlation between market returns and labor surprises. However, in general equilibrium, the impact on the correlation — purely from policy expectations — is quantitatively very small, even when the policy rule is counterfactually too aggressive.

Table 7: **Labor Market Surprises and Stock Returns**

	Data	Benchmark	No-LRR	No-LRR & No-Sticky	No-LRR & Perfect-Comp
$\text{Corr}(N_t^{\text{surprise}}, R_{M,t}^S)$	-0.27	-0.27	-0.98	1.00	0.93
$\text{Corr}(N_t^{\text{surprise}}, R_t^f)$	-0.11	-0.10	-0.77	0.00	-0.06

The table shows the model-implied correlation between labor market surprises, N^{surprise}, and the stock market return, R_m^S, or the risk-free interest rate, R_f. We define the labor market surprises as $N_t^{\text{surprise}} = N_t - E_{t-1}[N_t]$. We compare four alternative calibrations: (I) The benchmark model with parameters from Table 3, referred to as 'Benchmark', (II) A model excluding long-term productivity shocks, with $\sigma_{x,c} = \sigma_{x,i} = 0$, labeled as 'No-LRR', (III) A model devoid of long-term risk shocks and price stickiness, where $\phi_{p,c} = \phi_{p,i} = 0$, termed as 'No-LRR & No-Sticky', (IV) A model devoid of long-term risk shocks, sticky prices, and markups, implying perfect competition where $\mu_c = \mu_i \to \infty$, labeled as 'No-LRR & Perfect-Comp'. The model-implied moments are based on the average across annualized finite sample paths. In the data, N^{surprise} is constructed as the residual from an AR(1) model applied to the time series of aggregate annual employment (the sum of employees in the investment and consumption sectors, 1953–2019). R_f is measured as the real risk-free rate, calculated as the 3-month T-bill rate minus expected one-year-ahead inflation. Expected inflation is the fitted value from a predictive regression using a set of predictors—including inflation, the nominal 3-month T-bill rate, and the credit spread (Baa-Aaa)—all lagged by one period.

positive, in line with Stylized Fact 2(b).

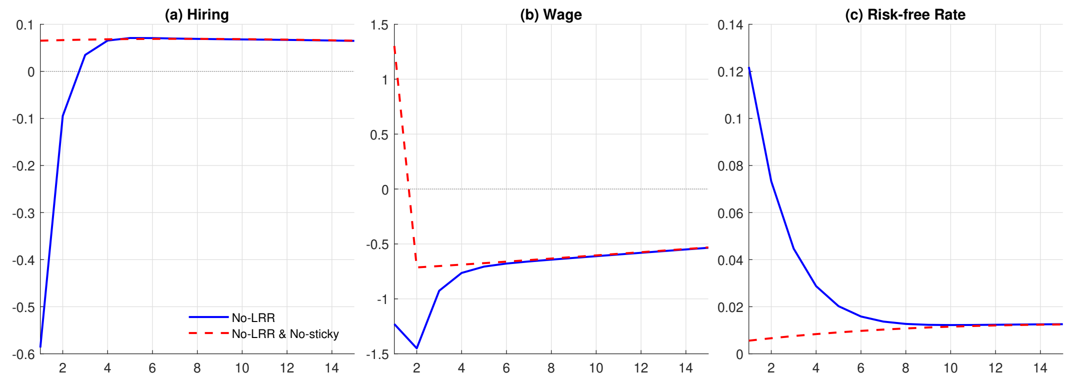
4.2.1 Inspecting the mechanism

To explain the mechanism, as before, we shut down long-run risks and plot in Figure 4 impulse responses from technological innovations to hiring, wages, and interest rates.

Positive technological innovations increase firms' marginal productivity of labor. When prices are flexible, firms respond by immediately hiring extra labor (red line in panel (a) of Figure 4), in contrast to Stylized Fact 1(a). The increased demand for labor raises wages as well (red line in panel (b) of Figure 4). Because investment returns and stock returns are perfectly correlated in this case, and positive innovations raise investment returns (see Section 4.1), stock returns also rise. This results in a positive correlation between unexpected hiring and the stock market.

However, as discussed in Section 4.1.1, when prices are sticky a positive technological innovation leads to a decline in the output gap, suggesting that hours should decrease in response to the positive technology shock. To see why, the decline in the output gap ultimately leads to a lower wage bill (blue line in panel (b) of Figure 4): an output gap drop exerts a downward pressure on the marginal costs of production — which depend not only on the relative price of capital (as previously discussed) — but also on hiring costs. The drop in firms' marginal costs raises markups as

Figure 4: **Model-Implied Impulse-Responses of Hiring, Wage, and Risk-free Rate**



The figure shows impulse responses of hiring, wage, and the real risk-free rate to one standard deviation aggregate technology shock. The solid blue line shows impulse responses from the 'No-LRR' model. The dash-dotted red line shows impulse responses from a 'No-LRR & No-Sticky', which is identical to the former calibration but without price stickiness ($\phi_{p,c} = \phi_{p,i} = 0$). The horizontal axis represents quarters. The vertical axis represents percent deviations from the steady state.

output prices are rigid in the short run (panel (e) of Figure 3).

The elevated markups are tantamount to a higher tax – they induce a rationing effect on the desired hiring, and, in sharp contrast to flexible prices, total employment contracts in the short run (blue line in panel (c)). This contractionary effect of positive innovations is consistent with Stylized Fact 1(a). At the same time, the elevated markups enhance valuations via higher monopolistic rents, as depicted in panel (f) of Figure 3, generating a negative unconditional comovement between stock returns and labor market surprises.

Furthermore, given the initial subdued response of output, coupled with an expected future surge in the output gap, the real interest rate exhibits an initial increase, as evidenced in panel (c) of Figure 4. This dynamic suggests a negative average comovement between the risk-free rate and labor surprises. In all, within our framework, labor or employment metrics are endogenously determined and, as such, cannot be directly interpreted as indicators of favorable or adverse underlying economic conditions.

The Role of Expectations. Expectations relate to our proposed mechanism for the negative correlation between labor market announcements and stock returns. In reality, labor market releases occur within a very short window, leaving little time for any realized effects of productivity to influence current cash flows. This timing, however, is immaterial for our conceptual mechanism.

What matters in our model is that a labor market surprise reveals information about productivity, which in turn shifts expectations of future profits (i.e., monopolistic rents). In our model, higher productivity—under sticky prices—raises future markups and thus the present value of future dividends, even if no cash-flow change occurs at the time of the announcement. We verify this in the model: when prices are sticky, the correlation between labor market surprises and ex-dividend valuations remains negative. Put differently, the conventional interpretation of the negative correlation between labor surprises and valuations is that markets *learn* about future monetary easing when labor data are weak, lowering *expected* discount rates. In contrast, our mechanism operates through *expectations* of higher future markups: when employment news is weaker than expected, agents *infer* higher productivity and anticipate greater monopolistic rents ahead.

4.3 Puzzle III: The cyclicality of equity yields term structure

We examine the implications of our model for the cyclicality of the equity yield term structure. As shown by Bansal et al. (2021), the slope of this term structure correlates positively with metrics of the business cycle, imposing a challenge for canonical models with long run risks. Using the model from section 2, we define the price of a dividend strip at time t maturing in n periods, $P_{t,n}$, recursively as follows:

$$P_{t,0} = d_t \tag{24}$$

$$P_{t,n} = \mathbb{E}_t\left[M_{t,t+1}P_{t+1,n-1}\right]. \tag{25}$$

As a result, the equity yield for maturity n is given by:

$$e_{t,n} = \frac{1}{n}\log\left(\frac{d_t}{P_{t,n}}\right).$$

We define the slope of the equity-yield term structure as the n-quarters to maturity equity yield net of next period's maturing equity yield: $\text{Slope}_{t,n} = e_{t,n} - e_{t,1}$. To examine its cyclicality, we run the following regression:

$$\text{Slope}_{t,n} = const + \phi_n \cdot dp_t + error,$$

where dp_t is the (log) market dividend yield. A procyclical slope implies that $\phi_n < 0$.

Table 8 provides the regression results using model-simulated paths for maturity $n \in \{8, 12, 16, 20\}$ quarters. In the context of the 'Benchmark' and the 'No-LRR' specifications, the model produces

Table 8: **Cyclicality of the Equity Yield Term Structure**

	ϕ_n				β_n		
Maturity (n)	Data	Benchmark	No LRR	No LRR & No sticky	Benchmark	No LRR	No LRR & No sticky
8	N.A.	-0.20	-0.46	0.00	0.23	0.53	-0.007
		$[-0.40,-0.05]$	$[-0.57,-0.33]$	$[0.00,0.01]$	$[0.061,0.47]$	$[0.38,0.66]$	$[-0.012,-0.002]$
12	N.A.	-0.21	-0.49	0.00	0.23	0.53	-0.007
		$[-0.42,-0.06]$	$[-0.61,-0.35]$	$[0.00,0.01]$	$[0.059,0.47]$	$[0.38,0.66]$	$[-0.015,-0.000]$
16	N.A.	-0.22	-0.51	0.00	0.23	0.53	-0.006
		$[-0.44,-0.06]$	$[-0.63,-0.36]$	$[0.00,0.01]$	$[0.06,0.47]$	$[0.39,0.66]$	$[-0.015,0.002]$
20	-0.33	-0.22	-0.51	0.00	0.23	0.53	-0.004
		$[-0.44,-0.06]$	$[-0.64,-0.37]$	$[0.00,0.01]$	$[0.06,0.47]$	$[0.39,0.66]$	$[-0.014,0.006]$

The table reports the model-implied coefficients for the following two regressions: $\text{Slope}_{t,n} = const + \phi_n \cdot dp_t + error$ and $E_t\left[g_{d,t,t+n}\right] - E_t\left[g_{d,t,t+1}\right] = const + \beta_n \cdot dp_t + error$. dp_t is the (log) market dividend yield and $n \in \{8,12,16,20\}$ is the maturity (quarters). $\text{Slope}_{t,n} = e_{t,n} - e_{t,1}$ is the slope of the equity-yield term structure and $g_{d,t,t+n} = \frac{1}{n}\ln(\frac{d_{t+n}}{d_t})$ is the n-period average dividend growth. The data moment is taken from Gormsen (2021). We report three alternative calibrations: (I) The benchmark model with parameters from Table 3, referred to as 'Benchmark', (II) A model excluding long-term productivity shocks, with $\sigma_{x,c} = \sigma_{x,i} = 0$, labeled as 'No-LRR', (III) A model devoid of long-term risk shocks and price stickiness, where $\phi_{p,c} = \phi_{p,i} = 0$, termed as 'No-LRR & No-Sticky'. All regression results are based on a thousand simulations, each of 160 quarters (after dropping the first 400 quarters). We report the average across all simulations as well as the 90% confidence interval.

negative regression coefficients between the slopes of the equity-yield term structure at different maturities and the dividend yield. Qualitatively, this procyclicality of the slope is consistent with the evidence presented by Bansal et al. (2021).[25] Quantitatively, with long run risk shocks, at the five-year horizon the regression coefficient (ϕ_{20}) nearly matches the empirical evidence by Gormsen (2021). Without long-run risk, the model-implied slope coefficient is larger than the data, in absolute value.

Conversely, in a theoretical framework without price rigidity the slopes' correlation with the dividend yield is positive and close to zero, implying a countercyclical (or approximately acyclical) fluctuation in the slope, counterfactually.

4.3.1 Inspecting the mechanism

The reconciliation of the slope's cyclicality arises directly from the dynamics outlined in Section 4.1.1 and 4.2.1. A positive technological innovation results in an immediate contraction in labor, as per Stylized Fact 1(a). This suggests that, relative to the case with flexible prices, the

[25] In addition, we conduct the same exercise for the expected equity return term structure, and find it is also procyclical in the model, consistent with Bansal et al. (2021).

expected (realized) dividend growth is higher (lower) in the short term, as future cash flows "catch up" to the flexible price scenario in the near horizon. The converse occurs in response to a negative innovation. Therefore, under our core mechanism, the slope of the expected dividend growth curve becomes more (less) negative during expansions (recessions). To illustrate these cash-flow dynamics, we perform the following regression:

$$E_t\left[g_{d,t,t+n}\right]-E_t\left[g_{d,t,t+1}\right]=const+\beta_n\cdot dp_t+error,$$

where $g_{d,t,t+n}=\frac{1}{n}\ln(\frac{d_{t+n}}{d_t})$ is the n-period average dividend growth. Table 8 shows that across all horizons, the slope of the expected dividend growth curve is countercyclical in the context of the 'Benchmark' and the 'No-LRR' specifications ($\beta_n>0$), while it is procyclical without price rigidity ($\beta_n<0$). Ceteris paribus, expected dividend growth rates and equity yields are inversely related. Thus, given the dynamics of expected dividend growth rates under the benchmark, the equity yield term structure slope is higher (lower) in good (bad) economic states, consistent with the data.

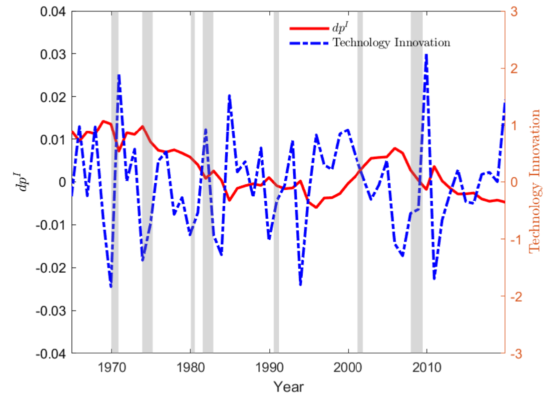
4.4 Model Extension

In Online Appendix Section OA.5 we show that the model (indirectly) speaks to another asset pricing puzzle: why both high book-to-market and high gross profitability are associated with higher expected returns. The model resolves their apparent contradiction by showing how innovation-driven contractions link lower profitability with low-risk states. Specifically, a positive technology shock initially raises productivity, but the resulting labor contraction subsequently outweighs this benefit, causing lower annual gross profits. This dynamic allows the model to replicate the conditional fact that both high book-to-market and high gross profits signal higher discount rates.

5 Return predictability

We demonstrate that our framework can go beyond offering theoretical insights for existing puzzles — it can also yield new applicable tools for financial markets predictability. We define and estimate investment-based dividend yields, which account for the dynamics of innovation-

Figure 5: **Technology Innovation and Investment-Based Dividend Yields**



The figure shows the annual time series of the filtered technology shocks, annualized by summing up the last four quarter innovations, along with investment-based dividend yields from 1964 to 2019.

driven contractions, and then show that they can explain a sizable variation of future excess returns, outperforming standard valuation ratios both in- and out-of-sample.

5.1 Extraction of investment-based dividend-yield paths

Investment Dividend Yield. The price of a claim that pays the investment return of sector $j \in \{c,i\}$ at time t is defined as $P^I_{j,t} = q_{j,t}$.Sector j's quarterly investment-return's dividend is defined as $Div^I_{j,t} = \partial V_{j,t}/\partial k_{j,t} - q_{j,t}$. These definitions imply that $R^I_{j,t+1} = \frac{Div^I_{j,t+1}+P^I_{j,t+1}}{P^I_{j,t}}$, where $R^I_{j,t+1}$ is the investment return of sector j. The one-year investment-based dividend yield is set to the sum of the investment-return dividends over the last four quarters divided by their current price: $dp^I_{j,t} = \frac{\Sigma_{k=0}^{3} Div^I_{j,t-k}}{P^I_{j,t}}$. Consequently, the economy-wide investment-based dividend yield is:

$$dp^I_t = \frac{V_{c,t-1}}{V_{c,t-1}+V_{i,t-1}} dp^I_{c,t} + \frac{V_{i,t-1}}{V_{c,t-1}+V_{i,t-1}} dp^I_{i,t}.$$

Empirical Path Extraction. Using equations (13) and (14), and imposing the restriction that short- and long- run technology shocks are perfectly correlated — as in the benchmark — we extract a path of technology innovations $\{\varepsilon^{\text{Data}}_t\}$ such that the model-implied path of aggregate technology growth (i.e., dz) matches the observed quarterly utilization-adjusted TFP growth rates of Fernald (2014) from 1964Q1 to 2019Q4. The start year is based on the availability of factor data from Fama and French (2015) and Chen and Velikov (2023). We set the model at its stochastic steady state and feed the model the finite path of $\{\varepsilon^{\text{Data}}_t\}$ to obtain a time series of investment-based

Table 9: **Investment-Based Dividend Yield and Risk Premia**

	Benchmark		**Perfect Competition**	
	Model	Data	Model	Data
$corr(dp_t^I, R_{t\to t+1}^e)$	-0.28	-0.35	0.23	-0.31
		[-3.09]		[-2.56]

The table presents the correlation coefficient between one-year excess returns, $R_{t\to t+1}^e$, and the investment-based dividend yields, dp_t^I, in both the model and the data. The model results are based on the median across finite sample simulations, either under the benchmark calibration or the perfect-competition configuration where $\mu_j \to \infty$. The empirical market excess returns are obtained from Goyal et al. (2024). The empirical dp^I data are filtered from the model by feeding empirically disciplined TFP shocks from Fernald (2014), using both the benchmark and the perfect competition configurations. Brackets report Newey-West t-statistics. The data are based on sample from 1964-2019.

dividend yields. Figure 5 shows the time series of the filtered technology innovations (annualized by summing up the innovations of the last four quarters) along with the investment-based dividend yields.

Investment-Based Dividend Yield and Risk Premia. We compute the correlation between investment-based dividend yields and one-year-ahead market excess returns in both the data and the model. The model estimates are based on the median values of the correlation implied by simulating finite paths – having the same length as the data – of investment-based dividend yields and stock market returns. Data estimates are obtained from the filtered time series of dp_t^I and the observed market excess returns. Table 9 shows that under the benchmark, investment-based dividend yields correlate negatively with risk premia, with a correlation of about -0.35, which is consistent with the data.

We repeat the same exercise when we shut down our core mechanism for contractionary innovations, under the assumption of perfect competition. Specifically, we set $\mu_j \to \infty$ and use the same technological innovations to extract dp_t^I from the model without markups. Using the same procedure described above, we recompute the correlation between perfect-competition investment-based dividend yields and future market excess returns. Table 9 shows that the model-implied correlation is positive, whereas the empirical counterpart is negative. This mismatch mirrors the comovement puzzle of investment and stock returns, addressed in Section 4.1.

5.2 Investment-based dividend yield and predictability

In-Sample Analysis. We examine the applicability of our benchmark investment-based dividend yield time series, dp^I, for return predictability, above and beyond the scope of our model. We compare its predictive power with that of other leading valuation ratios: the stock market dividend yield (dp) and the consumption-to-wealth ratio (cay). Specifically, we perform the following regression:

$$R^e_{t\to t+k} = const + \beta x_t + error, \tag{26}$$

where $R^e_{t\to t+k}$ refers to the cumulative excess market return up to k years ahead, and x_t is an economic predictor of interest.

Panel A of Table 10 shows that within our full sample period, both dp and cay struggle to explain future excess return variation. While the slope coefficients on dp and cay are positive, in line with existing studies, they are statistically insignificant. Across all horizons, the average R^2s produced by dp (cay) alone is about 0.0% (4.3%).

In contrast, the investment-based dividend yield, dp^I, generates economically large R^2s which increase with the predictive horizons. These range from 11% at the one-year-ahead horizon to 35% at the five-year-ahead horizon. This is quite remarkable, given that the dp^I time series, which is structured by the model, depends only on historical data of technology shocks up to time t, in a non-linear way, but not on any financial market data.[26]

In the bottom two rows of each sub-panel I, II and III in Table 10 we examine the ability of investment-based dividend yield to predict future excess returns jointly with the other predictors. The statistical significance of the slope coefficient on dp^I remains robust. The adjusted R^2s in these bivariate regressions are considerably higher compared to the univariate regressions using dp or cay as the sole predictor.

In Panel B of Table 10 we repeat the analysis for a sub-sample starting in 1980. In this time frame, dp and cay produce substantially larger R^2s, especially at longer predictive horizons. How-

[26]The literature has shown that investment rates themselves negatively predict market returns, and dp^I is conceptually correlated with investment. Nonetheless, the predictive power of dp^I remains unchanged after controlling for investment rates (see Table OA.6 in the Online Appendix).

ever, the predictive power of dp^I remains higher than both. In all, the analysis suggests that dp^I, which implicitly incorporates the dynamics of innovation-driven contractions, contains valuable information for equity markets, above and beyond market-based valuation ratios.

Out-of-Sample Analysis. We split our full sample period into two equal parts, ranging from 1964 to 1991, and from 1992 to 2019. We estimate equation (26) using the first sub-sample, and compute the out-of-sample (OOS) R^2 and mean-squared-error MSE using the second sub-sample. Specifically, the MSE is defined as $\text{MSE}_{\text{OOS}} = \frac{1}{T_{\text{Test}}} \sum_{t \in \text{Test}} \left(R^e_{t \to t+k} - \hat{R}^e_{t \to t+k} \right)^2$, where T_{Test} is the number of years between 1992 and 2019 and $\hat{R}^e_{t \to t+k}$ is the model's prediction. The OOS-R^2 is computed by $R^2_{\text{OOS}} = 1 - \frac{\sum_{t \in [1992,2019]} \left(R^e_{t \to t+k} - \hat{R}^e_{t \to t+k} \right)^2}{\sum_{t \in [1992,2019]} \left(R^e_{t \to t+k} - \bar{R}^e_{t \to t+k} \right)^2}$. The results are reported in Table 11.

Whereas both dp and cay produce a negative OOS-R^2, dp^I stands out by producing lower MSEs and positive OOS-R^2s. Its out-of-sample explanatory power ranges from 7% at the one-year horizon to above 15% at horizons greater than three years.

Cross-Sectional Analysis. In Online Appendix Section OA.6 we explore whether the dynamics of innovation-driven contractions, as incorporated in dp^I, may help to explain cross-sectional return spreads. Specifically, we augment the standard q-factor model of Hou, Xue, and Zhang (2015) with dp^I and examine the ability of the augmented model to explain a cross section of anomalies, previously documented in the literature. We find that including dp^I as an additional factor increases the average adjusted R^2 in factor model regressions and renders the abnormal return of several anomalies — including those based on short-term momentum or operating leverage — statistically insignificant.

6 Testing the mechanism

To validate the mechanism of innovation-driven contractions we perform two tests. First, we demonstrate that our model can quantitatively replicate the response of inputs to technological shocks from Table 1, without these moments being calibration targets. Second, we derive novel labor-market predictions that arise uniquely from the interaction of sticky prices and our two-sector structure, and confirm these empirically.

Table 10: **Return Predictability using Investment-Based Dividend Yields**

A. 1964-2019				B. 1980-2019			
dp	cay	dp^I	adj. R^2	dp	cay	dp^I	adj. R^2
I. Predictive horizon $k = 1$:							
1.99			0.00	1.89			-0.01
[1.05]				[0.75]			
	0.78		0.00		-0.44		-0.03
	[0.80]				[-0.23]		
		-10.96	0.11			-19.70	0.14
		[-3.09]				[-2.58]	
3.27		-12.50	0.14	1.05		-19.20	0.12
[1.69]		[-3.45]		[0.49]		[-2.45]	
	-1.47	-16.70	0.12		-1.28	-21.06	0.13
	[-1.26]	[-3.33]			[-0.83]	[-2.46]	
II. Predictive horizon $k = 3$:							
2.69			-0.01	7.36			0.03
[0.64]				[1.34]			
	3.21		0.06		-3.03		-0.01
	[1.42]				[-0.61]		
		-33.55	0.29		-50.47	0.23	
		[-3.65]			[-2.82]		
6.45		-36.59	0.32	5.26		-47.96	0.23
[1.59]		[-4.22]		[0.98]		[-2.52]	
	-2.77	-44.38	0.30		-5.28	-56.04	0.28
	[-1.27]	[-4.48]			[-1.48]	[-3.35]	
III. Predictive horizon $k = 5$:							
8.95			0.01	21.52			0.15
[1.68]				[2.86]			
	5.19		0.05		-8.28		0.04
	[1.54]				[-1.30]		
		-62.20	0.35			-74.72	0.17
		[-4.39]				[-2.73]	
16.13		-69.80	0.45	18.64		-65.81	0.29
[3.25]		[-5.81]		[2.56]		[-2.51]	
	-6.76	-88.60	0.40		-11.77	-87.16	0.28
	[-2.54]	[-8.33]			[-2.35]	[-3.76]	

The table shows the results of the projection $R^e_{t\to t+k} = const + \beta x_t + error$, where $R^e_{t\to t+k}$ refers to the cumulative excess market return up to k years ahead, where k varies from 1 to 5 years, and x_t is an economic predictor of interest: the stock market dividend yield (dp), the consumption-to-wealth ratio (cay), or the investment-based dividend yield dp^I filtered from the benchmark model using TFP data from Fernald (2014). The first two predictors and the market excess returns are obtained from Goyal et al. (2024). The numbers underneath each variable report the slope coefficient, whereas brackets reports Newey-West t-statistics. The columns adj. R^2 refer to adjusted R^2. In Panel A, the sample period is from 1964 to 2019, and in Panel B it is from 1980 to 2019.

Table 11: **Out-of-Sample Predictive Power of Investment-Based Dividend Yields**

		dp	cay	dp^I
$k=1$	MSE_{OOS}	0.06	0.03	0.03
	R^2_{OOS}	-0.93	-0.11	0.07
$k=2$	MSE_{OOS}	0.19	0.10	0.08
	R^2_{OOS}	-1.25	-0.13	0.12
$k=3$	MSE_{OOS}	0.31	0.19	0.14
	R^2_{OOS}	-0.91	-0.18	0.14
$k=4$	MSE_{OOS}	0.51	0.35	0.24
	R^2_{OOS}	-0.79	-0.21	0.15
$k=5$	MSE_{OOS}	0.86	0.56	0.39
	R^2_{OOS}	-0.94	-0.27	0.12

The table presents the out-of-sample performance of three linear projection models for the future cumulative excess returns $R^e_{t\to t+k}$ (where $k \in [1,2,3,4,5]$ years) using dp, cay, and dp^I as independent variables. Data for empirical projections (dp, cay, $R^e_{t\to t+k}$) are obtained from Goyal et al. (2024), and dp^I is filtered from the benchmark model using TFP data from Fernald (2014). The full sample is divided into two parts: the training set from 1964 to 1991, and the testing set from 1992 to 2019. The table shows Mean Squared Error (MSE) and OOS-R^2 to evaluate the out of sample performance of each predictor.

6.1 Theoretical Test: Matching Inputs Response to Innovations

To theoretically test our core mechanism, we examine the ability of the model to *quantitatively* reproduce Stylized Fact 1: that positive technological innovations induce a contractionary effect on labor and an insignificant impact on capital growth, thus mimicking the data. The ability of the model to replicate these empirical dynamics is important, as they played a key role in explaining asset-pricing puzzles in the former sections.

Using model simulated paths, we run the projections from equation (1) within the context of the model.[27] We perform regressions of annualized growth in hours and capital on the aggregate technological change, denoted dz. The duration of model-implied paths is identical to its empirical counterpart. Table 12 shows the median slope coefficient derived from a thousand finite sample simulations, accompanied by the model-implied confidence intervals. Importantly, all slope co-

[27] In the model analysis, we do not include lagged values of dz as all shocks are i.i.d.

Table 12: **Technological Innovations and Macroeconomic Growth: Model**

	Benchmark	No-LRR	No-LRR & No-Sticky	No-LRR & Perfect-Comp
(1) $b_{N,t}$	-0.43	-0.47	0.05	0.06
	[-0.56, -0.28]	[-0.53, -0.39]	[0.05, 0.05]	[0.06, 0.06]
(2) $b_{K,t}$	0.04	0.01	0.05	0.05
	[-0.04, 0.10]	[-0.02, 0.06]	[0.03, 0.08]	[0.02, 0.07]

The table reports the model-implied slope coefficients for the regression: $\Delta y_t = const + b_{y,t} \cdot dz_t + \varepsilon_t$. dz_t is the quarterly aggregate technological innovation. Δy_t is the log-growth rate of the quarterly macroeconomic variables in the model simulation, which include (1) Hours (ΔN_t); (2) Capital (ΔK_t). We report four alternative calibrations: (I) The benchmark model with parameters from Table 3, referred to as 'Benchmark', (II) A model excluding long-term productivity shocks, with $\sigma_{x,c} = \sigma_{x,i} = 0$, labeled as 'No-LRR', (III) A model void of long-term risk shocks and price stickiness, where $\phi_{p,c} = \phi_{p,i} = 0$, termed as 'No-LRR & No-Sticky', (IV) A model devoid of long-term risk shocks, sticky prices, and markups, implying perfect competition where $\mu_c = \mu_i \to \infty$, labeled as 'No-LRR & Perfect-Comp'. All regression results are based on a thousand simulations, each of 160 quarters (after dropping the first 400 quarters). We report the average across all simulations as well as the 90% confidence interval.

efficients are not targeted by our calibration — providing an over-identification angle to test our framework.

Several salient insights emerge from Table 12. First, the benchmark model replicates the contractionary or muted reactions of inputs to technological innovations. After a positive innovation, there is a marked decline in hours growth, with a slope coefficient of -0.43, juxtaposed against -0.38 in the data (as in Stylized Fact 1(a)). The model's response of capital growth to technological innovations is 0.04, matching the data. The slope's *insignificance* within the model aligns with the empirics (as in Stylized Fact 1(b)).

Second, in contrast to their importance for asset-pricing implications, long-run risk shocks are not material for the contractionary implications of technological innovations on macro aggregates. The slope coefficients under both the 'Benchmark' and 'No-LRR' configurations exhibit high similarity, with a pronounced decline in hours growth and an even more muted and insignificant capital growth correlation with short-term technological innovations.

Lastly, monopolistic competition and sticky prices are crucial to produce contractionary effects. Under both 'No-LRR & No-Sticky' and 'No-LRR & Perfect-Comp' configurations, the model fails to produce a contraction in the labor market and an insignificant response in the physical capital market. Hours rise after a positive technology shock, contrasting with Stylized Fact 1(a). Furthermore, while the point estimates are similar to the benchmark, the slope coefficient associated with capital growth turns statistically *significant*, contrasting with Stylized Fact 1(b).

While the negative effect of technological innovations on labor was explained in Section 4.2.1, the effect of these shocks on capital growth is more intricate (as hinted in Section 4.1.1), and necessitates the two-sector structure. On the one hand, investment quantity increases following a positive shock (see Figure 3 panel (b)). On the other hand, under sticky prices, the relative price of investment declines (see Figure 3 panel (c)). This counteracting dynamic is absent in a single-sector model. The joint impact manifests itself as a muted effect on capital growth expenditures, which turn statistically insignificant in finite samples, echoing the data.

We note that our model allows labor to adjust freely, while capital faces adjustment costs. Although this asymmetry potentially affects the absolute magnitudes of factor responses, it does not explain their sign. As Table 12 shows, holding the degree of capital adjustment costs fixed across all columns, labor reacts negatively to a productivity innovation only when prices are sticky and markups fluctuate. When prices are flexible, the response of capital growth to a positive innovation is strictly positive despite the presence of adjustment costs. Capital adjustment costs are nevertheless important for matching the relative volatility of investment to output (see Table 4), consistent with standard calibrations in the literature.

6.2 Empirical Test: Labor Market Predictions

To empirically test our core mechanism, we focus on the labor markets—where the contractionary effect of technological innovations is concentrated—and derive two novel predictions related to the specific implications of sticky prices and the two-sector structure.

First, in a typical production model, positive technological innovations initially increase wages due to increased demand for labor. However, in our setup, the opposite occurs: following positive shocks, wages persistently *decline*. As discussed in Section 4.2.1, with sticky prices, innovations lead to downward pressure on inflation and the marginal costs of production, which depend also on wages (see panel (b) of Figure 4).

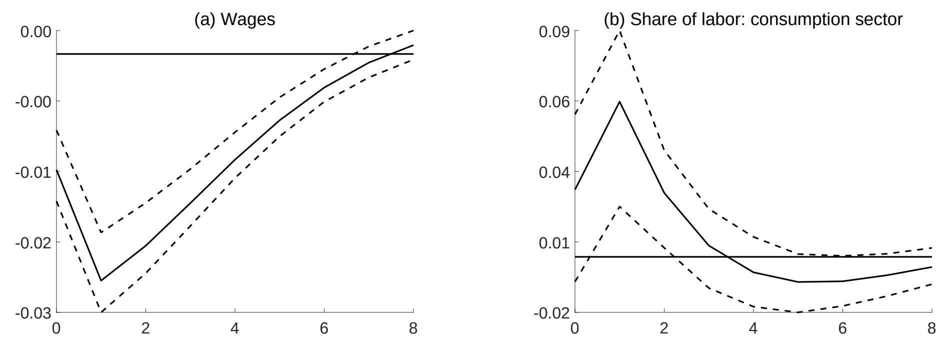
Second, Fernald (2014) shows that in the data, technology in the investment sector is more sizable than in the consumption sector (i.e., $\sigma_{z,i} > \sigma_{z,c}$). Consequently, in a standard production environment devoid of sticky prices, technological innovations increase total labor and lead to a relative reallocation of labor away from the consumption sector and into the investment sector (i.e., the share of labor attributed to the consumption sector $\frac{n_c}{n_c+n_i}$ decreases). In contrast, as previously explained, the combination of sticky prices and the two-sector structure results in technological shocks decreasing total labor and the relative price of capital goods in the short term. Since this relative price represents the output price in the investment sector, it implies that the marginal revenue product of labor for investment firms decreases relative to that of consumption firms. As a result, while short-term labor contracts in both sectors, it drops more significantly in the investment sector, causing $\frac{n_c}{n_c+n_i}$ to *increase* in the short run. However, in future periods, the relative price of capital overshoots — converging to the flexible price case — leading $\frac{n_c}{n_c+n_i}$ to decline below its steady-state level over the longer run (see Figure OA.5 in the Online Appendix).

We test these dynamic predictions using annual data from 1964 to 2019, based on the availability of labor-related data. We source wage data from the St. Louis Fred based on the average hourly earnings of production and nonsupervisory employees. While the hours worked in each sector are not directly observed, we use Compustat data along with the sectoral classifications from Gomes, Kogan, and Yogo (2009) to construct the total employment of consumption firms and investment firms (i.e., the sum of sector-level *EMP*). We define the empirical relative share of labor of consumption-producing firms as the total employment of consumption firms divided by the sum of total employment in both sectors. Data on utilization-adjusted TFP (technology), capital growth, and the relative price of capital are obtained from Fernald (2014).

We then estimate a $VAR(1)$ model with the following variables: technological growth, capital growth, the relative price of capital, wages, and the relative share of labor in the consumption sector, in that order. The first three variables are placed before the rest since they capture the state variables for each firm in our economy. To ensure stationarity, all non-growth variables are HP-filtered.

Figure 6 presents the impulse response functions for one standard deviation structural technology shocks on wages (panel (a)) and the relative share of labor in the consumption sector (panel

Figure 6: **Technology Shocks to Wages and Relative Labor in Consumption Sector**



The figure presents empirical impulse response functions for one standard deviation structural technology shocks on wages (panel (a)) and the relative share of labor in the consumption sector (panel (b)). The impulse-responses are obtained from a $VAR(1)$ model with the following variables: technological growth, capital growth, the relative price of capital (HP-filtered), wages (HP-filtered), and the relative share of labor in the consumption sector (HP-filtered), in that order. The vertical axes denote standard deviation change relative to the steady-state. Dashed lines represent 90% confidence intervals. Data are from 1964 to 2019.

(b)). Consistent with our model's implications, technological shocks lead to a persistent decrease in wages, confirming our first prediction.[28] Moreover, technology shocks initially increase the relative share of labor in the consumption sector. In the medium run, however, this share declines below the steady state, aligning with our second prediction.

7 Conclusion

We empirically and theoretically examine the phenomenon of innovation-driven contractions—whereby positive technology shocks induce short-term contractions before expansion. While well-documented in the macro literature, this mechanism has been largely overlooked in financial markets. Our study bridges this gap by bringing this seminal finding into an asset pricing context. We show that this single mechanism unifies several conditional "disconnections" between valuations and the real economy.

Two facts anchor our analysis: (i) positive technology shocks contract labor on impact while leaving capital growth statistically insignificant, and (ii) the disconnections intensify when prices are stickier across portfolios and over time. A two-sector New-Keynesian model with Rotemberg

[28] Following Basu et al. (2006), we note that while wages are generally procyclical in the data, this is not due to supply-side (i.e., technology) shocks, but rather to sizable and procyclical demand shocks, which our model abstracts from for simplicity.

pricing and Epstein–Zin preferences, disciplined by these facts, quantitatively accounts for the negative contemporaneous comovement of investment and stock returns, the "bad labor news is good news for stocks" phenomenon, and the procyclical slope of the equity-yield term structure. Moreover, investment-based dividend yields, filtered from a model that generates innovation-driven contractions, exhibit remarkably high predictive power for future market excess returns.

The model passes an over-identification test by reproducing input responses to technology shocks without targeting them and delivers auxiliary predictions borne out in the data: wages fall on impact and labor temporarily reallocates toward the consumption sector. Creative destruction is not the first-order driver, and policy-expectation channels are too small to explain the signs.

Future production-based models can benefit from incorporating this channel to better align with both time-series and cross-sectional evidence. Promising directions include studying the implications of innovation-driven contractions for the bond term structure, for models with heterogeneous firms and intangibles, and for environments with richer financial frictions.

Appendix

A Monetary authority

A monetary authority sets the nominal log-interest rate $r_t^{\$}$ according to a Taylor (1993) rule:

$$r_t^{\$} = \rho_r r_{t-1}^{\$} + (1-\rho_r)\left(r_{ss}^{\$} + \rho_\pi(\pi_t - \pi_{ss}) + \rho_y(\Delta Y_t - \Delta Y_{ss})\right) \tag{A.1}$$

where π_t is log inflation (in the consumption sector) defined as $\pi_t = \log\left(\frac{P_{c,t}}{P_{c,t-1}}\right)$, and ΔY_t is log-growth of real total output, $\Delta Y_t = \log\left(\frac{Y_{c,t}+P_{i,t}/P_{c,t}Y_{i,t}}{Y_{c,t-1}+P_{i,t-1}/P_{c,t-1}Y_{i,t-1}}\right) \cdot r_{ss}^{\$}, \pi_{ss}$, and Δy_{ss} are the steady state log-levels of nominal interest rate, inflation, and output growth.

B Equilibrium

In equilibrium, $W_t, P_{i,t}$, and π_t are set to clear all markets:

- Labor market clearing:

$$\int_0^1 n_{c,t}(n)dn + \int_0^1 n_{i,t}(n)dn = N_t. \tag{A.2}$$

- Consumption good market clearing:

$$C_t + \int_0^1 \frac{\phi_{P,c}}{2}\left[\frac{p_{c,t}(n)}{\Pi_c p_{c,t-1}(n)} - 1\right]^2 Y_{c,t} dn = Y_{c,t}. \tag{A.3}$$

- Investment good clearing:

$$\int_0^1 \Phi_{c,k}\left(\frac{i_{c,t}(n)}{k_{c,t}(n)}\right) k_{c,t}(n) dn + \int_0^1 \Phi_{i,k}\left(\frac{i_{i,t}(n)}{k_{i,t}(n)}\right) k_{i,t}(n) dn \tag{A.4}$$

$$+ \int_0^1 \frac{\phi_{P,i}}{2}\left[\frac{p_{i,t}(n)}{\Pi_i p_{i,t-1}(n)} - 1\right]^2 Y_{i,t} dn = Y_{i,t} \tag{A.5}$$

- Zero net supply of nominal bonds:

$$\frac{1}{R_t^{\$}} = E_t\left[M_{t+1}^{\$}\right] \tag{A.6}$$

An equilibrium consists of prices and allocations such that taking prices as given, (i) the household's allocations solve equation (16); (ii) firms' allocations solve equation (10); (iii) labor, consumption good, investment good, and bond markets clear. We solve a symmetric equilibrium where intermediate good firms in each sector employ the same amount $n_{j,t}(n) = n_{j,t}$, hold the same amount of capital $k_{j,t}(n) = k_{j,t}$, and select the same price $p_{j,t}(n) = p_{j,t}$.

C First-Order Conditions

This section describes the equilibrium first-order conditions of the model. The first-order condition of firm $n \in [0,1]$ in sector $j \in \{c,i\}$

$$0 = q_{j,t} - P_{it}\frac{\partial \Phi_{j,k}(i_{j,t}(n), k_{j,t}(n))}{\partial i_{j,t}(n)} k_{j,t}(n) \tag{A.7}$$

$$0 = W_t n_{j,t}(n) - (1-\alpha_j)\theta_{j,t} Z_{j,t} k_{j,t}(n)^{\alpha_j}(n_{j,t}(n))^{1-\alpha_j} \tag{A.8}$$

$$0 = -q_{j,t} + E_t\Big[M_{t+1}^{\$}\Big\{ -P_{i,t+1}\left(\Phi_{j,k}\left(i_{j,t+1}, k_{j,t+1}(n)\right) + \frac{\partial \Phi_{j,k}\left(i_{j,t+1}(n), k_{j,t+1}(n)\right)}{\partial k_{j,t+1}(n)} k_{j,t+1}(n)\right) + q_{j,t+1}(1-\delta)$$

$$+ \theta_{j,t+1} Z_{j,t+1}\alpha_j k_{j,t+1}(n)^{\alpha_j - 1}(n_{j,t+1}(n))^{1-\alpha_j}\Big\}\Big] \tag{A.9}$$

$$0 = (1-\mu_j)\left[\frac{p_{j,t}(n)}{P_{j,t}}\right]^{-\mu_j} + \theta_{j,t}\mu_j\left[\frac{p_{j,t}(n)}{P_{j,t}}\right]^{-\mu_j - 1}\frac{1}{P_{j,t}} + \phi_{P,j}E_t\left[M_{t+1}^{\$}\left(\frac{Y_{j,t+1}}{Y_{j,t}}\right)\left[\frac{p_{j,t+1}(n)}{\Pi_j p_{j,t}(n)} - 1\right]\frac{p_{j,t+1}^2(n)}{\Pi_j p_{j,t}^2(n)}\right]$$

$$-\phi_{P,j}\left\{\left[\frac{p_{j,t}(n)}{\Pi_j p_{j,t-1}(n)} - 1\right]\frac{p_{j,t}(n)}{\Pi_j p_{j,t-1}(n)} + \frac{1}{2}\left[\frac{p_{j,t}(n)}{\Pi_j p_{j,t-1}(n)} - 1\right]^2\right\} \tag{A.10}$$

$$0 = k_{j,t+1}(n) - (1-\delta) k_{j,t}(n) - i_{j,t}(n) \tag{A.11}$$

$$0 = y_{j,t}(n) - Z_{j,t}k_{j,t}(n)^{\alpha_j}(n_{j,t}(n))^{1-\alpha_j}, \tag{A.12}$$

where $q_{j,t}$ is the price of a marginal unit of installed capital in sector j, the Lagrange multiplier of constraint (7), and $\theta_{j,t}$ is the marginal cost of producing an additional unit of intermediate good in sector $j \in \{c,i\}$, the Lagrange multiplier of constraint (11).

The first-order condition of the household

$$0 = \frac{W_t}{P_{c,t}} - \frac{C_t}{1-\xi N_t^{\eta}}\xi\eta N_t^{\eta-1}. \tag{A.13}$$

The nominal SDF, nominal interest rate, as well as the household utility, are given in Eq. (17), (A.1), and (15), respectively. The last equilibrium conditions include four market clearing conditions (labor, investment goods, consumption goods, and bond market) specified in Eq. (A.2), (A.3), (A.5), and (A.6), respectively. We are looking for a symmetric equilibrium in which $p_{j,t}(n) = P_{j,t}, n_{j,t}(n) = n_{j,t}$, and $k_{j,t}(n) = k_{j,t}$ for all $n \in [0,1]$ and $j \in \{c,i\}$. Thus, the above equations can be rewritten in terms of only aggregate quantities. There are 32 endogenous variables:

$\{C_t, N_t, Y_{c,t}, Y_{i,t}, N_{c,t}, N_{i,t}, K_{c,t}, K_{i,t}, i_{c,t}, i_{i,t}, q_{c,t}, q_{i,t}, \theta_{c,t}, \theta_{i,t}, P_{i,t}, P_{c,t}, W_t, R_t^{\$}, U_t, M_t^{\$}, R_{j,t}^{S(unlevered)},$
$R_{M,t}^{S(unlevered)}, R_{j,t}^{e}, d_{j,t}^{\$}, V_{j,t}^{\$}, R_{j,t}^{I}, R_{M,t}^{I}\}$.

In turn, there are 28 equations: 13 equations for household's and firms' first-order conditions (in both sectors), 12 definitions of return and dividends, four market clearing conditions, and three definitions of SDF, utility, and Taylor rule). Other quantities, such as the real SDF and firm valuations, are derived from the endogenous decision variables, see, e.g., Eq. (10).

References

Ai, H., Li, J. E., Li, K., Schlag, C., 2019. The collateralizability premium. The Review of Financial Studies, forthcoming .

Alvarez, F., Jermann, U. J., 2005. Using asset prices to measure the persistence of the marginal utility of wealth. Econometrica 73, 1977–2016.

Anschukov, A., Bhamra, H. S., Kuehn, L.-A., 2024. Leverage dynamics and learning about economic crises. Tech. Rep. 4898492, SSRN, available at SSRN: `https://ssrn.com/abstract=4898492`.

Ayyagari, M., Demirgüç-Kunt, A., Maksimovic, V., 2024. The rise of star firms: Intangible capital and competition. The Review of Financial Studies 37, 882–949.

Bansal, R., Miller, S., Song, D., Yaron, A., 2021. The term structure of equity risk premia. Journal of Financial Economics 142, 1209–1228.

Bansal, R., Yaron, A., 2004. Risks for the long run: A potential resolution of asset pricing puzzles. The journal of Finance 59, 1481–1509.

Basu, S., Bundick, B., 2017. Uncertainty shocks in a model of effective demand. Econometrica 85, 937–958.

Basu, S., Fernald, J., Liu, Z., 2013. Technology shocks in a two-sector dsge model. Working Paper .

Basu, S., Fernald, J. G., Kimball, M. S., 2006. Are technology improvements contractionary? American Economic Review 96, 1418–1448.

Bauer, M. D., Bernanke, B. S., Milstein, E., 2023. Risk appetite and the risk-taking channel of monetary policy. Journal of Economic Perspectives 37, 77–100.

Beaudry, P., Galizia, D., Portier, F., 2020. Putting the cycle back into business cycle analysis. American Economic Review 110, 1–47.

Belo, F., Deng, Y., Salomao, J., 2024. Estimating and testing investment-based asset pricing models. Journal of Financial Economics 162, 103945.

Belo, F., Li, J., Lin, X., Zhao, X., 2017. Labor-force heterogeneity and asset prices: The importance of skilled labor. The Review of Financial Studies 30, 3669–3709.

Belo, F., Lin, X., 2012. The inventory growth spread. The Review of Financial Studies 25, 278–313.

Belo, F., Lin, X., Bazdresch, S., 2014. Labor hiring, investment, and stock return predictability in the cross section. Journal of Political Economy 122, 129–177.

Belo, F., Lin, X., Yang, F., 2018. External Equity Financing Shocks, Financial Flows, and Asset Prices. The Review of Financial Studies 32, 3500–3543.

Bilbiie, F. O., Ghironi, F., Melitz, M. J., 2012. Endogenous entry, product variety, and business cycles. Journal of Political Economy 120, 304–345.

Boyd, J. H., Hu, J., Jagannathan, R., 2005. The stock market's reaction to unemployment news: Why bad news is usually good for stocks. The Journal of Finance 60, 649–672.

Bretscher, L., Hsu, A., Tamoni, A., 2020. Fiscal policy driven bond risk premia. Journal of Financial Economics 138, 53–73.

Chen, A. Y., Velikov, M., 2023. Zeroing in on the expected returns of anomalies. Journal of Financial and Quantitative Analysis 58, 968–1004.

Christiano, L., Fisher, J., 2003. Stock market and investment goods prices: Implications for macroeconomics.

Christiano, L. J., Eichenbaum, M., Evans, C. L., 2005. Nominal rigidities and the dynamic effects of a shock to monetary policy. Journal of political Economy 113, 1–45.

Cochrane, J. H., 1991. Production-based asset pricing and the link between stock returns and economic fluctuations. The Journal of Finance 46, 209–237.

Corhay, A., Li, J. E., Tong, J., 2022. Markup shocks and asset prices. Working Paper .

Croce, M. M., 2014. Long-run productivity risk: A new hope for production-based asset pricing? Journal of Monetary Economics 66, 13–31.

Croce, M. M., Nguyen, T. T., Raymond, S., Schmid, L., 2019. Government debt and the returns to innovation. Journal of Financial Economics 132, 205–225.

De Loecker, J., Eeckhout, J., Mongey, S., 2021. Quantifying market power and business dynamism in the macroeconomy. Tech. rep., National Bureau of Economic Research.

Dou, W., Ji, Y., Reibstein, D., Wu, W., 2019. Customer capital, financial constraints, and stock returns. Journal of Finance, forthcoming .

Eisfeldt, A. L., Schubert, G., Zhang, M. B., 2023. Generative ai and firm values. Tech. rep., National Bureau of Economic Research.

Elenev, V., Law, T. H., Song, D., Yaron, A., 2022. Fearing the fed: How wall street reads main street. Working Paper, JHU .

Epstein, L. G., Zin, S. E., 1991. Substitution, risk aversion, and the temporal behavior of consumption and asset returns: An empirical analysis. Journal of political Economy 99, 263–286.

Fama, E. F., French, K. R., 1992. The cross-section of expected stock returns. the Journal of Finance 47, 427–465.

Fama, E. F., French, K. R., 2015. A five-factor asset pricing model. Journal of Financial Economics 116, 1 – 22.

Fernald, J., 2014. A quarterly, utilization-adjusted series on total factor productivity. Working Paper. Federal Reserve Bank of San Francisco .

Galí, J., 2010. Monetary policy and unemployment. In: *Handbook of monetary economics*, Elsevier, vol. 3, pp. 487–546.

Galı, J., Gertler, M., Lopez-Salido, J. D., 2001. European inflation dynamics. European economic review 45, 1237–1270.

García-Feijóo, L., Jorgensen, R. D., 2010. Can operating leverage be the cause of the value premium? Financial Management 39, 1127–1154.

Garlappi, L., Song, Z., 2017. Capital utilization, market power, and the pricing of investment shocks. Journal of Financial Economics 126, 447–470.

Gofman, M., Segal, G., Wu, Y., 2020. Production networks and stock returns: The role of vertical creative destruction. The Review of Financial Studies 33, 5856–5905.

Gomes, J. F., Kogan, L., Yogo, M., 2009. Durability of output and expected stock returns. Journal of Political Economy 117, 941–986.

Gonçalves, A. S., Xue, C., Zhang, L., 2020. Aggregation, capital heterogeneity, and the investment capm. The Review of Financial Studies 33, 2728–2771.

Gormsen, N. J., 2021. Time variation of the equity term structure. The Journal of Finance 76, 1959–1999.

Goyal, A., Welch, I., Zafirov, A., 2024. A comprehensive 2022 look at the empirical performance of equity premium prediction. The Review of Financial Studies 37, 3490–3557.

Greenwood, J., Hercowitz, Z., Krusell, P., 1997. Long-run implications of investment-specific technological change. The American economic review pp. 342–362.

Hou, K., Mo, H., Xue, C., Zhang, L., 2019. Which factors? Review of Finance 23, 1–35.

Hou, K., Mo, H., Xue, C., Zhang, L., 2021. An augmented q-factor model with expected growth. Review of Finance 25, 1–41.

Hou, K., Xue, C., Zhang, L., 2015. Digesting anomalies: An investment approach. The Review of Financial Studies 28, 650–705.

Huang, Q., Papanikolaou, D., Kogan, L., 2025. Tech dollars: Technological innovation and exchange rates. Tech. Rep. 4667334, SSRN.

İmrohoroğlu, A., Tüzel, Ş., 2014. Firm-level productivity, risk, and return. Management Science 60, 2073–2090.

Jermann, U. J., 1998. Asset pricing in production economies. Journal of monetary Economics 41, 257–275.

Jones, C. S., Tuzel, S., 2013. Inventory investment and the cost of capital. Journal of Financial Economics 107, 557 – 579.

Kaltenbrunner, G., Lochstoer, L. A., 2010. Long-run risk through consumption smoothing. The Review of Financial Studies 23, 3190–3224.

Keane, M., Neal, T., 2023. Instrument strength in iv estimation and inference: A guide to theory and practice. Journal of Econometrics .

Kilic, M., 2017. Asset pricing implications of hiring demographics. Working paper .

Kilic, M., Wachter, J. A., 2018. Risk, unemployment, and the stock market: A rare-event-based explanation of labor market volatility. The Review of Financial Studies 31, 4762–4814.

Kogan, L., Li, J., Zhang, H. H., Zhu, Y., 2023. Operating leverage and asset pricing anomalies. Working Paper .

Kogan, L., Papanikolaou, D., Seru, A., Stoffman, N., 2017. Technological innovation, resource allocation, and growth. The quarterly journal of economics 132, 665–712.

Kogan, L., Papanikolaou, D., Stoffman, N., 2013. Winners and losers: Creative destruction and the stock market. Tech. rep., National Bureau of Economic Research.

Kuehn, L.-A., 2009. Disentangling investment returns and stock returns: The importance of time-to-build. Working Paper, CMU .

Kuehn, L.-A., Schmid, L., 2014. Investment-based corporate bond pricing. The Journal of Finance 69, 2741–2776.

Kung, H., 2015. Macroeconomic linkages between monetary policy and the term structure of interest rates. Journal of Financial Economics 115, 42–57.

Liu, L. X., Whited, T. M., Zhang, L., 2009. Investment-based expected stock returns. Journal of Political Economy 117, 1105–1139.

Liu, Y., Shaliastovich, I., 2022. Government policy approval and exchange rates. Journal of Financial Economics 143, 303–331.

Novy-Marx, R., 2013. The other side of value: The gross profitability premium. Journal of financial economics 108, 1–28.

Papanikolaou, D., 2011. Investment shocks and asset prices. Journal of Political Economy 119, 639 – 685.

Pasten, E., Schoenle, R., Weber, M., 2021. Sectoral heterogeneity in nominal price rigidity and the origin of aggregate fluctuations. In: *Sectoral Heterogeneity in Nominal Price Rigidity and the Origin of Aggregate Fluctuations: Pasten, Ernesto| uSchoenle, Raphael| uWeber, Michael*, [Sl]: SSRN.

Ready, R., Roussanov, N., Ward, C., 2017. Commodity trade and the carry trade: A tale of two countries. The Journal of Finance 72, 2629–2684.

Rotemberg, J. J., 1982. Sticky prices in the united states. Journal of Political Economy 90, 1187–1211.

Sbordone, A. M., 2002. Prices and unit labor costs: a new test of price stickiness. Journal of Monetary economics 49, 265–292.

Segal, G., 2019. A tale of two volatilities: Sectoral uncertainty, growth, and asset prices. Journal of Financial Economics 134, 110–140.

Smets, F., Wouters, R., 2007. Shocks and frictions in us business cycles: A bayesian dsge approach. American economic review 97, 586–606.

Taylor, J. B., 1993. Discretion versus policy rules in practice. In: *Carnegie-Rochester conference series on public policy*, Elsevier, vol. 39, pp. 195–214.

Tuzel, S., Zhang, M. B., 2017. Local risk, local factors, and asset prices. The Journal of Finance 72, 325–370.

van Binsbergen, J., Brandt, M., Koijen, R., 2012. On the timing and pricing of dividends. American Economic Review 102, 1596–1618.

Vavra, J., 2014. Inflation dynamics and time-varying volatility: New evidence and an ss interpretation. The Quarterly Journal of Economics 129, 215–258.

Weil, P., 1989. The equity premium puzzle and the riskfree rate puzzle. Working Paper. National Bureau of Economic Research .

Xu, N. R., You, Y., 2022. Main street's pain, wall street's gain. Working Paper .

Zhang, L., 2005. The value premium. The Journal of Finance 60, 67–103.

Online Appendix for
"Innovation-Driven Contractions:
A Missing Link for Asset Pricing Puzzles"

This Online Appendix contains additional analysis to accompany the manuscript (sections are listed in the order they are first cited in the main text). Section OA.1 replicates Basu, Fernald, and Liu (2013) and contrasts their model features with ours. Section OA.2 evaluates labor-targeted monetary-policy rules and shows that they have a limited quantitative effect on the stock–labor-surprise correlation. Section OA.3 provides details on the firm-level analysis, testing the creative-destruction channel against a sticky-price rationing mechanism. Section OA.4 converts the Rotemberg adjustment costs to the average price duration in a Calvo pricing framework. Section OA.5 links book-to-market and gross profitability to dividend yields, explaining why both characteristics are associated with higher discount rates. Section OA.6 examines the cross-sectional implications of the investment-based dividend yield. Section OA.7 provides the detrended problem for the analysis in Appendix C. Section OA.8 reports additional results.

OA.1 Comparison to Basu, Fernald, and Liu (2013)

Overview. An unpublished working paper by Basu, Fernald, and Liu (2013) (henceforth BFL) presents a New Keynesian model in which technology shocks induce short-term contractions. The BFL model shares some common ingredients with our framework—namely, nominal price rigidity and a separation of production into investment and consumption sectors. Nonetheless, our model incorporates two notable differences: (1) household preferences follow Epstein and Zin (1991), rather than habit formation as in BFL; (2) technology shocks have permanent (unit root) effects accompanied by a long-run risk component, rather than having a persistent but mean-reverting effect as in BFL.

Economically, these differences significantly differentiate our model's implications, particularly in asset pricing. In this appendix, we replicate the findings of Basu et al. (2013). Notably, Basu et al. (2013) do not explore unconditional or conditional asset-pricing moments. Our replication reveals that their setup produces several counterfactual results related to the disconnection puzzles we aim to resolve. We trace these shortcomings directly to the two departures noted above.

Replication of Macro Dynamics. We begin by solving the quantitative model of BFL. Despite empirical evidence from Basu et al. (2006) that *common* (or aggregate) technological shocks induce labor contractions, the BFL model generates a contraction only from investment-specific technology shocks.[1] Following their analysis, we focus on impulse response functions (IRFs) showing the effects of investment-sector technology shocks. Figure OA.1 compares IRFs from the original BFL paper (left column) with those from our replication (right column). The visual alignment confirms successful replication.

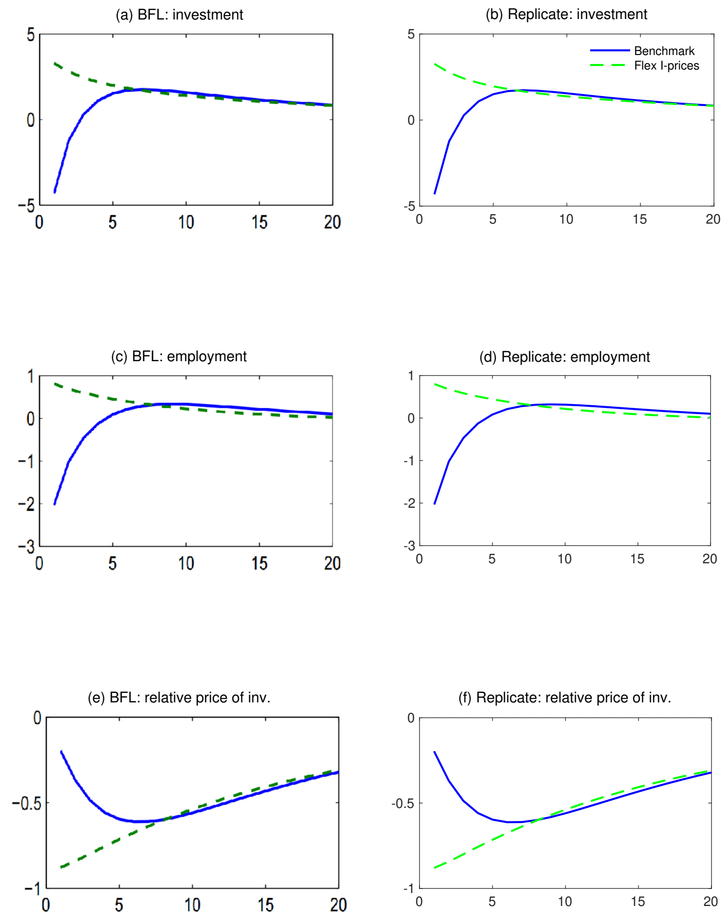
In BFL, a positive investment-specific technology shock leads to an immediate contraction in employment (consistent with our Stylized Fact 1(a)). However, this contraction is not confined solely to labor markets in their model. Specifically, the technology shock leads to a sharp drop in investment (capital growth), contradicting our Stylized Fact 1(b).

This discrepancy arises from the response of the relative price of investment to technology shocks in BFL. In our model, the decline in this price is short-lived —soon after the initial shock, the relative price overshoots to the flexible-price benchmark (see Figure 3).[2] Conversely, in BFL, technology shocks follow a highly persistent autoregressive process. Moreover, under habit formation (effectively an IES less than one), the wealth effect dominates: despite positive productivity news and enhanced marginal productivity of capital, the representative agent prefers higher current consumption and lower investment. This combination forces the relative price of investment (panel (e)) into a prolonged, U-shaped decline, continuing to fall for several quarters before recovering. In other words, the agent in their model postpones investment, as it anticipates further declines in investment prices. Consequently, both investment rates and the relative price of investment per-

[1] Beyond evidence presented in Table 1, we verify in untabulated results that the contractionary effect of technological innovations equally applies to consumption-sector shocks and is not confined to the investment sector alone, as in BFL.

[2] This overshoot occurs because our technology shocks feature a unit root, and the substitution effect dominates (with an intertemporal elasticity of substitution greater than one). Thus, positive technology shocks in our model increase the demand for capital, raising investment rates immediately and in the near future.

Figure OA.1: Impulse Responses to an Investment-Sector Technology Shock in the BFL (2013) Model



The figure compares the impulse responses of investment, employment, and the relative price of investment with respect to the investment-sector technology shock from the original BFL (2013, Figure 4) paper (left column panels) against our replication (right column panels). The solid blue line shows impulse responses from the benchmark. The dash-dotted green line shows impulse responses without price adjustment in the investment sector.

sistently decline, resulting in an unambiguous drop in capital growth following the technology shock.

Importantly, this prolonged U-shaped negative path for the relative price of investment generates several asset-pricing counterfactuals, as we demonstrate next.

Counterfactual implications for asset prices. BFL employ a combination of persistent (mean-reverting) technology shocks and habit formation (IES less than one). As shown by Jermann (1998) and Kaltenbrunner and Lochstoer (2010), this combination effectively generates a high unconditional equity premium. However, it produces several counterfactual conditional asset-pricing dynamics.[3] To illustrate, we use our BFL replication to simulate market returns, risk-free rates, investment returns, and labor surprises. Table OA.1 presents key correlations between asset prices and real variables implied by BFL.

Puzzle I. Panel A shows that, similar to our model, BFL can generate a negative contemporaneous correlation between investment and stock returns. The underlying mechanism, involving the drop in the relative price of capital, parallels our framework. Yet, this addresses only one aspect of the comovement puzzle. In the data, the correlation between stock returns and one-year-ahead investment returns turns positive. While our model replicates this feature (see Table 5), Panel A of Table OA.1 shows that in BFL, the correlation between stock returns and future investment returns remains negative, counterfactually, persisting up to four years ahead. This failure traces directly to BFL's inability to replicate Stylized Fact 1(b), linked to the overly persistent decline in the relative price of investment, which—unlike in our model—does not recover quickly. This reflects a combination of mean reverting productivity shocks coupled with a strong wealth effect. Those inherent features of BFL imply that this counterfactual correlation remains under different calibrations.

Puzzle II. As the BFL model can generate a labor decline following a positive technology shock, Panel B indicates it can also produce a negative unconditional correlation between labor surprises and the stock market. However, unlike our model (Table 7), their model generates a counterfactual positive correlation between the risk-free rate and labor surprises. Moreover, when cyclical variation in price stickiness is introduced, their model predicts that the correlation between stock returns and labor surprises turns negative (positive) when the nominal interest rate is low (high), opposing evidence from Boyd et al. (2005) and Table OA.5. Both counterfactuals directly result from habit formation altering the cyclical properties of the risk-free rate. Nonetheless, habit formation is necessary in BFL for achieving a high unconditional risk premium, given their persistent mean-reverting shocks.

Puzzle III. Projecting the equity yield term structure slope on the dividend-price ratio, Panel C shows that BFL generates a statistically insignificant positive slope, implying a countercyclical or at best acyclical relationship, counter to evidence by Gormsen (2021). Two factors explain this

[3] Related, Alvarez and Jermann (2005) show that the SDF is mostly driven by permanent shocks, in contrast to the setup of BFL.

Table OA.1: Statistical Moments from BFL (2013)

Moment Description	BFL (2013)
Panel A: Investment and Stock Return Correlations (Ref: Table 5)	
$\text{corr}(R^I_{M,t}, R^S_{M,t})$	-0.06
$\text{corr}(R^I_{M,t+1}, R^S_{M,t})$	-0.20
$\text{corr}(R^I_{M,t+2}, R^S_{M,t})$	-0.12
Panel B: Labor Market Surprises (Ref: Table 7 & Table OA.5)	
$\text{corr}(N^{\text{surprise}}, R^S_{M,t})$	-0.34
$\text{corr}(N^{\text{surprise}}, R^S_{M,t})$ under low $r^{\$}_t$	-0.13
$\text{corr}(N^{\text{surprise}}, R^S_{M,t})$ under high $r^{\$}_t$	0.12
$\text{corr}(N^{\text{surprise}}, R^f_t)$	0.24
Panel C: Cyclicality and Regression Slopes (Ref: Table 8 & Table 12)	
ϕ_{20} (Equity Yield Slope)	2.99 [-26.82, 5.13]

This table reports statistical moments from our replication of the BFL (2013) framework. R^I and R^S are investment and stock returns, respectively. N^{surprise} denotes labor market surprises. ϕ_{20} is the regression coefficient of the 20-quarter equity yield slope on the dividend yield. Confidence intervals are reported in brackets.

result in BFL. First, the relative price of capital persistently declines up to 10 quarters ahead, unlike our model's immediate overshoot and recovery. Investment rates similarly decline over the medium term. Consequently, short-term dividends do not exhibit the "catch-up" dynamics of our model — they are expected to be lower short-term due to a persistent fall in the capital stock. Second, habit formation transforms the dividend yield from procyclical to countercyclical under mean-reverting shocks. Together, these factors render ambiguous impact of innovation-driven contractions on the slope's cyclicality in BFL, contrasting sharply with our model.

OA.2 Labor-Targeted Monetary Policy

Several studies argue that the stock market's response to a negative labor surprise can, counter-intuitively, be positive, as investors expect policymakers to persistently decrease interest rates. In this section, we show that, in contrast to this common logic, within a general equilibrium New Keynesian model such policy expectations induce only a small effect on the comovement between returns and labor market news. These findings emphasize the central quantitative role of innovation-driven contractions in generating the negative comovement between stock returns and labor surprises, above and beyond policy revisions.

In a standard model, the monetary policy rule responds to both the inflation gap and the output gap, with a weight of 0.5 on the latter (see equation A.1). To push the theoretical argument about policy expectations to the extreme, we make two revisions to the baseline monetary policy rule.

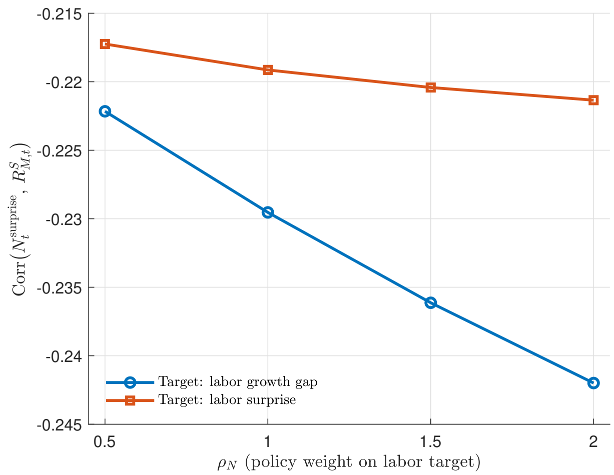
First, we assume that the policymaker responds directly to labor market news. Specifically, we replace the output gap term in equation (A.1) with one of the following labor-driven variants: (i) a labor growth gap, $\rho_N(\Delta N_t - \Delta N_{ss})$, or (ii) a labor surprise gap, $\rho_N N_t^{\text{surprise}}$, with $N_t^{\text{surprise}} \equiv N_t - E_{t-1}[N_t]$. Under each of these variants, the policy interest rate is hardwired to drop in response to "disappointing" labor market news, all else equal.

Second, while the dual mandate typically translates to a weight of 0.5 on the output gap (or labor gap) component, we deliberately push the coefficient on the labor gap gradually from 0.5 to 2, making monetary policy potentially very "aggressive." All other parameters for the policy rule are identical to the benchmark calibration in Table 2.

Figure OA.2 plots the equilibrium correlation between labor surprises and stock returns under both policy variants above, as a function of the coefficient on the labor gap (ρ_N) on the horizontal axis. First, when ρ_N is 0.5, as in the benchmark model, the correlation is negative and very similar in magnitude to that reported in Table 7. Second, increasing ρ_N—placing more weight on the labor target—makes the correlation qualitatively lower. Intuitively, a higher ρ_N strengthens valuations through the discount-rate channel when labor is low, pushing the stock–labor-surprise correlation further negative. However, quantitatively, the marginal change in the correlation is small and close to zero. Under policy variant (i), the correlation drops by about -0.02 when ρ_N rises from 0.5 to 2. Under variant (ii), the absolute change in the correlation is even smaller. Consequently, changes in investors' expectations about either monetary policy conduct or the nominal interest rate path produce only a minute effect on the correlation between labor surprises and stock returns.

While interest-rate expectations can cushion bad macroeconomic news, in equilibrium, the absolute drop in the correlation under the most aggressive policy is about 0.02. This effect alone is far too small to flip the sign of the correlation—which, in the absence of innovation-driven contractions, amounts to 0.93 (see Table 7).

Figure OA.2: **Correlations between labor surprise and market return under labor target policy**



The figure presents the correlation between labor-based policy targets and market returns as a function of the monetary-policy weight on the labor target, ρ_N.

OA.3 Innovation and Firm Level Analysis: Details

In the main text, we argue that innovation-driven contractions are primarily rooted in nominal price rigidity (the sticky price hypothesis), rather than the displacement of competitor firms (the creative destruction hypothesis). To provide empirical support for our modeling choice, we present firm-level evidence designed to explicitly test the differential predictions of these two mechanisms.

Specifically, for firm i at industry j, we run panel regressions following the empirical specification of Kogan et al. (2017) and Huang, Papanikolaou, and Kogan (2025):

$$y_{i,j,t} = \alpha_i + \delta_{j,t} + \beta Acw_{i,t-1} + \gamma' X_{i,t} + \varepsilon_{i,j,t},$$

where $Acw_{i,t-1}$ is firm's i lagged innovation intensity constructed following the citation-weighted patent value methodology of Kogan et al. (2017), $X_{i,t}$ is a vector of firm-level controls, α_i is a firm fixed effect, and $\delta_{j,t}$ is an industry by time fixed effect. The controls include: firm size (log of total assets, AT), book-to-market ratio (BM), and leverage (Lev)—all constructed according to the methodology of Hou, Mo, Xue, and Zhang (2019).

The independent variables include the log growth of: (1) firm i employment (item EMP), (2) firm i total capital (item AT), (3) competitors' employment, which is calculated as the total employment (sum of *EMP*) of all other firms in the same 2-digit SIC industry and year, excluding firm i, and (4) firm i's markup, defined as the ratio of sales to adjusted operating expenses, where operating expenses exclude R&D and 30% of SG&A, following Ayyagari, Demirgüç-Kunt, and Maksimovic (2024). The sample is based on annual Compustat data from 1953 to 2019.

The sticky price hypothesis posits that following a technological improvement, firms with nominal rigidities are unable to lower prices. Instead, they increase markups and reduce their *own* labor inputs to capitalize on efficiency gains (that is, $\beta > 0$, for outcome item (4)). In contrast, the creative destruction hypothesis argues that innovators expand and displace their competitors, suggesting that employment reductions should be concentrated within competitor firms, not the innovators themselves (that is, β should be insignificant for outcome item (1), but $\beta < 0$ for outcome variable (4)). Stylized fact 1(b) should generally imply that β is insignificant for outcome variable (2).

The regression results in Table 2 provide compelling evidence in favor of the sticky price mechanism. In particular, the lack of a negative labor spillover effect is inconsistent with the reallocation of creative destruction narrative. The table shows that the contractionary effect of innovation is indeed concentrated on labor and is primarily an *intra-firm* phenomenon, providing an empirical basis for the paper's focus on a mechanism rooted in nominal price rigidity.

OA.4 The mapping in a Calvo pricing framework

Following Kung (2015), we convert the Rotemberg adjustment costs to the average price duration in a Calvo pricing framework. Define the real marginal cost $MC_{j,t} = \frac{\theta_{j,t}}{P_{j,t}}$ where $j \in \{c, i\}$. Log-linearizing the price-setting equation (A.10) around the nonstochastic steady state yields

$$\hat{\pi}_{j,t} = \gamma_1 \hat{mc}_{j,t} + \gamma_2 E_t \left[\hat{\pi}_{j,t+1}\right],\ j \in \{c, i\}$$

where $\gamma_1 = \frac{\mu_j - 1}{\phi_{p,j}}$ and $\gamma_2 = \beta(\mu_{z,c}\mu_{z,i}^{\frac{\alpha_c}{1-\alpha_i}})^{1-\frac{1}{\psi}}$. The notation $\hat{x}$ denotes log deviations from the steady-state.

Under a log-linear approximation, the relationship between the price adjusting cost parameter $\phi_{p,j}$ and the fraction of firms resetting their price, $1 - \kappa_j$, in an equivalent Calvo setting, is given by:

$$\phi_{p,j} = \frac{(\mu_j - 1)\kappa_j}{(1-\kappa_j)(1-\beta\kappa_j)},$$

and the implied average price duration is $\frac{1}{1-\kappa_j}$ quarters.

In our calibration, $\beta = 0.9955$, $\mu_i = 4$, $\mu_c = 2.4$, and $\phi_{p,c} = \phi_{p,i} = 25$. It implies $\kappa_i = 0.71$ and $\kappa_c = 0.79$, suggesting an average price duration of $\frac{1}{1-\kappa_i} = 3.4$ quarters in investment sector and $\frac{1}{1-\kappa_c} = 4.8$ quarters in consumption sector. This is consistent with the empirical evidence in Gali, Gertler, and Lopez-Salido (2001) and Sbordone (2002) that the average price duration is four quarters in the data.

OA.5 The relation of B/M and profits to dividend-yields

The studies of Fama and French (1992); Hou, Mo, Xue, and Zhang (2021); Novy-Marx (2013) show that firms with higher book-to-market and higher profitability have higher expected returns. Studies such as Zhang (2005) and İmrohoroğlu and Tüzel (2014) offer a reconciliation of the former observation. Specifically, value firms, characterized by lower productivity, face increased capital adjustment costs, thus amplifying their risk profile. However, this rationale poses a puzzle when trying to explain why high gross profits, associated with higher productivity in standard production models, are also associated with a higher risk premium.

A full quantitative reconciliation of the gross profitability premium entails a model with a cross section of firms. This, admittedly, is beyond the scope and focus of our model. Rather than using a cross section, we show a key novel insight: low productivity — associated with greater risk — can produce not only high book-to-market ratios but also *low* gross profits under the mechanism of innovation-driven contractions. To demonstrate this point, we focus on the time series association of both characteristics with the risk premium. As discussed below, aggregate-level data shows that both book-to-market and gross profits have a positive association with discount rates, and our model is able to replicate this empirical pattern.

We start by augmenting our benchmark model with stochastic volatility, allowing for variation in risk premia.[4] The incorporation of stochastic volatility into our model framework is impor-

[4]In particular, we postulate that the conditional log-volatility of the aggregate technology shocks adheres to an

tant only for generating temporal variations in the risk premium and dividend yield, but not for cash flow dynamics. As shown in Panel B of Table OA.2, the model, once augmented with this volatility component, continues to produce macro moments that align closely with the data, while preserving the previously established correlations between stock returns, investment returns, and labor surprises.

Table OA.2: **Dividend-price ratio, Risk Premia, B/M, and Gross Profits**

Panel A: Time series comovement with aggregate dividend-price ratio						
	Data			Model		
	(1)	(2)	(3)	(1)	(2)	(3)
GP_t^M	0.82		0.23	0.94		0.74
t-stat	[8.55]		[3.51]	[22.64]		[16.81]
BM_t^M		0.93	0.74		0.81	0.28
t-stat		[12.57]	[11.36]		[13.64]	[6.29]

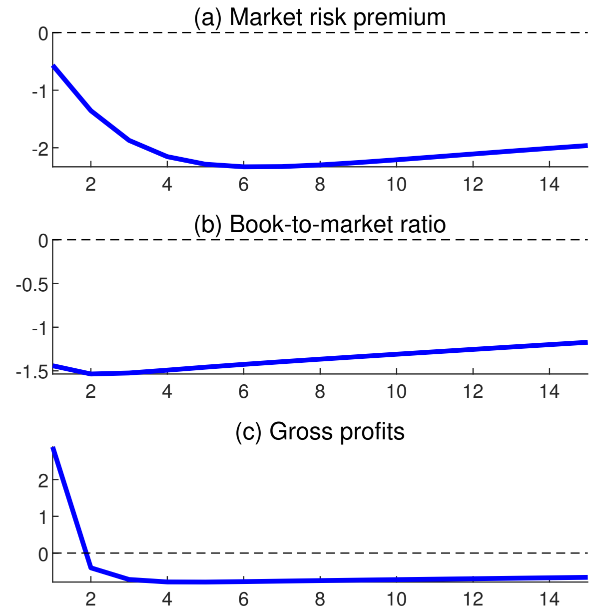
Panel B: Other moments					
Moments	Value	Moments	Value	Moments	Value
$E(\Delta C)(\%)$	1.93	$b_{N,t}$	-0.36	$\text{Corr}(R^I_{M,t}, R^S_{M,t})$	-0.11
$\sigma(\Delta Y)(\%)$	3.57	$b_{K,t}$	0.04	$\text{Corr}(R^I_{M,t+1}, R^S_{M,t})$	0.08
$\sigma(\Delta C)/\sigma(\Delta Y)$	0.93			$\text{Corr}(\frac{I_{t+1}}{I_t}, R^S_{M,t})$	0.12
$\sigma(\Delta I)/\sigma(\Delta Y)$	2.73			$\text{Corr}(R^I_{c,t}, R^S_{c,t})$	-0.11
$\sigma(\Delta N)/\sigma(\Delta Y)$	0.40			$\text{Corr}(R^I_{c,t+1}, R^S_{c,t})$	0.09
$E(R^e_M)(\%)$	4.49			$\text{Corr}(R^I_{i,t}, R^S_{i,t})$	-0.18
$\sigma(R^e_M)(\%)$	19.68			$\text{Corr}(R^I_{i,t+1}, R^S_{i,t})$	0.07
$E(r^f)(\%)$	1.30			$\text{Corr}(N_t^{\text{surprise}}, R^S_{M,t})$	-0.29
$\sigma(r^f)(\%)$	1.44			$\text{Corr}(N_t^{\text{surprise}}, R^f_t)$	-0.05

The table shows model-implied moments for the framework augmented with stochastic countercyclical volatility. In Panel A, we report the slope coefficients and the t-statistics (in brackets) from regressions, performed in both the model and the data, where the dependent variable is the annualized aggregate dividend-to-price ratio and the independent variables are the aggregate book-to-market ratio or aggregate gross-profits. Data for empirical projections are obtained from Goyal et al. (2024). Each variable is scaled by its unconditional standard deviation. The sample spans the period from 1953 to 2019. In Panel B, we report other model-implied moments as in Table 4 - Table 7, under the augmented model.

Next, we perform regressions using model-simulated paths and the data. We project the annualized aggregate dividend yield (i.e., dividend-to-price ratio), which commonly proxies for the discount rate, on current annual aggregate gross profits or/and aggregate book-to-market ratios. Both the dependent and the independent variables are standardized. In both the model and the

AR(1) process, characterized by an autocorrelation coefficient of 0.98 and a standard deviation amounting to 0.006%. This parameterization mirrors the specifications in Bansal and Yaron (2004). Furthermore, we posit a perfectly negative correlation between aggregate technology innovations and volatility shocks, ensuring that the time-varying volatility exhibits a countercyclical pattern, consistent with the data.

Figure OA.3: **Model-Implied Impulse-Responses of Risk Premium, B/M, and Profits**



The figure shows model-implied impulse responses of the market risk premium, book-to-market ratio, and the aggregate gross profit to one standard deviation positive aggregate technology innovation, using the augmented stochastic volatility framework. The horizontal axis represents quarters. The vertical axis represents percent deviations from the steady state.

data, all slope coefficients are positive and significant, as shown in Panel A of Table OA.2. Moreover, book-to-market and gross profits do not crowd each other out in the model: both are jointly associated with higher dividend yields, in line with the data.[5]

To explain how our single capital type and single first-moment shock model can account for the joint positive impact of book-to-market and gross profits on discount rates, we present in Figure OA.3 the impulse responses originating from technological innovations, to aggregate gross profits, book-to-market ratios, and the market risk premium. A positive technological innovation leads to a decrease in the risk premium (and lowers the dividend-yield), an immediate consequence of countercyclical volatility, as illustrated in panel (a). At the same time, this innovation amplifies firm valuations by increasing monopolistic rents while leaving the predetermined capital stock unaffected. This suggests a persistent reduction in the book-to-market ratio, as shown in panel (b), thereby yielding a positive correlation with the conditional risk premium.

[5]Supplemental table OA.7 also shows that in the data, both the aggregate book-to-market and aggregate gross profits positively co-move with the aggregate earning-to-price ratio.

Furthermore, the technological shock exerts an immediate and positive impact on gross profits due to enhanced productivity. In a standard flexible-price model, these gross profits would persistently remain elevated, leading to a counterfactual negative correlation between profitability and risk premia (or dividend yields).

However, within our model, a counteracting dynamic emerges that suppresses gross profits after the initial shock, as shown in panel (c). Specifically, technological innovations trigger a transient contraction in labor, which, in subsequent periods, outweighs the benefits of increased productivity, resulting in below trend profitability, starting one quarter after the initial shock. Consequently, technological innovations are related to reduced (annual) gross profits. This dynamic suggests that the correlation between profitability and the risk premium turns positive, in line with the data.[6]

OA.6 Investment-Based Dividend Yield and the Cross-Section

We check whether the investment-based dividend yield dp^I helps to explain the cross section of equity return anomalies. Admittedly, dp^I is a non-tradable factor as it is a function of past technology shocks. Consequently, the analysis only aims to offer diagnostic insight into the potential relationship between the drivers of cross-sectional return spreads and the underlying force of innovation-driven contractions.

To this end, we utilize a collection of 179 anomalies examined by Chen and Velikov (2023). We consider two sets of explanatory factors. First, as a benchmark, we consider the q-factor model of Hou et al. (2015). Second, we augment the q-factor model with dp^I as an additional factor. For each anomaly return, $R_{i,t}$, we run the following regression:

$$R_{i,t} = \alpha + \beta' f_t + error.$$

Table OA.3 reports the average abnormal return, α, along with the average adjusted R^2 across all anomalies using both sets of factors. When dp^I is appended to the q-factors, the adjusted R^2 increase by about 1%. In addition, we find that there are 12 anomalies whose alpha changes from being statistically significant — using only the q-factors —to insignificant — when augmenting these factors with dp^I. The list of these anomalies is detailed in Table OA.4. Notable anomalies

[6]Incorporating this mechanism into future cross-sectional models can assist in producing both the value and the profitability spreads in a parsimonious manner.

include spreads based on six-month or seasonal momentum and operating leverage.

Table OA.3: **Cross-sectional Implications of Investment-Based Dividend Yields**

	q-factors	q-factors + dp^I
α	4.153	4.121
adj. R^2	0.245	0.253

This table presents the results of using the q-factor model of Hou et al. (2015) and the q-factor model augmented with dp^I to explain anomalies. The 179 anomalies come from the GitHub repository of Chen and Velikov (2023). The reported values in the table are the average α and adjusted R^2 across all 179 regressions.

Table OA.4: **List of Factors and Their Descriptions**

No.	Variable	Description
1	AM	Total assets to market, Fama and French (1992)
2	AOP	Analyst Optimism, Frankel and Lee (1998)
3	Activism1	Takeover vulnerability, Cremers and Nair (2005)
4	Coskewness	Coskewness, Harvey and Siddique (2000)
5	IndRetBig	Industry return of big firms, Hou (2007)
6	Leverage	Market leverage, Bhandari (1988)
7	Mom12mOffSeason	Momentum without the seasonal part, Heston and Sadka (2008)
8	Mom6m	Momentum (6 month), Jegadeesh and Titman (1993)
9	MomSeason06YrPlus	Off season reversal years 6 to 10, Heston and Sadka (2008)
10	OPLeverage	Operating leverage, Novy-Marx (2010)
11	PredictedFE	Predicted Analyst forecast error, Frankel and Lee (1998)
12	zerotradeAlt12	Days with zero trades, Liu (2006)

This table shows the lists of factors that can not be interpreted (non-zero alpha) by the q-factors model of Hou et al. (2015) but can be interpreted (zero alpha) after augmenting with dp^I.

OA.7 Detrended problem

Covariance-stationary first-order conditions can be achieved by rescaling the nonstationary variables of the problem as follows: (a) divide $k_{c,t}, k_{i,t}, i_{c,t}, i_{i,t}, Y_{i,t}$ by $Z_{i,t-1}^{\frac{1}{1-\alpha_i}}$; (b) divide $C_t, Y_{c,t}, U_t$

by $Z_{c,t-1}Z_{i,t-1}^{\frac{\alpha_c}{1-\alpha_i}}$; (c) divide $W_t, d^{\$}_{i,t}, d^{\$}_{c,t}, V^{\$}_{i,t}, V^{\$}_{c,t}$ by $P_{c,t}Z_{c,t-1}Z_{i,t-1}^{\frac{\alpha_c}{1-\alpha_i}}$; (d) divide $\theta_{c,t}$ by $P_{c,t}$; (e) divide $\theta_{i,t}, q_{i,t}, q_{c,t}, P_{i,t}$ by $P_{c,t}Z_{c,t-1}Z_{i,t-1}^{\frac{\alpha_c-1}{1-\alpha_i}}$. After plugging the rescaled variables in the first-order equations, the equilibrium conditions can be written using stationary variables (in particular, using the rescaled variables and using the growth rates of $Z_{i,t}, Z_{c,t}$, and of $P_{c,t}$).

Therefore, we can rewrite the first-order conditions of firm $n \in [0,1]$ in sector $j \in \{c,i\}$:

$$0 = \widetilde{q_{i,t}} - \widetilde{P_{it}} \frac{\partial \Phi_{i,k}\left(\widetilde{i_{i,t}}(n), \widetilde{k_{i,t}}(n)\right)}{\partial \widetilde{i_{i,t}}(n)} \widetilde{k_{i,t}}(n) \tag{A.14}$$

$$0 = \widetilde{q_{c,t}} - \widetilde{P_{it}} \frac{\partial \Phi_{c,k}\left(\widetilde{i_{c,t}}(n), \widetilde{k_{c,t}}(n)\right)}{\partial \widetilde{i_{c,t}}(n)} \widetilde{k_{c,t}}(n) \tag{A.15}$$

$$0 = \widetilde{W_t} n_{i,t}(n) - (1-\alpha_i) \frac{Z_{i,t}}{Z_{i,t-1}} \widetilde{\theta_{i,t}} \widetilde{k_{i,t}}(n)^{\alpha_i} n_{i,t}(n)^{1-\alpha_i} \tag{A.16}$$

$$0 = \widetilde{W_t} n_{c,t}(n) - (1-\alpha_c) \frac{Z_{c,t}}{Z_{c,t-1}} \widetilde{\theta_{c,t}} \widetilde{k_{c,t}}(n)^{\alpha_c} n_{c,t}(n)^{1-\alpha_c} \tag{A.17}$$

$$\begin{aligned} 0 = & -\widetilde{q_{i,t}} + E_t\Big[\big(\frac{P_{c,t+1}}{P_{c,t}} \frac{Z_{c,t}}{Z_{c,t-1}} \big(\frac{Z_{i,t}}{Z_{i,t-1}}\big)^{\frac{\alpha_c-1}{1-\alpha_i}}\big) M^{\$}_{t+1} \Big\{ -\widetilde{P_{i,t+1}} \Phi_{i,k}\left(\widetilde{i_{i,t+1}}(n), \widetilde{k_{i,t+1}}(n)\right) \\ & - \widetilde{P_{i,t+1}} \frac{\partial \Phi_{i,k}\left(\widetilde{i_{i,t+1}}(n), \widetilde{k_{i,t+1}}(n)\right)}{\partial \widetilde{k_{i,t+1}}(n)} \widetilde{k_{i,t+1}}(n) + \widetilde{q_{i,t+1}}(1-\delta) + \widetilde{\theta_{i,t+1}} \alpha_i \frac{Z_{i,t+1}}{Z_{i,t}} \widetilde{k_{i,t+1}}(n)^{\alpha_i - 1} n_{i,t+1}(n)^{1-\alpha_i} \Big\} \Big] \end{aligned} \tag{A.18}$$

$$\begin{aligned} 0 = & -\widetilde{q_{c,t}} + E_t\Big[\big(\frac{P_{c,t+1}}{P_{c,t}} \frac{Z_{c,t}}{Z_{c,t-1}} \big(\frac{Z_{i,t}}{Z_{i,t-1}}\big)^{\frac{\alpha_c-1}{1-\alpha_i}}\big) M^{\$}_{t+1} \Big\{ -\widetilde{P_{i,t+1}} \Phi_{c,k}\left(\widetilde{i_{c,t+1}}(n), \widetilde{k_{c,t+1}}(n)\right) \\ & - \widetilde{P_{i,t+1}} \frac{\partial \Phi_{c,k}\left(\widetilde{i_{c,t+1}}(n), \widetilde{k_{c,t+1}}(n)\right)}{\partial \widetilde{k_{c,t+1}}(n)} \widetilde{k_{c,t+1}}(n) + \widetilde{q_{c,t+1}}(1-\delta) + \widetilde{\theta_{c,t+1}} \alpha_c \frac{Z_{c,t+1}}{Z_{c,t}} \widetilde{k_{c,t+1}}(n)^{\alpha_c - 1} n_{c,t+1}(n)^{1-\alpha_c} \Big\} \Big] \end{aligned} \tag{A.19}$$

$$\begin{aligned} 0 = & (1-\mu_i) \left[\frac{\widetilde{p_{i,t}}(n)}{\widetilde{P_{i,t}}} \right]^{-\mu_i} + \widetilde{\theta_{i,t}} \mu_i \left[\frac{\widetilde{p_{i,t}}(n)}{\widetilde{P_{i,t}}} \right]^{-\mu_i - 1} \frac{1}{\widetilde{P_{i,t}}} \\ & + \phi_{P,i} E_t \left[M^{\$}_{t+1} \left(\frac{\big(\frac{Z_{i,t}}{Z_{i,t-1}}\big)^{\frac{1}{1-\alpha_i}} \widetilde{Y_{i,t+1}}}{\widetilde{Y_{i,t}}} \right) \left[\frac{\frac{P_{c,t+1}}{P_{c,t}} \frac{Z_{c,t}}{Z_{c,t-1}} \big(\frac{Z_{i,t}}{Z_{i,t-1}}\big)^{\frac{\alpha_c-1}{1-\alpha_i}} \widetilde{p_{i,t+1}}(n)}{\Pi_i \widetilde{p_{i,t}}(n)} - 1 \right] \frac{\big(\frac{P_{c,t+1}}{P_{c,t}} \frac{Z_{c,t}}{Z_{c,t-1}} \big(\frac{Z_{i,t}}{Z_{i,t-1}}\big)^{\frac{\alpha_c-1}{1-\alpha_i}}\big)^2 \widetilde{p_{i,t+1}}^2(n)}{\Pi_i \widetilde{p_{i,t}}^2(n)} \right] \\ & - \phi_{P,i} \left\{ \left[\frac{\frac{P_{c,t}}{P_{c,t-1}} \frac{Z_{c,t-1}}{Z_{c,t-2}} \big(\frac{Z_{i,t-1}}{Z_{i,t-2}}\big)^{\frac{\alpha_c-1}{1-\alpha_i}} \widetilde{p_{i,t}}(n)}{\Pi_i \widetilde{p_{i,t-1}}(n)} - 1 \right] \frac{\frac{P_{c,t}}{P_{c,t-1}} \frac{Z_{c,t-1}}{Z_{c,t-2}} \big(\frac{Z_{i,t-1}}{Z_{i,t-2}}\big)^{\frac{\alpha_c-1}{1-\alpha_i}} \widetilde{p_{i,t}}(n)}{\Pi_i \widetilde{p_{i,t-1}}(n)} + \frac{1}{2} \left[\frac{\frac{P_{c,t}}{P_{c,t-1}} \frac{Z_{c,t-1}}{Z_{c,t-2}} \big(\frac{Z_{i,t-1}}{Z_{i,t-2}}\big)^{\frac{\alpha_c-1}{1-\alpha_i}} \widetilde{p_{i,t}}(n)}{\Pi_i \widetilde{p_{i,t-1}}(n)} - 1 \right]^2 \right\} \end{aligned} \tag{A.20}$$

$$\begin{aligned} 0 = & (1-\mu_c) \left[\frac{p_{c,t}(n)}{P_{c,t}} \right]^{-\mu_c} + \widetilde{\theta_{c,t}} \mu_c \left[\frac{p_{c,t}(n)}{P_{c,t}} \right]^{-\mu_c - 1} + \phi_{P,c} E_t \left[M^{\$}_{t+1} \left(\frac{\frac{Z_{c,t}}{Z_{c,t-1}} \big(\frac{Z_{i,t}}{Z_{i,t-1}}\big)^{\frac{\alpha_c}{1-\alpha_i}} \widetilde{Y_{c,t+1}}}{\widetilde{Y_{c,t}}} \right) \left[\frac{\frac{P_{c,t+1}}{P_{c,t}}}{\Pi_c} - 1 \right] \frac{\big(\frac{P_{c,t+1}}{P_{c,t}}\big)^2}{\Pi_c} \right] \\ & - \phi_{P,c} \left\{ \left[\frac{\frac{P_{c,t}}{P_{c,t-1}}}{\Pi_c} - 1 \right] \frac{\frac{P_{c,t}}{P_{c,t-1}}}{\Pi_c} + \frac{1}{2} \left[\frac{\frac{P_{c,t}}{P_{c,t-1}}}{\Pi_c} - 1 \right]^2 \right\} \end{aligned} \tag{A.21}$$

$$0 = \big(\frac{Z_{i,t}}{Z_{i,t-1}}\big)^{\frac{1}{1-\alpha_i}} \widetilde{k_{i,t+1}}(n) - (1-\delta) \widetilde{k_{i,t}}(n) - \widetilde{i_{i,t}}(n) \tag{A.22}$$

$$0 = (\frac{Z_{i,t}}{Z_{i,t-1}})^{\frac{1}{1-\alpha_i}} \widetilde{k_{c,t+1}}(n) - (1-\delta)\widetilde{k_{c,t}}(n) - \widetilde{i_{c,t}}(n) \tag{A.23}$$

$$0 = \widetilde{y_{i,t}}(n) - \frac{Z_{i,t}}{Z_{i,t-1}} \widetilde{k_{i,t}}(n)^{\alpha_i} n_{i,t}(n)^{1-\alpha_i}, \tag{A.24}$$

$$0 = \widetilde{y_{c,t}}(n) - \frac{Z_{c,t}}{Z_{c,t-1}} \widetilde{k_{c,t}}(n)^{\alpha_c} n_{c,t}(n)^{1-\alpha_c}, \tag{A.25}$$

where $\widetilde{q_{j,t}}$ is the detrended price of a marginal unit of installed capital in sector j, the Lagrange multiplier of constraint (7), and $\widetilde{\theta_{j,t}}$ is the detrended marginal cost of producing an additional unit of intermediate good in sector $j \in \{c,i\}$, the Lagrange multiplier of constraint (11).

The detrended first-order condition of the household

$$0 = \widetilde{W_t} - \frac{\widetilde{C_t}}{1-\xi N_t^{\eta}} \xi \eta N_t^{\eta-1}. \tag{A.26}$$

And the detrended equations of definitions of the nominal SDF, nominal interest rate, as well as the household utility are as follows:

$$M_{t+1}^{\$} = \beta(\frac{Z_{c,t}}{Z_{c,t-1}}(\frac{Z_{i,t}}{Z_{i,t-1}})^{\frac{\alpha_c}{1-\alpha_i}})^{-1/\psi}(\frac{\widetilde{C_{t+1}}}{\widetilde{C_t}})^{-1/\psi}(\frac{1-\xi N_{t+1}^{\eta}}{1-\xi N_t^{\eta}})^{1-1/\psi}(\frac{\widetilde{U_{t+1}}}{(E_t\widetilde{U_{t+1}}^{1-\gamma})^{\frac{1}{1-\gamma}}})^{1/\psi-\gamma}\frac{P_{c,t}}{P_{c,t+1}} \tag{A.27}$$

$$r_t^{\$} = \rho_r r_{t-1}^{\$} + (1-\rho_r)\left(r_{ss}^{\$} + \rho_\pi(\pi_t - \pi_{ss}) + \rho_y(\Delta y_t - \Delta y_{ss})\right) \tag{A.28}$$

$$\widetilde{U_t} = \left\{(1-\beta)\left[\widetilde{C_t}(1-\xi N_t^{\eta})\right]^{1-1/\psi} + \beta(E_t\widetilde{U_{t+1}}^{1-\gamma})^{\frac{1-1/\psi}{1-\gamma}}(\frac{Z_{c,t}}{Z_{c,t-1}}(\frac{Z_{i,t}}{Z_{i,t-1}})^{\frac{\alpha_c}{1-\alpha_i}})^{1-1/\psi}\right\}^{\frac{1}{1-1/\psi}} \tag{A.29}$$

OA.8 Additional results

Table OA.5: **Conditional Labor Market Surprises and Stock Returns**

	Low		High	
Sorted variable	Corr($N_t^{\text{surprise}}, R_{M,t}^S$)	Corr($N_t^{\text{surprise}}, R_t^f$)	Corr($N_t^{\text{surprise}}, R_{M,t}^S$)	Corr($N_t^{\text{surprise}}, R_t^f$)
Nominal interest rate	0.13	0.01	-0.56	-0.38

The table shows the model-implied correlation between labor market surprises, N^{surprise}, and the stock market return, R_m^S, or the risk-free interest rate, R_f with stochastic procyclical price stickiness in the 'No-LRR' economy. In the AR(1) process modeling the stickiness, we let $\phi_{p,i}^{ss} = \phi_{p,c}^{ss} = \phi_{p,i} = \phi_{p,c}$ and $\rho_{p,i} = \rho_{p,c} = \rho_{x,i} = \rho_{x,c}$ as the benchmark calibration in Table 3. We define the labor market surprises as $N_t^{\text{surprise}} = N_t - E_{t-1}[N_t]$. The low (high) portfolio includes all firms with the sorted variable below (above) the 30th (70th) percentile of the cross-sectional distribution each quarter. Our result is robust to other cutoffs. The correlation is calculated over the next 12 quarters for each group, where we take the average across finite sample paths.

Table OA.6: **Return Predictability using Investment-Based Dividend Yields (Control Investment Rates)**

A. 1964-2019				B. 1980-2019			
dp	cay	dp^I	adj. R^2	dp	cay	dp^I	adj. R^2
I. Predictive horizon $k=1$:							
1.99			0.06	1.26			0.01
[1.10]				[0.60]			
	0.78		0.06		0.82		0.01
	[0.86]				[0.45]		
		-9.36	0.13			-21.00	0.20
		[-2.38]				[-2.64]	
3.12		-10.93	0.16	0.21		-20.89	0.18
[1.81]		[-2.80]		[0.12]		[-2.63]	
	-1.10	-13.97	0.13		-0.03	-21.03	0.18
	[-1.02]	[-2.81]			[-0.02]	[-2.54]	
II. Predictive horizon $k=3$:							
2.71			0.14	5.10			0.17
[0.86]				[1.50]			
	3.21		0.22		1.14		0.15
	[1.53]				[0.24]		
		-29.07	0.35			-55.00	0.46
		[-2.75]				[-3.41]	
6.00		-32.09	0.38	2.39		-53.71	0.45
[2.08]		[-3.21]		[0.82]		[-3.17]	
	-1.63	-35.88	0.35		-1.11	-55.94	0.44
	[-0.82]	[-3.13]			[-0.37]	[-3.76]	
III. Predictive horizon $k=5$:							
8.99			0.29	17.19			0.36
[2.08]				[3.29]			
	5.18		0.33		-0.38		0.25
	[1.97]				[-0.05]		
		-51.62	0.50			-83.66	0.51
		[-3.81]				[-3.90]	
15.07		-59.21	0.58	13.30		-76.52	0.56
[5.26]		[-5.10]		[3.50]		[-3.73]	
	-4.07	-68.65	0.51		-3.89	-86.97	0.50
	[-1.68]	[-5.18]			[-0.75]	[-4.39]	

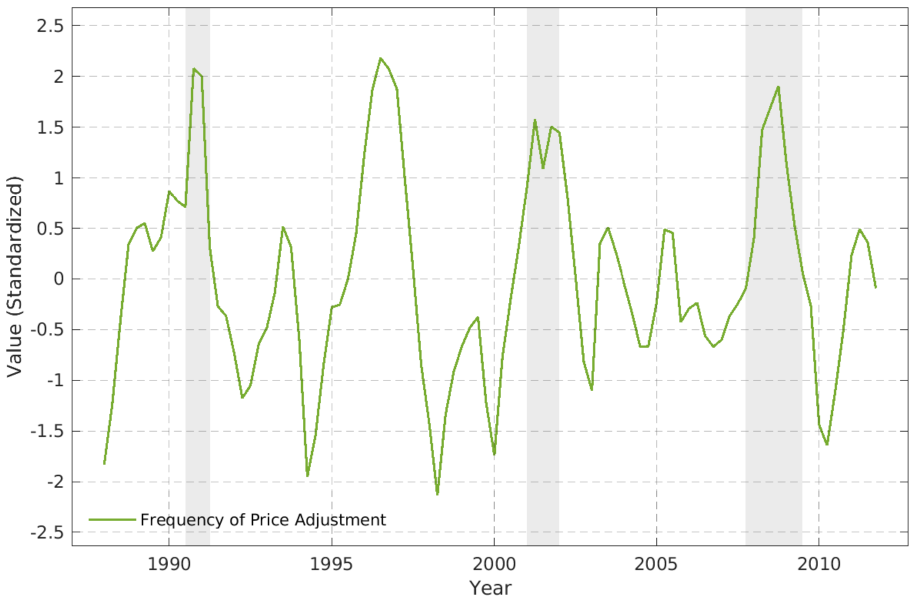
The table shows the results of the projection $R^e_{t\to t+k} = \text{const} + \beta x_t + \gamma (I/K)_t + \varepsilon_t$, where $R^e_{t\to t+k}$ denotes the cumulative excess market return up to k years ahead, with k varying from 1 to 5 years, and x_t is an economic predictor of interest: the stock market dividend yield (dp), the consumption-to-wealth ratio (cay), or the investment-based dividend yield dp^I filtered from the benchmark model using TFP data from Fernald (2014). The first two predictors, the investment-to-capital ratio $(I/K)_t$ (included as a control variable), and the market excess returns are all obtained from Goyal et al. (2024). The numbers underneath each variable report the slope coefficient, whereas brackets report Newey-West t-statistics. The columns adj. R^2 refer to adjusted R^2. In Panel A, the sample period is from 1964 to 2019, and in Panel B it is from 1980 to 2019.

Table OA.7: Aggregate Earnings-to-Price Ratio, Book-to-Market, and Gross Profitability

	EP (1)	EP (2)	EP (3)
GP	0.75***		0.14
	[5.51]		[1.55]
BM		0.88***	0.78***
		[12.48]	[7.14]
adj. R^2	0.56	0.78	0.78

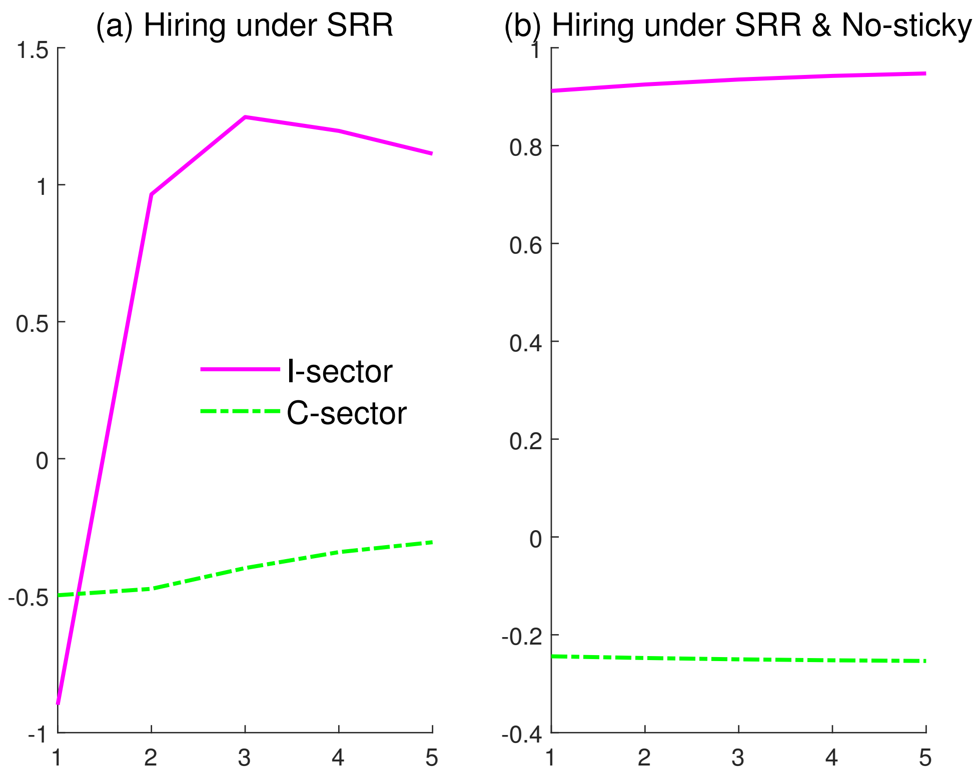
This table shows how the aggregate book-to-market ratio and aggregate gross profitability affect the aggregate earning-to-price ratio. *EP* is the earnings-to-price ratio, which is computed as the 12-month sum of earnings on the S&P 500 index divided by the price index of the S&P 500. *BM* is the aggregate book-to-market ratio, computed as the ratio of book value to market value for the Dow Jones Industrial Average. *GP* is the aggregate gross profitability ratio. All these variables are scaled. We omit the constant term for brevity. The sample spans the period from 1953 to 2019. Standard errors are computed using the Newey-West estimator with one year lag. We include t-statistics in the brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Figure OA.4: **Frequency of Price Adjustment (Time Series)**



The figure presents the time series of the standardized frequency of price adjustment, which is used as a key variable in the main text. The underlying quarterly data on the frequency of price adjustment is from Vavra (2014). We apply a Hodrick-Prescott (HP) filter to the original series to retain its cyclical component. The resulting series is then standardized by its standard deviation. The shaded areas indicate NBER-dated recessions. Data are from 1988Q1 to 2011Q4.

Figure OA.5: **Technology Shocks to Hiring**



The figure shows impulse responses of model-detrended hiring in both I-sector (the solid magenta line) and C-sector (the dash-dotted green line) to one standard deviation shock of aggregate technology. Panel (a) shows impulse responses under the SRR shock. Panel (b) show impulse responses from the economy that is identical to the former calibration but without price stickiness ($\phi_{p,c} = \phi_{p,i} = 0$). The horizontal axis represents quarters. The vertical axis represents percent deviations from the steady state.