Innovation-Driven Contractions: A Key to Unravel Asset Pricing Puzzles ⋆

Gill Segal and Chao Ying

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Abstract

We study the macroeconomic mechanism and financial implications of the surprising phenomenon where positive technological innovations induce short-term contractions, using a two-sector New-Keynesian model. The interaction between sticky prices and production divisions into investment and consumption sectors explains why technological innovations decrease labor with muted impact on capital. These non-standard macro dynamics reconcile asset-pricing puzzles, including the negative correlation between investment and stock returns, valuation surging after bad labor-market news, the positive association of gross profits and book-to-market with risk premia, and the equity-yield term-structure procyclicality. Lastly, investment-based dividend yields, filtered from our model, are empirically useful for return-predictability applications.

JEL Classification: G12, E32

Keywords: Production, Asset Pricing, Sticky Prices, Technology, Labor, Risk Premium

⋆Segal: (Gill_Segal@kenan-flagler.unc.edu), Kenan-Flagler Business School, University of North Carolina at Chapel Hill; Ying: (chaoying@cuhk.edu.hk), Chinese University of Hong Kong. We are grateful for the comments from Ravi Bansal, Frederico Belo, Xuhui Chen, Ric Colacito, Alex Corhay, Wei Dou, Michael Gallmeyer, Christian Heyerdahl-Larsen, Walter Pohl, Andreas Stathopoulos, Roberto Steri, Kevin Schneider, Stijn Van Nieuwerburgh, Chi-Yang Tsou, Chenjie Xu, Yifan Zhu, and seminar participants from 2024 Corporate Policy and Asset Pricing (COAP) conference, 2024 European Finance Association (EFA) Meeting, Stanford Institute for Theoretical Economics (SITE) - Frontiers in Asset Pricing and 2024 Summer Finance Symposium. We thank Zhonghao Li for his excellent research assistance.

Technological innovations are key contributors to sustainable economic growth. While their long-term impact on the economy is unambiguously positive, prior macroeconomic literature has shown that these innovations can surprisingly lead initially to short-term production contractions. For instance, technological improvements often decrease firms' input usage and revenues in the near future, surging only in the longer run.[1] Despite its importance, quantitative theories that explain this empirical observation remain largely unexplored. What mechanism can drive these unexpected macroeconomic dynamics? And how do these short-term technologically driven downturns impact valuations and risk premia?

This study delves into these questions, arguing that the resolution of the macroeconomic dynamics is pivotal, as it can shed new light on several asset pricing puzzles. While existing theories — overlooking these transient contractions from technology shocks — were shown to successfully explain the *unconditional* moments of risk premia and macro fundamentals, they largely struggle in generating realistic *conditional* fluctuations in equity, physical capital, and labor markets, jointly. In contrast, our proposed model that reconciles these macro dynamics can rationalize the negative correlation between stock returns and investment returns or hiring news, along with other challenging stylized facts within a unified framework. Furthermore, investment returns filtered from our model bear empirical applicability. Their dividend yields have high predictive power for future stock returns in the data.

We start by expanding the evidence that technological innovations lead to short-term downturns in input markets, extending it to more recent years.[2] We find that in the short run, the contractionary effect of a positive innovation to technology is concentrated within the labor markets. The extended sample analysis reveals, however, a more nuanced impact on capital markets: The immediate effect of these innovations on capital growth or investment

[1]See related literature for a comprehensive discussion.

[2]Throughout the paper, we use the term technological innovations to refer to TFP shocks are are purified from the effects of varying utilization and non-perfect competition, isolating the technological component.

expenditures is rather small and statistically insignificant, contrasting earlier findings.

Subsequently, we propose a general equilibrium model to explain the intricate evidence. Importantly, the model features two sectors: consumption and investment. Each sector faces nominal price rigidities. The household features recursive preferences, allowing to derive novel quantitative implications for financial markets.

Without sticky prices, technological innovations increase firms' current and expected marginal product of labor and capital. Consequently, firms immediately increase their investments and hiring, counterfactually. The surge in capital demand also increases the relative price of investment goods. In contrast, with empirically disciplined sticky prices, the short-term effect of technology shocks is more subtle. Sticky prices imply that the marginal cost of production (relative to output price) falls sharply, leading to higher markups. This curtails firms' labor demand, resulting in diminished hiring in the immediate term, as in the data. While all firms capitalize on higher marginal productivity of capital by increasing investment rates, the relative price of investment goods decreases, thereby muting the impact of technological shocks on short-term capital growth, consistent with our empirical findings.

We emphasize that the combination of sticky prices with the two-sector structure of our model is critical to explain the evidence, and presents a non-trivial departure from traditional frameworks for studying asset prices. An off-the-shelf—one-sector—New Keynesian model cannot account for the intricate dynamics. In such 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. Likewise, in standard two-sector models—lacking sticky prices— aggregate 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.[3]

[3]Importantly, investment-specific technology shocks in two-sector models result in a decline in the relative

Beyond reconciling the macro-dynamics, the main contribution of our study is to quantitatively demonstrate the importance of innovation-led contractions for asset prices. This phenomenon can explain several empirical regularities, which a priori suggest a potential disconnection between real economic activity and the stock market, but a posteriori can be well understood under fair pricing.

First, existing literature points to a fundamental challenge for production-based asset pricing. 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. The latter is quite puzzling, since under perfect competition or constant markups, both returns should perfectly comove, as occurs in extant production frameworks. Our model, however, can produce this stylized fact using a single type of capital good. Following a positive innovation, firm valuations and stock returns increase due to enhanced monopolistic rents. At the same time, in our two-sector setup, investment returns 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 simultaneous drop in investment returns. However, the negative impact of nominal rigidity on the price of capital is transitory, suggesting higher future investment returns, resulting in a positive relation between stock returns and one-year-ahead investment returns, as in the data.

Second, numerous studies showed that deteriorating macro conditions, particularly those in the labor market, often coincide with elevated stock valuations, suggesting an apparent disjunction between fundamentals and prices. The common explanation for the inverse relationship between labor market surprises and the stock market often hinges on offsetting monetary or fiscal policies. While such policies may soften the negative impact of adverse news on valuations, this rationale may not quantitatively explain, in general-equilibrium,

price of capital and in a short-term contraction in consumption. However, they cause a surge in labor and a rise in the marginal utility (negative risk-price), contrasting with the empirical effects of aggregate technology.

why these policies would overcompensate to the extent of reversing the sign of the market reaction. Furthermore, existing research argues that a spike in unexpected unemployment signifies a "bad" state. In contrast, we argue that unexpected employment is endogenous and should not be perceived as an exogenous negative shock. Indeed, our model suggests that, on average, "good" shocks to technology are associated with higher valuations but, in line with the data, also with a pronounced unexpected drop in employment. Notably, the correlation between labor market surprises and the stock market also exhibits time variation, typically turning negative (positive) in expansions (recessions). Accounting for the empirical cyclicality in nominal price rigidity allows our model to also replicate this temporal variation.

Third, prior research demonstrated that firms characterized by high book-to-market ratios, low productivity, and high profitability all command a higher risk premium. Explaining these spreads jointly poses a challenge. Growth firms typically have high productivity. If such firms are deemed safer, then reconciling why high-profitability firms—which traditionally exhibit high productivity—also command a higher expected return becomes non-trivial. To provide a fresh angle on the matter, we augment the model with countercyclical stochastic volatility, which only helps to produce realistic fluctuations in expected returns. Our augmented model offers a simple reconciliation. A positive technology shock lowers the risk premium and the book-to-market ratio, consistent with standard models. However, the positive effect of heightened productivity on output is outweighed by the negative effect of transitory innovation-driven contractions, leading to an overall reduction in gross profits over the short run. Consequently, as borne in aggregate-level data, both lower book-to-market ratios and reduced profitability relate to lower dividend yields and conditional risk premia.

Fourth, innovation-led contractions affect the term structure of equity yields. In the benchmark, 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 increase in the short-run. Thus, in good states, the expected dividend growth is larger in shorter-horizons relative to longer-horizons.

To test our macroeconomic mechanism, we derive two novel implications for the labor markets. Our model predicts that with sticky prices, a positive technological innovation decreases wages and increases labor flow into the consumption sector relative to the investment sector in the short run. We confirm these predictions using impulse response analysis.

Last but not least, we use our framework along with observed paths of utilization-adjusted technological innovations to filter out empirical paths of investment returns and their associated investment-based divided yields. In both the model and the data, investment-based divided yields predict stock returns negatively. In a sample from 1960 to 2019, their R^2 exceed those of the stock-market dividend yields or of the consumption-to-wealth ratio, reaching 29% at the five-year-ahead predictive horizon.

While we do not exclude other explanations for the former puzzles, the takeaway is that the different stylized facts—previously seen as separate—can be interestingly unified under the mechanism of innovation-driven contractions. The rich interplay between technological innovations and macroeconomic outcomes, as previously shown in macro studies, improves the time-series properties of equity and investment returns in relation to physical investment and labor. Incorporating these dynamics into future models, whether through a New Keynesian framework or other mechanisms of choice, holds the potential of advancing production-based asset pricing to succeed in both cross-sectional and time-series dimensions.

Related literature. A pivotal research by Basu, Fernald, and Kimball (2006) presents comprehensive empirical evidence, showing that when utilization-adjusted aggregate technology increases, input metrics, including hours and employment indices counterintuitively fall. Non-residential investment declines as well. Several years following the technological shock, inputs revert to their baseline, and output's trajectory rises. Beyond the macroeconomic scope, the implications of this evidence for asset pricing remain unexplored. In our study, we extend the evidence, finding that the contractionary impact of technological innovations is primarily focused in labor markets, but not in capital markets or output. As noted previously, such dynamics are hard to explain under perfect competition or constant markups.[4] Without explicitly ruling out other explanations, we provide a quantitative resolution based on nominal price rigidity in the tradition of New-Keynesian models,[5] but with two distinct production sectors. Furthermore, we show that this transient "disconnection" between macro aggregates and innovation spills over to broader "disconnections" between macroeconomic variables and valuations in financial markets.

Liu, Whited, and Zhang (2009) uncover a production-based asset price puzzle. Using the generalized method of moments, they equate average investment returns with average stock returns. With a single type of capital, the contemporaneous correlation between stock and investment returns is significantly negative, which is incongruent with the implications of q-theory. This incongruence presents a challenge in the context of production-based asset pricing. Existing frameworks (e.g., Jermann, 1998; Kaltenbrunner and Lochstoer, 2010; Croce, 2014, among others) can jointly explain the *unconditional* moments of investment (as well as other macro moments) and risk premia, including their average levels and volatility. However, they largely fail to produce realistic *conditional* dynamics between the two. With perfect competition or constant markups, as is commonly assumed, the contemporaneous

[4]Notably, even elaborate perfect-competition models, with heterogeneous agents and creative destruction, could potentially struggle in fully reconciling the data. In these models, positive tech shocks are typically 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, this economic depression is typically pervasive, suppressing not only labor but also aggregate investment — in contrast to Table 1, while also leading to a negative risk price for displacement shocks (see Kogan, Papanikolaou, and Stoffman (2013)) – in contrast to the positive risk price for *aggregate* productivity.

[5]This feature is shared with Smet and Wouters (2008) among others. However, we emphasize that a single-sector NK model will counterfactually produce a contraction in investment expenditures and output following a technology shock (see, e.g., Basu and Bundick (2017)). Moreover, these macro-studies refrain from a close examination of the implications of asset pricing, which is the novelty of our study.

correlation between investment and stock returns is bound to be (close to) one.[6] Liu et al. (2009) postulate that temporal lags in investment might change the synchronicity of this correlation. Corroborating this hypothesis, Kuehn (2009) studies a model in which investment takes a long time to build, offering a theoretical foundation for this observation.

Our analysis suggests that, while time-to-build might serve as a sufficient condition to reconcile this anomaly, it may not be fully necessary. We construct a two-sector model in which the time to build lasts only one period, similar to the frameworks presented by Papanikolaou (2011) and Garlappi and Song (2017).[7] Within these existing models, the comovement puzzle still exists, but we depart from those models by integrating nominal rigidities. In the presence of price stickiness, the relative price of capital goods decreases following a technological innovation, which can account for the decline in investment returns, despite a simultaneous surge in stock returns. Crucially, the countercyclical nature of capital goods prices, as implied by our model, aligns with the empirical findings of Greenwood, Hercowitz, and Krusell (1997) and Christiano and Fisher (2003), which underscore that investment goods prices are negatively correlated with the business cycle.

Several studies highlight an anomaly where "bad" macro news can be "good" news for equity markets. Boyd, Hu, and Jagannathan (2005), Elenev, Law, Song, and Yaron (2022), and Xu and You (2022) show that stock prices generally rise in response to announcements of higher unemployment. Our model complements existing explanations through its ability to reconcile this observation without reliance on aggressive monetary or fiscal policy shocks.

Furthermore, higher book-to-market and higher profitability command a higher risk pre-

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

[7]Our model ingredients also share similarity with Segal (2019) and Bianchi, Kung, and Tirskikh (2023). However, while the former study uncertainty shocks, our research question—related to first-moment contractionary innovations—and focus—related to the different stylized facts—are substantially different. Moreover, our model is more parsimonious, as the calibration only relies on one aggregate technology shock.

mium (see Hou, Mo, Xue, and Zhang, 2021; Novy-Marx, 2013). Reconciling these two spreads is a complex theoretical task. Ai, Li, and Tong (2021) argue that the riskiness of high-profitability (value) firms emerges from the transitory (permanent) component of productivity. Kogan, Li, and Zhang (2022) show that variable production costs create an operating hedge, which explains both spreads. Zhu (2023) argues that real options may also reconcile both premiums. We contribute another insight to this literature by offering a streamlined solution, as our model captures the relation of book-to-market and gross profits with risk premia within a single capital good and single first-moment shock framework.

Lastly, Binsbergen, Brandt, and Koijen (2012) and Bansal, Miller, Song, and Yaron (2021) document that the equity yield (expected dividend growth) term-structure slope is positive (negative) during economic expansions, while it turns negative (positive) in recessions. Gormsen (2021) provides evidence that the term structure of the equity yields is negatively correlated with dividend yields. Bansal et al. (2021) accounts for the procyclical slope with a regime-switching model that dictates the cyclicality of expected dividend growth. Li and Xu (2023) use an intermediary-based model in an endowment economy to explain the evidence. Our model also generates the procyclicality of the slope, but with dividends being endogenous and their growth cyclicality dependent on innovation-led contractions.

In a broader context, our paper is related to studies that connect production decisions to expected returns (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), Tuzel and Zhang (2017), Belo, Lin, and Yang (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), and Kogan, Li, Zhang, and Zhu (2023), among others). We find that investment-based dividend yields, which account for innovation-driven contractions, are good predictors of future market returns.

1 Motivating Evidence and Model

Evidence. Consistent with the methodology presented by Basu et al. (2006), we provide updated empirical findings pertaining to the immediate implications of technological advancements on factors of production. Our dataset encompasses a quarterly span from 1960Q1 to 2019Q4. We source real per-capita consumption expenditures (encompassing nondurables and services), gross domestic product, and investment expenditures from the Bureau of Economic Analysis (BEA). Employment metrics are obtained from the Bureau of Labor Statistics (BLS). The utilization-adjusted technology data, adhering to the methodology of Fernald (2014), are obtained from the Federal Reserve Bank of San Francisco.

We employ a simple projection:

$$\Delta y_t = const + b \cdot dz_t + \varepsilon_t, \tag{1}$$

where dz_t is quarterly aggregate technological innovation, and Δy_t represents the log-growth rate of the macroeconomic variable of interest. The findings are tabulated in Table 1.

Consistent with the extensive evidence of Basu et al. (2006), we find that technology innovations are associated with a significant reduction in hours worked, composition-adjusted labor input, and lower employment in good-producing sectors. However, in the extended sample, the impact of these innovations on capital usage is inconclusive. Both measures of investment expenditures and capital growth load positively on dz, but the slope coefficient is statistically insignificant. Accordingly, the immediate impact on consumption and output is positive, yet, muted in the short-run (amounting to approximately 4% standard deviation increase).

Model. We introduce a quantitative two-sector New Keynesian model to reconcile the evidence. Production is split into a consumption sector and an investment sector, the latter producing investment goods. Each sector comprises a mass of firms operating under

Table 1: **Technological Innovations and Macroeconomic Growth: Data**

	Dependent variable (growth rate)						
Regressor	(1) Hours	(2) Payroll	(3) Composition-adjusted Labor	(4) Capital	(5) Investment	(6) Consumption	(7) Output
b	-0.34	-0.25	-0.07	0.04	0.12	0.12	0.21
t-stat	-4.68	-2.15	-3.11	1.51	0.28	2.06	2.86

The table reports the slope coefficients and the t-statistics for the regression: $\Delta y_t = const + b \cdot dz_t + \varepsilon_t$. dz_t is quarterly aggregate technological innovation. Δy_t is the log-growth rate of the macroeconomic variables, which include (1) Hours; (2) All Employees in Manufacturing; (3) Composition-adjusted labor input as in Fernald (2014); (4) Capital; (5) Investment; (6) Consumption; (7) Output. The sample is quarterly from 1960Q1 to 2019Q4. We report Newey and West (1987) robust t-statistics.

monopolistic competition and experiencing nominal price rigidity. This rigidity implies that markups vary endogenously over time. The intermediate inputs from these firms are combined to produce a final investment good, which is sold to firms, and a final consumption good, which is sold to households. The household, owner of all firms, supplies labor elastically for production while optimizing its lifetime recursive utility. A monetary authority, adhering to a standard Taylor rule, sets interest rates, thereby setting endogenous inflation. The dual sector structure is pivotal in reconciling the data as it facilitates the segregation of capital expenditures into two potentially counteracting components: the quantity of investment and the price of investment.

1.1 Aggregation

The aggregator in the consumption (investment) sector produces composite or final consumption (investment) goods, denoted $Y_{c,t}$ $(Y_{i,t})$. $Y_{c,t}$ will be used for consumption by the household, while $Y_{i,t}$ will be equal to aggregate investment goods in the economy. Production of the composite consumption (investment) good 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:

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

The parameter $\mu_j, \quad j \in \{c, i\}$, 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), and the prices are taken as given. The first-order condition of equation (3) yields the demand 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 final good-producing firm 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

$$P_{j,t} = \left[\int_0^1 (p_{j,t}(n))^{1-\mu_j} dn\right]^{\frac{1}{1-\mu_j}}, \quad j \in \{c, i\}. \tag{5}$$

1.2 Intermediate good production

1.2.1 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 and subject to sectoral technology shocks $Z_{j,t}$:

$$y_{j,t}(n) = Z_{j,t} k_{j,t}(n)^{\alpha_j} n_{j,t}(n)^{1-\alpha_j}, \quad j \in \{c, i\}, \tag{6}$$

where α_j is the capital share of output of intermediaries in sector j, and $Z_{j,t}, \quad j \in \{c, i\}$, are the sectoral technology shocks.

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 given by:

$$\Phi_{j,k} \left(i_{j,t}(n), k_{j,t}(n) \right) = \frac{i_{j,t}(n)}{k_{j,t}(n)} + \frac{\phi_{k,j}}{2} \left(\frac{i_{j,t}(n)}{k_{j,t}(n)} - \delta \right)^2 \tag{7}$$

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

$$k_{j,t+1}(n) = (1 - \delta) k_{j,t}(n) + i_{j,t}(n). \tag{8}$$

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

$$\Phi_{P,j} \left(p_{j,t}(n), p_{j,t-1}(n) \right) = \frac{\phi_{P,j}}{2} \left[\frac{p_{j,t}(n)}{\Pi_j p_{j,t-1}(n)} - 1 \right]^2 p_{j,t}(n) Y_{j,t}, \quad j \in \{c, i\}, \tag{9}$$

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 an intermediate good producer of type n in sector j, in terms of nominal consumption goods, is given by:

$$d^{\$}_{j,t}(n) = p_{j,t}(n) y_{j,t}(n) - W_t n_{j,t}(n) - P_{i,t} \Phi_{j,k} \left(\frac{i_{j,t}(n)}{k_{j,t}(n)} \right) k_{j,t}(n) - \Phi_{P,j} \left(p_{j,t}(n), p_{j,t-1}(n) \right). \tag{10}$$

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:

$$V^{\$}_{j,t}(n) = \max_{\{n_{j,s}(n),k_{j,s}(n),p_{j,s}(n)\}} E_t \Sigma_{s=t}^{\infty} M^{\$}_{t,t+s} d^{\$}_{j,t+s}(n), \tag{11}$$

subject to equation (8), equation (10), and the demand constraint:

$$\left[\frac{p_{j,t}(n)}{P_{j,t}}\right]^{-\mu_j} Y_{j,t} \leq Z_{j,t} k_{j,t}(n)^{\alpha_j} n_{j,t}(n)^{1-\alpha_j}, \quad j \in \{c, i\}. \tag{12}$$

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:

$$V_{j,t}(n) = V^{\$}_{j,t}(n)/P_{c,t}; \quad d_{j,t}(n) = d^{\$}_{j,t}(n)/P_{c,t}. \tag{13}$$

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 $\triangle P_{i,t} = \frac{P_{i,t}/P_{c,t}}{P_{i,t-1}/P_{c,t-1}}$.

1.2.2 Technology

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

$$\frac{Z_{j,t}}{Z_{j,t-1}} = g_{z,j} + x_{j,t} + \sigma_{z,j}\varepsilon^{j}_{z,t}, \quad j \in \{c, i\} \tag{14}$$

$$x_{j,t} = \rho_{x,j} x_{j,t-1} + \sigma_{x,j}.\varepsilon^{j}_{x,t}, \tag{15}$$

where $\rho_{x,j} \in (-1, 1)$ measures the persistence of long-term technology growth, similar to Croce (2014), and $\sigma_{x,j}$ denotes long-run shocks' standard deviation. The shocks $\varepsilon^{c}_{z,t}$, $\varepsilon^{i}_{z,t}$, $\varepsilon^{i}_{x,t}$ and $\varepsilon^{c}_{x,t}$ are standard normal and independent over time.

1.3 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:

$$U_t = \left\{(1-\beta)\left[C_t\left(1-\xi N_t^{\eta}\right)\right]^{1-1/\psi} + \beta\left(E_t U_{t+1}^{1-\gamma}\right)^{\frac{1-1/\psi}{1-\gamma}}\right\}^{\frac{1}{1-1/\psi}} \tag{16}$$

where β is the time discount rate[8], 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:

$$\max_{\{C_s,N_s\}} U_t, \quad \text{s.t. } P_{c,t}C_t = W_t N_t + \int_0^1 d^{\$}_{c,t}(n)dn + \int_0^1 d^{\$}_{i,t}(n)dn \tag{17}$$

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:

$$M^{\$}_{t+1} = \beta\left(\frac{C_{t+1}}{C_t}\right)^{-1/\psi}\left(\frac{1-\xi N_{t+1}^{\eta}}{1-\xi N_t^{\eta}}\right)^{1-1/\psi}\left(\frac{U_{t+1}}{\left(E_t U_{t+1}^{1-\gamma}\right)^{\frac{1}{1-\gamma}}}\right)^{1/\psi-\gamma}\frac{P_{c,t}}{P_{c,t+1}} \tag{18}$$

1.4 Monetary authority

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

$$r^{\$}_t = \rho_r r^{\$}_{t-1} + (1-\rho_r)\left(r^{\$}_{ss} + \rho_\pi\left(\pi_t - \pi_{ss}\right) + \rho_y\left(\Delta Y_t - \Delta Y_{ss}\right)\right) \tag{19}$$

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.

[8]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.

1.5 Equilibrium

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

- Labor market clearing:

$$\int_0^1 n_{c,t}(n)dn + \int_0^1 n_{i,t}(n)dn = N_t. \tag{20}$$

- Consumption good market clearing:

$$C_t + \int_0^1 \frac{\phi_{P,c}}{2}\left[\frac{p_{c,t}(n)}{\Pi_c p_{c,t-1}(n)} - 1\right]^2 Y_{c,t}dn = Y_{c,t}. \tag{21}$$

- Investment good clearing:

$$\int_0^1 \Phi_{c,k}\left(\frac{i_{c,t}(n)}{k_{c,t}(n)}\right)k_{c,t}(n)dn + \int_0^1 \Phi_{i,k}\left(\frac{i_{i,t}(n)}{k_{i,t}(n)}\right)k_{i,t}(n)dn \tag{22}$$

$$+\int_0^1 \frac{\phi_{P,i}}{2}\left[\frac{p_{i,t}(n)}{\Pi_i p_{i,t-1}(n)} - 1\right]^2 Y_{i,t}dn = Y_{i,t} \tag{23}$$

- Zero net supply of nominal bonds:

$$\frac{1}{R_t^{\$}} = E_t\left[M_{t+1}^{\$}\right] \tag{24}$$

An equilibrium consists of prices and allocations such that taking prices as given, (i) the household's allocations solves equation (17); (ii) firms' allocations solve equation (11); (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 $p_{j,t}(n) = p_{j,t}$.

1.6 Returns

1.6.1 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 (10) and (11).

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

$$R^{S(unlevered)}_{M,t} = \frac{V_{c,t-1}}{V_{c,t-1} + V_{i,t-1}} R^{S(unlevered)}_{c,t} + \frac{V_{i,t-1}}{V_{c,t-1} + V_{i,t-1}} R^{S(unlevered)}_{i,t}. \tag{25}$$

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

$$R^{e}_{j,t} = \phi_{lev}(R^{S(unlevered)}_{j,t} - R^{f}_{t}) + \sigma_d \varepsilon_{j,d,t} \quad j \in \{c, i, m\}, \tag{26}$$

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 $R^{S}_{j,t}$ is defined as the sum of the market excess return and the risk-free rate. Lastly, the real risk-free rate satisfies: $\frac{1}{R^f_t} = E_t\left[M_{t+1}\right]$.

1.6.2 Investment Returns

The first-order conditions of each sector are detailed in the appendix. Optimality implies that the marginal real value of capital in sector $j \in \{c, i\}$ is given by:

$$\partial V_j / \partial k_{j,t} = -P_{i,t}\left(\Phi_{j,k}(i_{j,t}, k_{j,t}) + \frac{\partial \Phi_{j,k}\left(i_{j,t}, k_{j,t}\right)}{\partial k_{j,t}} k_{j,t}\right) + q_{j,t}(1-\delta) + \alpha_j \theta_{j,t} Z_{j,t} k^{\alpha_j - 1}_{j,t} n^{1-\alpha_j}_{j,t},$$

where $q_{j,t}$ is the price of a marginal unit of installed capital in sector j, and $\theta_{j,t}$ is the marginal cost of producing an additional unit of intermediate good in sector j (i.e., inverse of the markup). Consequently, the investment return in each sector is given by:

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

The market investment return is therefore defined as:

$$R^{I}_{M,t} = \frac{V_{c,t-1}}{V_{c,t-1} + V_{i,t-1}} R^{I}_{c,t} + \frac{V_{i,t-1}}{V_{c,t-1} + V_{i,t-1}} R^{I}_{i,t}. \tag{27}$$

2 Quantification

2.1 Calibration

The model is calibrated at the quarterly frequency. The parameters are detailed in Table 2. We divide these into several categories.

Technology. We set the technological drift of both sectors, $g_{z,i} = g_{z,c}$, 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, $\rho_{x,c} = \rho_{x,i}$, at 0.975 to match the first-order autocorrelation of output growth. The standard deviations of long-run technology shocks is 10% of the volatility of short-run technology shocks, consistent with Croce (2014), which only helps to pin down the unconditional level of the equity premium. For parsimony, we assume that technology shocks in both sectors are perfectly correlated such that the model collapses to a single aggregate technology framework (denoted Z_{agg}), corresponding to the former empirical evidence on common technological shocks.

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 compounded 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%, identical to the value

Table 2: **Model Parametrization**

Symbol	Parameter	Value
A. Technology		
$g_{z,i}$	Technological drift - investment sector	1.0032
$g_{z,c}$	Technological drift - consumption sector	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
$\rho_{x,i}$	Persistence of long-run growth - investment sector	0.975
$\rho_{x,c}$	Persistence of long-run growth - consumption sector	0.975
$\sigma_{x,i}$	Volatility of long-run growth - investment sector (%)	0.1*σ_{zi}
$\sigma_{x,c}$	Volatility of long-run growth - investment sector (%)	0.1*σ_{zc}
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.

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). 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). Specifically, we set ϕ_p to 25, close to Kung (2015), corresponding to a price duration of approximately four quarters.[9] 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 standard and identical to Basu and Bundick (2017). Specifically, 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.

[9] See Online Appendix section IA.2 for details on this mapping.

2.2 Aggregate Moments

Table 3 reports annual macroeconomic and asset-price 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). Each quarterly model path is converted into annual non-overlapping observations by compounding the last four quarters.

We distinguish between 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 shocks and without price stickiness, $\phi_{p,c} = \phi_{p,i} = 0$ (henceforth 'No-LRR & No-Sticky'), (IV) a model without long-run risk shocks, no sticky prices, and no markups, suggesting perfect competition where $\mu_c = \mu_i \to \infty$ (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

Table 3: **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
$E(R_M^e)(\%)$	4.71	3.97	0.46	0.59	0.14
$\sigma(R_M^e)(\%)$	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 2, 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.

has a volatility of 19.31%, and the risk-free rate shows a volatility of about 1%.

Comparing the 'No-LRR' configuration and the 'Benchmark' shows that long-run technological innovations exert a minimal impact on aggregate macroeconomic moments. The primary contribution of long-run shocks is to amplify the unconditional equity premium. In their absence, the equity premium contracts to 0.46%.

The moments implied by both 'No-LRR & No-Sticky' and 'No-LRR & Perfect-Comp' configurations exhibit marked similarity. The presence of sticky prices is instrumental in generating realistic business-cycle fluctuations of input variables. In both configurations, the volatility of investment and hours is notably lower compared to the data.

3 Macro and Prices Dynamics

3.1 Macro Dynamics

In this section we show that under the benchmark model, positive technological innovations induce a contractionary effect on labor, and an insignificant impact on capital growth, mimicking the data. We then highlight the importance of sticky prices and the two-sector structure for these dynamics.

3.1.1 Inputs response to technological innovations

Using paths simulated from the model, we run the projections from equation (1) within the context of the model. Specifically, we perform regressions of annualized growth in hours, capital, output, and consumption on the aggregate technological change, denoted Z_{agg}. The duration of each model-implied path is identical to its empirical counterpart. Table 4 shows the median slope coefficient derived from a thousand finite sample simulations, accompanied by the model-implied confidence intervals. Importantly, all slope coefficients are not directly targeted by our calibration.

Several salient insights emerge from Table 4. 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 -0.34 in the data. The model's response of capital growth to technological innovations is 0.04, matching the data. In addition, the slope's *insignificance* within the model aligns with the empirics. The output and consumption responses to technological innovations are positive and also align with the data.

Second, the contractionary implications of technological innovations on inputs do not depend on long-run risks. Specifically, long-run technological shocks do not substantially

Table 4: **Technological Innovations and Macroeconomic Growth: Model**

	Benchmark	No-LRR	No-LRR & No-Sticky	No-LRR & Perfect-Comp
(1) $b_{N,t}$	-0.43 [-0.56, -0.28]	-0.47 [-0.53, -0.39]	0.05 [0.05, 0.05]	0.06 [0.06, 0.06]
(2) $b_{K,t}$	0.04 [-0.04, 0.30]	0.01 [-0.02, 0.06]	0.04 [0.03, 0.08]	0.03 [0.02, 0.07]
(3) $b_{C,t}$	0.69 [0.57, 0.85]	0.64 [0.63, 0.67]	0.84 [0.83, 0.85]	0.74 [0.73, 0.76]
(4) $b_{Y,t}$	0.72 [0.64, 0.86]	0.68 [0.64, 0.72]	1.03 [1.02, 1.04]	1.05 [1.04, 1.06]

The table reports the model-implied slope coefficients for the regression: $\Delta y_t = const + b_{y,t} \cdot dZ_{agg,t} + \varepsilon_t$. $dZ_{agg,t}$ 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); (3) Consumption (ΔC_t); (4) Output (ΔY_t). We report four alternative calibrations: (I) The benchmark model with parameters from Table 2, 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 $\mu_c = \mu_i \to \infty$, labled 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.

change the conditional dynamics of inputs or outputs. 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. This echos the negligible impact of long-run risk shocks on unconditional moments, as shown in Table 3.

Lastly, the presence of sticky prices is crucial in producing a contractionary effect on the utilization of inputs. 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 growth counterfactually rises after a positive technology shock. Furthermore, while the point estimates are similar to the benchmark, the slope coefficient associated with capital growth turns statistically *significant*, in contrast to the data. Although the model's slope coefficients for consumption and output growth slightly exceed the data, these coefficients are reduced by approximately 25% under the benchmark relative to configurations devoid of sticky prices. In all, without sticky prices, technological innovations exert a disproportionate expansionary impact on input and output variables compared to the benchmark or the data.

3.1.2 Inspecting the mechanism

To distill the mechanism responsible for the contractionary effect of innovations on labor and an insignificant effect on capital within the benchmark model, we strategically shut down the long-term technology component. Subsequently, we plot model-implied impulse responses from short-run technological shocks to macroeconomic aggregates, contrasting the case with sticky prices (represented in blue) against those devoid of such rigidity (represented in red), as shown in Figure 1.

In a model without sticky prices, a technological innovation increases firms' contemporaneous and future marginal productivity of both labor and capital. This prompts firms to immediately raise their investment and hiring, as shown by the red lines in panels (b) and (c) of Figure 1. The latter observation– mirroring the positive slope coefficient for hours without sticky prices in Table 4 – is incongruent with empirical observations. The increased demand for capital raises the relative price of capital goods (red line in panels (d) of Figure 1), and thereby increases firms' marginal production costs. Higher investment combined with a higher relative price of capital imply that capital growth strictly increases following the technological innovation — explaining the significant slope coefficient on capital without sticky prices in Table 4 — and contrasting the data.

The introduction of sticky prices substantially changes the implications of innovations on marginal costs. To see why, note that after a positive technological innovation, output under reacts to the supply shock, compared to the scenario with flexible prices (as evidenced in panel (a) of Figure 1). This muted output response occurs because 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 (as formalized in equation (A.3)).

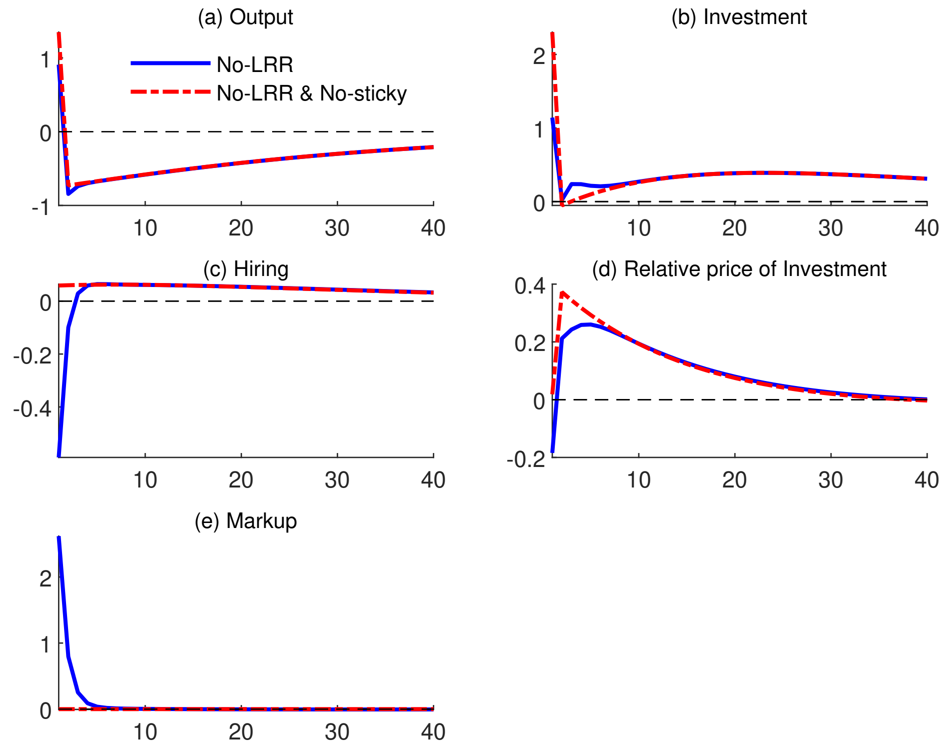
Within the New-Keynesian framework, inflation is proportional to the expected discounted valuation of future marginal costs. In our model, the marginal cost of output depends on wages and the relative price of capital. Thus, the decline in inflation gap under sticky prices, in turn, implies a downward 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 can decline after a positive technological innovation, as illustrated by the blue line in panel (d). This countercyclical behavior of capital goods prices is consistent with the empirical findings of Greenwood et al. (1997) and Christiano and Fisher (2003), which emphasize a negative correlation between investment goods prices and output.

The decline in output gap suggests that hours should decrease in response to the positive technology shock. Put differently, the drop in firms' marginal costs raises markups as output prices are rigid in the short run (panel (e) Figure 1). The elevated markups 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 is consistent with the evidence of Basu et al. (2006), and our updated evidence in Table 1.

The two-sector structure is key to explaining the impact of innovations on capital growth, which is more intricate. On the one hand, investment increases (though the response is more subdued compared to the flexible price scenario). On the other hand, the relative price of

Figure 1: **Model-Implied Impulse-Responses of Macro Variables**



The figure shows impulse responses of model-detrended real output, investment expenditures, hiring, the relative price of investment, wage, and markup 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.

investment declines. 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 (as shown in Tables 1 and 4).

In Section 4.1 we provide novel empirical evidence to test our specific mechanism, related to the impact of technological innovations on wages and labor reallocation between the two sectors.

3.2 Asset Prices Dynamics and Implications

In this section, we show how the transitory contractionary effects of technological innovations reconcile apparent disconnections between macroeconomic conditions and financial market valuations.

3.2.1 The relation of investment and stock returns

Cochrane (1991) show that the expected returns on stocks and investments exhibit a high correlation. Driven by this finding, Liu et al. (2009) uncover an asset pricing anomaly. Utilizing the generalized method of moments approach, they match mean investment returns with mean equity returns. The contemporaneous correlation between equity and investment returns is found to be mildly negative. At the same time, the correlation between equity returns and future investment returns is positive. Notably, the former observation contradicts the conventional predictions of q-theory as postulated by Hayashi (1982).

Our model addresses this comovmement anomaly with only a single the of capital good. As shown in Panel (A) of Table 5, both the 'Benchmark' and the 'No-LRR' configurations produce 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 benchmark model.[10] Moreover, the correlation between market stock returns and either one-year-ahead investment returns or one-year-ahead investment growth is positive, mirroring the empirical patterns. Conversely, in configurations without sticky prices — having either constant markup or perfect competition — investment and stock returns are (almost)

[10]This negative correlation is not contingent on the specific functional form of capital adjustment costs or investment returns in our model; We confirm that the correlation between market stock returns and concurrent investment *growth* is significantly negative (-0.1) under the benchmark. Recent studies (e.g., Gonçalves, Xue, and Zhang (2020)) also suggest that the correlation between fundamental returns and stock returns might be mildly positive (around 0.1). This close-to-zero estimate falls within the model's confidence interval implied by finite sample simulations.

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

	Data	Benchmark	No-LRR	No-LRR & No-Sticky	No-LRR &Perfect-Comp
Panel A: Data and market moments					
$\text{Corr}(R^I_{M,t}, R^S_{M,t})$	-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
$\text{Corr}(\frac{I_{t+1}}{I_t}, R^S_{M,t})$	0.10	0.14	0.10	0.04	-0.01
Panel B: Consumption-sector moments					
$\text{Corr}(R^I_{c,t}, R^S_{c,t})$		-0.16	-0.27	0.83	0.99
$\text{Corr}(R^I_{c,t+1}, R^S_{c,t})$		0.09	0.63	0.12	0.29
Panel C: Investment-sector moments					
$\text{Corr}(R^I_{i,t}, R^S_{i,t})$		-0.22	0.88	0.99	1.00
$\text{Corr}(R^I_{i,t+1}, R^S_{i,t})$		0.07	0.38	0.01	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 for the market (Panel A), the consumption sector (Panel B), and the investment sector (Panel C). We also report the correlation between future investment growth (I_{t+1}/I_t) and stock returns for the market. For each moment, we compare four alternative calibrations: (I) The benchmark model with parameters from Table 2, 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.

perfectly positively correlated. This counterfactual outcome 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). Panels (B) and (C) further substantiate these patterns for individual sectors, namely consumption and investment.

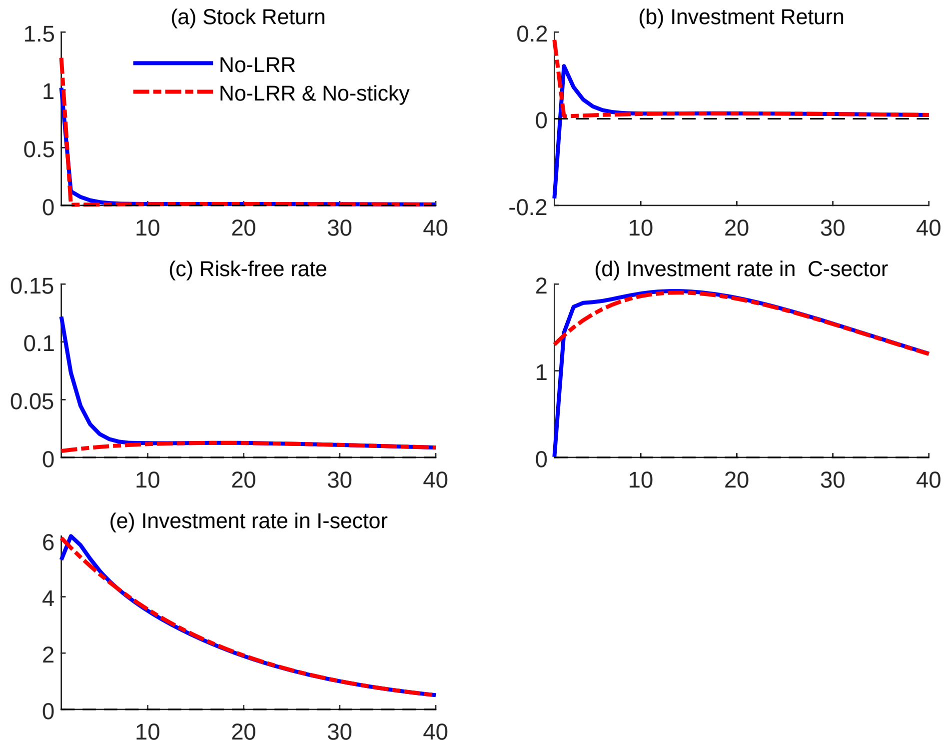
To explain the anomaly's resolution, we shut down long-run risks and plot impulse response functions from technological innovations to investment rates, market stock returns, and investment returns in Figure 2.

First, under both the flexible and sticky price cases, technological shocks raise firms' valuations, as illustrated in panel (a) of Figure 2. In the latter case, the higher valuation arises due to elevated markups and monopolistic rents. Second, within a two-sector New-Keynesian framework featuring monopolistic power, stock returns and investment returns are not equal state-by-state. Specifically, 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 across sectors, as evidenced in panels (d) and (e) of Figure 2. This broadly aligns with the impact of technological shocks on investment in the data, as shown in Table 1. In the presence of capital frictions (i.e., adjustment costs), heightened investment rates should also increase the shadow price of capital, and consequently, the return on investment. This dynamic, also featured in a conventional competitive single-sector model, induces a counterfactual strong positive correlation between stock and investment returns, as depicted by the red line in panel (b).

However, as previously discussed, technological shocks can decrease the relative price of capital when consumption prices exhibit sufficient rigidity. Ceteris paribus, this decreases the shadow price of capital in the short term, and thereby investment returns. When the degree of price rigidity is empirically disciplined, the latter force dominates, as indicated by the blue line in panel (b), resulting in a mild negative comovement between investment returns and stock returns, consistent with the data.

However, the 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. This renders higher future investment returns and explains the positive lead-lag relationship between market and investment returns in both the model and the data.

Figure 2: **Model-Implied Impulse-Responses of Returns and Investment Rates**



The figure shows impulse responses of stock return, investment return, risk-free rate, the investment rate in the consumption sector, and the investment rate in the investment sector 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.

3.2.2 Labor markets and stock returns

Several studies have identified a puzzling phenomenon in which negative macroeconomic indicators can have a positive impact on the performance of the equity market. Boyd et al. (2005) and Elenev et al. (2022) show that equity valuations typically 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. 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, 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.

Indeed, our model reconciles this puzzle without resorting to aggressive exogenous policy shocks. We derive labor surprises within the model framework by subtracting expected hiring from realized hiring. As presented in Table 6, under both the 'Benchmark' and 'No-LRR' configurations, the correlation between labor surprises and either market stock returns or the risk-free rate is negative, reflecting the average empirical case documented by Boyd et al. (2005).[11] However, in cases where sticky prices are shut down, this correlation inverts to a positive counterfactual value.

The origin of this average negative correlation can be directly attributed to the macro dynamics of our model. Technological innovations precipitate a hiring contraction due to increased markups, as illustrated in panel (c) of Figure 1, while simultaneously enhancing valuations via monopolistic rents, as depicted in panel (a) of Figure 2. 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 2. This dynamic suggests a negative average comovement between the risk-free rate and labor surprises. Within our framework, labor or employment metrics are endogenously determined

[11] We confirm this negative correlation in our sample using related data. We sum the number of employees (Compustat Annual item EMP) every year from 1960 to 2019. We then hp-filter the time series and apply an AR(1) model to obtain residuals, treated as labor surprises. The correlation between labor surprises and market stock returns is around -0.25 in the data, aligning with our model.

Table 6: **Labor Market Surprises and Stock Returns**

	Benchmark	No-LRR	No-LRR & No-Sticky	No-LRR & Perfect-Comp
$\text{Corr}(N_t^{\text{surprise}}, R_{M,t}^S)$	-0.27	-0.98	1.00	0.93
$\text{Corr}(N_t^{\text{surprise}}, R_t^f)$	-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 2, 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.

and, as such, cannot be directly interpreted as indicators of favorable or adverse underlying economic conditions.

It should be noted that 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 materially replicate this finding, when accounting for the findings of Vavra (2014) that price changes are countercyclical in the data. Specifically, we incorporate this insight by augmenting the 'No-LRR' model configuration with procyclical degree of price rigidity. The results are reported in Table IA.3. During expansions, when the nominal interest rate is high, the logic outlined before applies, leading to a negative correlation between labor surprises and the market. However, during recessions, when the nominal interest rate, the aggregate output growth, or the realized excess return are low, the degree of price stickiness falls, decreasing the role of the monetary authority and attenuating markup fluctuations. Thus, as in the perfect competition case, the correlation between the stock market and labor market surprises turns positive.

3.2.3 B/M, profits and stock returns

The studies of Fama and French (1992); Hou et al. (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 how 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. Incorporating this key insight into future cross-sectional models can assist in producing both spreads in a parsimonious manner. To demonstrate this, we focus on the time series association of both characteristics with the risk premium. As discussed below, such associations are also borne in aggregate-level data.

We start by augmenting our benchmark model with stochastic volatility, allowing for variation in risk premia.[12] The incorporation of stochastic volatility into our model framework is important only for generating temporal variations in the risk premium, but not for cash flow dynamics. As shown in Panel C of Table 7, the model, once augmented with this volatility component, continues to produce macro moments that align closely with the data,

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

while preserving the previously established correlations between stock returns, investment returns, and labor surprises.

Table 7: **Dividend-price ratio, Risk Premia, B/M, and Gross Profits**

Panel A: Relation between risk premia and characteristics			
Moments	Corr($GP_t^M, E_t[R^e_{M,t+1}]$)	Corr($GP_t^c, E_t[R^e_{c,t+1}]$)	Corr($GP_t^i, E_t[R^e_{i,t+1}]$)
Value	-0.22	-0.17	-0.25
Moments	Corr($BM_t^M, E_t[R^e_{M,t+1}]$)	Corr($BM_t^c, E_t[R^e_{c,t+1}]$)	Corr($BM_t^i, E_t[R^e_{i,t+1}]$)
Value	-0.33	-0.34	-0.14

Panel B: Time series comovement with aggregate dividend-price ratio						
	Data			Model		
	(1)	(2)	(3)	(1)	(2)	(3)
GP_t^M	0.82		0.15	0.94		0.74
t-stat	[8.31]		[2.57]	[22.64]		[16.81]
BM_t^M		0.95	0.82		0.81	0.28
t-stat		[18.42]	[13.52]		[13.64]	[6.29]

Panel C: Other moments					
Moments	Value	Moments	Value	Moments	Value
$E(\Delta C)(\%)$	1.93	$b_{N,t}$	-0.36	Corr($R^I_{M,t}, R^S_{M,t}$)	-0.11
$\sigma(\Delta Y)(\%)$	3.57	$b_{K,t}$	0.04	Corr($R^I_{M,t+1}, R^S_{M,t}$)	0.08
$\sigma(\Delta C)/\sigma(\Delta Y)$	0.93	$b_{C,t}$	0.73	Corr($\frac{I_{t+1}}{I_t}, R^S_{M,t}$)	0.12
$\sigma(\Delta I)/\sigma(\Delta Y)$	2.73	$b_{Y,t}$	0.75	Corr($R^I_{c,t}, R^S_{c,t}$)	-0.11
$\sigma(\Delta N)/\sigma(\Delta Y)$	0.40			Corr($R^I_{c,t+1}, R^S_{c,t}$)	0.09
$E(R^e_M)(\%)$	4.49			Corr($R^I_{i,t}, R^S_{i,t}$)	-0.18
$\sigma(R^e_M)(\%)$	19.68			Corr($R^I_{i,t+1}, R^S_{i,t}$)	0.07
$E(r^f)(\%)$	1.30			Corr($N_t^{\text{surprise}}, R^S_{M,t}$)	-0.29
$\sigma(r^f)(\%)$	1.44			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 correlations between conditional annual risk premia ($E_t[R^e_{j,t+1}]$) and either annual gross profits (GP_t^j) or the annual book-to-market ratio (BM_t^j) for the market and both sectors, where $j \in \{M, c, i\}$. In Panel B, 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 1960 to 2019. In Panel C, we report other model-implied moments as in Table 3 - Table 6, under the augmented model.

To compute model-implied variations in the risk premium, we calculate the conditional expected returns in each state, adjusted for the risk-free rate. Panel A of Table 7 reports the model-implied correlations between risk premia and gross profits or book-to-market ratios. Notably, both book-to-market and gross profits exhibit a positive correlation with the aggregate risk premium. This also holds for each sector separately.

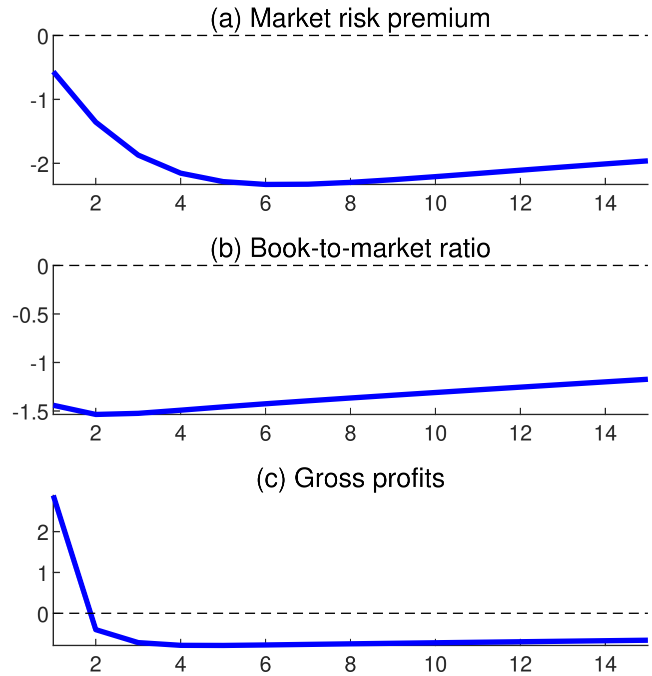
In addition, we perform regressions using model-simulated paths and the data. We project the annualized aggregate dividend yield (i.e., dividend-to-price ratio), which commonly proxies for the discount rate, on current annual aggregate gross profits or/and aggregate book-to-market ratios. Both the dependent and the independent variables are standardized. In both the model and the data, all slope coefficients are positive and significant, as shown in Panel B of Table 7. 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.[13]

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 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, 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.

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

[13] Table IA.4 in the Internet Appendix 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.

Figure 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.

would persistently remain elevated, leading to a counterfactual negative correlation between profitability and risk premia.

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 conditional risk premium turns positive, in line with the data.

3.2.4 Term structure of equity yields

Using the augmented model from the previous subsection we define the price of a dividend strip at time t maturing in n periods, $P_{t,n}$, recursively as follows:

$$P_{t,0} = d_t \tag{28}$$

$$P_{t,n} = \mathbb{E}_t \left[M_{t,t+1} P_{t+1,n-1} \right]. \tag{29}$$

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 the cyclicality of the slope, 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 negative regression coefficients between the slopes at different maturities and the dividend yield. Qualitatively, the procyclicality of the slope is consistent with the evidence presented by Bansal et al. (2021). Quantitatively, at the five-year horizon, the regression coefficient matches the empirical evidence by Gormsen (2021). Conversely, in a theoretical framework without price stickiness, the slopes' correlation with the dividend yield is positive, implying a counterfactual countercyclical fluctuation of the slope.

The reconciliation of the slope's cyclicality arises directly from the macro dynamics outlined in Section 3.1. A positive technological innovation results in an immediate contraction in labor. This suggests that, relative to the case without price rigidity, the expected (real-

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

	Data	Benchmark	No LRR	No LRR & No sticky
ϕ_8	N.A.	-0.182 [-0.406, -0.034]	-0.412 [-0.575, -0.220]	0.002 [0.001, 0.004]
ϕ_{12}	N.A.	-0.194 [-0.434, -0.036]	-0.440 [-0.614, -0.223]	0.004 [0.001, 0.006]
ϕ_{16}	N.A.	-0.200 [-0.447, -0.037]	-0.454 [-0.634, -0.230]	0.005 [0.002, 0.008]
ϕ_{20}	-0.33	-0.203 [-0.455, -0.037]	-0.462 [-0.646, -0.234]	0.006 [0.002, 0.009]

The table reports the model-implied slope coefficients for the regression: $\text{Slope}_{t,n} = const + \phi_n \cdot dp_t + error$. dp_t is the (log) market dividend yield and $n \in \{8, 12, 16, 20\}$ is the maturity (quarters). The data moment is taken from Gormsen (2021). We report three alternative calibrations: (I) The benchmark model with parameters from Table 2 with stochastic countercyclical volatility as in subsection 3.2.3, 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.

ized) 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, the slope of the expected dividend growth curve becomes more (less) negative during expansions (recessions). Expected dividend growth rates and equity yields are inversely related. Thus, the equity yield term structure slope is higher (lower) in good (bad) economic states.

4 Empirical Analysis

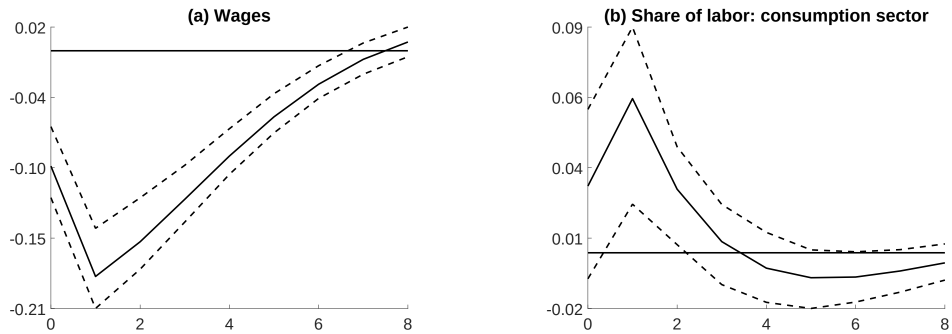
4.1 Testing the Mechanism

The aggregate macro dynamics produced by our model are consistent with our updated evidence and the broader literature (see Basu et al. (2006) and Christiano and Fisher (2003)). To 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 previously, with sticky prices, innovations lead to downward pressure on inflation and marginal costs of production, which depend not only on the relative price of capital but also on wages (see Figure IA.1 in the Online Appendix).

Second, Fernald (2014) shows that in the data, technology in the investment sector is more sizable than in 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,

Figure 4: **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 1965 to 2019.

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 IA.2 in the Online Appendix).

We test these dyanmic predictions using annual data from 1965 to 2019, based on the availability of labor-related data. We source wage data from the 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 4 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 (b)). Consistent with our model's implications, technological shocks lead to a persistent decrease in wages, confirming our first prediction.[14] 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.

4.2 Empirical Application: Return Predictability

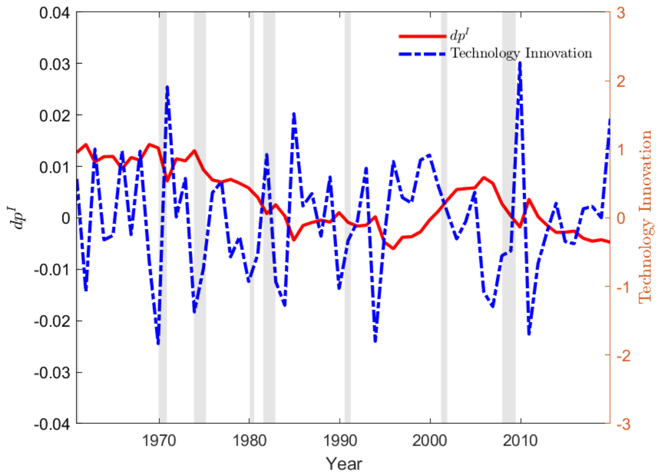
In this section we demonstrate that our framework can go beyond offering theoretical insights for existing stylized facts — it can also yield new applicable tools for financial market predictability. We first define and estimate investment-based dividend yields, which account for the dynamics of innovation-driven contractions, and then demonstrate that they can explain a sizable variation of future excess returns.

4.2.1 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 $P^I_{j,t} = q_{j,t}$. The sector's j quarterly investment-return 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 the sector j. The one-year investment-

[14] 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.

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 1960Q1 to 2019Q4.

based dividend yield is set to the sum of the investment-return dividends over the last four quarters divided by their current price: $dp^I_{j,t} = \frac{\sum_{k=0}^{3} Div^I_{j,t-k}}{P^I_{j,t}}$. 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 (14) and (15), 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 $\{\varepsilon_t^{\text{Data}}\}$ such that the model-implied path of aggregate technology growth (i.e., the log growth of Z_{agg}) matches the observed quarterly utilization-adjusted TFP growth rates of Fernald (2014) from 1960Q1 to 2019Q4. We then set the model at its stochastic steady state and feed the model the finite path of $\{\varepsilon_t^{\text{Data}}\}$ to obtain a time series of investment-based 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.

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

	Benchmark		Perfect Competition	
	Model	Data	Model	Data
$corr(dp^I_t, R^e_{t\to t+1})$	-0.28	-0.29	0.23	-0.23
		[-2.85]		[-2.21]

The table presents the correlation coefficient between one-year excess returns, $R^e_{t\to t+1}$, and the investment-based dividend yields, dp^I_t, 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 reports Newey-West t-statistics. The data are based on sample from 1960-2019.

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^I_t 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 -0.28, both in the model and in 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^I_t 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 3.2.1.

4.2.2 Investment-Based Dividend Yield and Predictability

In-Sample Analysis. In this section, 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:

$$R^e_{t \to t+k} = const + \beta x_t + error, \tag{30}$$

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.

Panels A of Table 10 show that within our full sample period, both dp and cay struggle to explain future excess return variation. While the slope coefficient 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 0.4% (4.4%).

In contrast, the investment-based dividend yield, dp^I, generates economically large R^2s which increase with the predictive horizons. These range from 7% at the one-year-ahead horizon to 29% 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.

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. We note that 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. However, the predictive power of dp^I remains higher than both. In all, the analysis suggests that dp^I, which implicitly incorporates for 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 1960 to 1990, and from 1991 to 2019. We estimate equation (30) 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 1991 and 2019 and $\hat{R}^e_{t \to t+k}$ is the model's prediction. The OOS-R^2 is computed by $R^2_{\text{OOS}} = 1 - \frac{\sum_{t \in [1991,2019]} \left(R^e_{t \to t+k} - \hat{R}^e_{t \to t+k} \right)^2}{\sum_{t \in [1991,2019]} \left(R^e_{t \to t+k} - \bar{R}^e_{t \to t+k} \right)^2}$. 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 8% at the one-year horizon to 16% at horizons greater than three years.

Cross-Sectional Analysis. In Online Appendix Section IA.3 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.

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

A. 1960-2019					B. 1980-2019			
dp	*cay*	dp^I	adj. R^2	a	*dp*	*cay*	dp^I	adj. R^2
I. Predictive horizon $k = 1$:								
2.19			0.00		1.89			-0.01
[1.15]					[0.75]			
	0.80		0.00			-0.44		-0.03
	[0.83]					[-0.23]		
		-8.44	0.07				-19.70	0.14
		[-2.50]					[-2.58]	
3.26		-9.79	0.10		1.05		-19.20	0.12
[1.70]		[-2.85]			[0.49]		[-2.45]	
	-0.44	-9.78	0.05			-1.28	-21.06	0.13
	[-0.41]	[-2.38]				[-0.83]	[-2.46]	
II. Predictive horizon $k = 3$:								
2.88			-0.01		7.36			0.03
[0.68]					[1.34]			
	3.23		0.06			-3.03		-0.01
	[1.45]					[-0.61]		
		-27.00	0.22				-50.47	0.23
		[-3.02]					[-2.82]	
6.10		-29.54	0.25		5.26		-47.96	0.23
[1.49]		[-3.44]			[0.98]		[-2.52]	
	-0.30	-27.93	0.20			-5.28	-56.04	0.28
	[-0.13]	[-2.75]				[-1.48]	[-3.35]	
III. Predictive horizon $k = 5$:								
9.21			0.02		21.52			0.15
[1.72]					[2.86]			
	5.15		0.05			-8.28		0.04
	[1.56]					[-1.30]		
		-51.75	0.29				-74.72	0.17
		[-3.66]					[-2.73]	
15.54		-58.22	0.38		18.64		-65.81	0.29
[3.08]		[-4.58]			[2.56]		[-2.51]	
	-2.30	-58.81	0.28			-11.77	-87.16	0.28
	[-0.73]	[-3.90]				[-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 1960 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}	0.05	0.03	0.03
	R^2_{OOS}	-0.57	-0.09	0.08
$k=2$	MSE_{OOS}	0.16	0.10	0.07
	R^2_{OOS}	-0.81	-0.10	0.13
$k=3$	MSE_{OOS}	0.26	0.19	0.14
	R^2_{OOS}	-0.54	-0.16	0.16
$k=4$	MSE_{OOS}	0.46	0.33	0.24
	R^2_{OOS}	-0.59	-0.15	0.16
$k=5$	MSE_{OOS}	0.82	0.53	0.38
	R^2_{OOS}	-0.83	-0.18	0.16

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 1960 to 1990, and the testing set from 1991 to 2019. The table shows Mean Squared Error (MSE) and OOS-R^2 to evaluate the out of sample performance of each predictor.

5 Conclusion

We examine the intricate relationship between technological innovations and their macroeconomic and financial implications. While technological advancements foster long-term economic growth, they can paradoxically lead to short-term contractions in input markets. Through our general equilibrium model, we quantify a mechanism underlying these dynamics, with a particular emphasis on the role of sticky prices, as well as the separation of production to investment versus consumption goods.

We argue that the incorporation of these non-standard dynamics, which has been overlooked by existing asset-pricing studies, can offer a resolution of several empirical anomalies. First, we address the contemporaneous negative correlation between stock returns and returns on capital. Second, our model offers insight into the counterintuitive inverse relationship between labor market fluctuations and stock market valuations. We also shed fresh light on why seemingly contradictory characteristics — high book-to-market ratios and high profitability — can command higher risk premiums even under a model with a single first-moment shock and single type of capital. Unlike the flexible-price case, the framework produces a procyclical slope for the equity yield term structure.

Moreover, investment-based dividend yield time series, filtered from a model that generates innovation-driven contractions, shows remarkably high predictive power, both in- and out-of-sample, for future market excess returns.

While we do not rule-out other explanations for the former puzzles, our message is simple: The stylized facts, previously perceived as distinct challenges in the literature, could be cohesively explained through the mechanism of contractionary innovations. Furthermore, the intricate interplay between technological innovations and macroeconomic factors, as previously established in the macro literature, substantially improves the time series properties of investment returns in regard to their conditional relationship with physical investment and labor fundamentals. As such, we believe that incorporating these macro dynamics into future asset-pricing studies – via a New Keynesian framework or other approach – is an important step forward for production-based frameworks to work well both in the cross-sectional dimension as well as the time-series dimension.

Future research should further explore the implications of short-term technological contractions on the term structure of bond yields, on models with heterogeneous firms, or delve into the endogeneity of sticky prices via menu costs. This latter exploration can shed light on the time-varying correlation between fundamentals and equity prices, relevant in a period of rapidly accelerating technological advancements.

Appendix

A Details of the numerical solution

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

$$0 = q_{j,t} - P_{it}\frac{\partial \Phi_{j,k}(i_{j,t}(n), k_{j,t}(n))}{\partial i_{j,t}(n)} k_{j,t}(n) \tag{A.1}$$

$$0 = W_t n_{j,t}(n) - (1-\alpha_j)\theta_{j,t} Z_{j,t} k_{j,t}(n)^{\alpha_j}(n_{j,t}(n))^{1-\alpha_j} \tag{A.2}$$

$$0 = -q_{j,t} + E_t\Big[M^{\$}_{t+1}\Big\{ - P_{i,t+1}\left(\Phi_{j,k}\left(i_{j,t+1}, k_{j,t+1}(n)\right) + \frac{\partial \Phi_{j,k}\left(i_{j,t+1}(n), k_{j,t+1}(n)\right)}{\partial k_{j,t+1}(n)} k_{j,t+1}(n)\right) + q_{j,t+1}\left(1-\delta\right)$$
$$+ \theta_{j,t+1} Z_{j,t+1}\alpha_j k_{j,t+1}(n)^{\alpha_j - 1}(n_{j,t+1}(n))^{1-\alpha_j}\Big\}\Big] \tag{A.3}$$

$$0 = (1-\mu_j)\left[\frac{p_{j,t}(n)}{P_{j,t}}\right]^{-\mu_j} + \theta_{j,t}\mu_j\left[\frac{p_{j,t}(n)}{P_{j,t}}\right]^{-\mu_j - 1}\frac{1}{P_{j,t}} + \phi_{P,j}E_t\left[M^{\$}_{t+1}\left(\frac{Y_{j,t+1}}{Y_{j,t}}\right)\left[\frac{p_{j,t+1}(n)}{\Pi_j p_{j,t}(n)} - 1\right]\frac{p^2_{j,t+1}(n)}{\Pi_j p^2_{j,t}(n)}\right]$$
$$- \phi_{P,j}\left\{\left[\frac{p_{j,t}(n)}{\Pi_j p_{j,t-1}(n)} - 1\right]\frac{p_{j,t}(n)}{\Pi_j p_{j,t-1}(n)} + \frac{1}{2}\left[\frac{p_{j,t}(n)}{\Pi_j p_{j,t-1}(n)} - 1\right]^2\right\} \tag{A.4}$$

$$0 = k_{j,t+1}(n) - \left(1-\delta\right)k_{j,t}(n) - i_{j,t}(n) \tag{A.5}$$

$$0 = y_{j,t}(n) - Z_{j,t}k_{j,t}(n)^{\alpha_j}(n_{j,t}(n))^{1-\alpha_j}, \tag{A.6}$$

where $q_{j,t}$ is the price of a marginal unit of installed capital in sector j, the Lagrange multiplier of constraint (8), 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 (12).

The first-order condition of the household

$$0 = \frac{W_t}{P_{c,t}} - \frac{C_t}{1-\xi N_t^{\eta}}\xi\eta N_t^{\eta-1}. \tag{A.7}$$

The nominal SDF, nominal interest rate, as well as the household utility, are given in Eq. (18), (19), and (16), respectively. The last equilibrium conditions include four market clearing conditions (labor, investment goods, consumption goods, and bond market) specified in Eq. (20), (21), (23), and (24), 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. (11).

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Internet Appendix for "Innovation-Driven Contractions: A Key to Unravel Asset Pricing Puzzles"

Gill Segal Chao Ying

This Internet Appendix contains additional analysis to accompany the manuscript. Section IA.1 provides the detrended problem for the analysis in Appendix A. Section IA.2 converts the Rotemberg adjustment costs to the average price duration in a Calvo pricing framework. Section IA.3 studies the cross-sectional implications of the investment-based dividend yield. Section IA.4 provides additional results.

IA.1 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 $j \in \{c, i\}$:

$$0 = \widetilde{q_{i,t}} - \widetilde{P_{it}} \frac{\partial \Phi_{i,k}\left(\widetilde{i_{i,t}}(n), \widetilde{k_{i,t}}(n)\right)}{\partial \widetilde{i_{i,t}}(n)} \widetilde{k_{i,t}}(n) \tag{A.8}$$

$$0 = \widetilde{q_{c,t}} - \widetilde{P_{it}} \frac{\partial \Phi_{c,k}\left(\widetilde{i_{c,t}}(n), \widetilde{k_{c,t}}(n)\right)}{\partial \widetilde{i_{c,t}}(n)} \widetilde{k_{c,t}}(n) \tag{A.9}$$

$$0 = \widetilde{W_t} n_{i,t}(n) - (1-\alpha_i)\,\frac{Z_{i,t}}{Z_{i,t-1}}\widetilde{\theta_{i,t}}\widetilde{k_{i,t}}(n)^{\alpha_i} n_{i,t}(n)^{1-\alpha_i} \tag{A.10}$$

$$0 = \widetilde{W_t} n_{c,t}(n) - (1-\alpha_c)\,\frac{Z_{c,t}}{Z_{c,t-1}}\widetilde{\theta_{c,t}}\widetilde{k_{c,t}}(n)^{\alpha_c} n_{c,t}(n)^{1-\alpha_c} \tag{A.11}$$

$$\begin{aligned} 0 = &-\widetilde{q_{i,t}} + E_t\Big[\Big(\frac{P_{c,t+1}}{P_{c,t}}\frac{Z_{c,t}}{Z_{c,t-1}}\big(\frac{Z_{i,t}}{Z_{i,t-1}}\big)^{\frac{\alpha_c-1}{1-\alpha_i}}\Big)M^{\$}_{t+1}\Big\{-\widetilde{P_{i,t+1}}\Phi_{i,k}\left(\widetilde{i_{i,t+1}}(n),\widetilde{k_{i,t+1}}(n)\right) \\ &-\widetilde{P_{i,t+1}}\frac{\partial\Phi_{i,k}\left(\widetilde{i_{i,t+1}}(n),\widetilde{k_{i,t+1}}(n)\right)}{\partial\widetilde{k_{i,t+1}}(n)}\widetilde{k_{i,t+1}}(n) + \widetilde{q_{i,t+1}}\,(1-\delta) + \widetilde{\theta_{i,t+1}}\alpha_i\frac{Z_{i,t+1}}{Z_{i,t}}\widetilde{k_{i,t+1}}(n)^{\alpha_i-1}n_{i,t+1}(n)^{1-\alpha_i}\Big\}\Big] \end{aligned} \tag{A.12}$$

$$\begin{aligned} 0 = &-\widetilde{q_{c,t}} + E_t\Big[\Big(\frac{P_{c,t+1}}{P_{c,t}}\frac{Z_{c,t}}{Z_{c,t-1}}\big(\frac{Z_{i,t}}{Z_{i,t-1}}\big)^{\frac{\alpha_c-1}{1-\alpha_i}}\Big)M^{\$}_{t+1}\Big\{-\widetilde{P_{i,t+1}}\Phi_{c,k}\left(\widetilde{i_{c,t+1}}(n),\widetilde{k_{c,t+1}}(n)\right) \\ &-\widetilde{P_{i,t+1}}\frac{\partial\Phi_{c,k}\left(\widetilde{i_{c,t+1}}(n),\widetilde{k_{c,t+1}}(n)\right)}{\partial\widetilde{k_{c,t+1}}(n)}\widetilde{k_{c,t+1}}(n) + \widetilde{q_{c,t+1}}\,(1-\delta) + \widetilde{\theta_{c,t+1}}\alpha_c\frac{Z_{c,t+1}}{Z_{c,t}}\widetilde{k_{c,t+1}}(n)^{\alpha_c-1}n_{c,t+1}(n)^{1-\alpha_c}\Big\}\Big] \end{aligned} \tag{A.13}$$

$$\begin{aligned} 0 = &(1-\mu_i)\left[\frac{\widetilde{p_{i,t}}(n)}{\widetilde{P_{i,t}}}\right]^{-\mu_i} + \widetilde{\theta_{i,t}}\mu_i\left[\frac{\widetilde{p_{i,t}}(n)}{\widetilde{P_{i,t}}}\right]^{-\mu_i-1}\frac{1}{\widetilde{P_{i,t}}} \\ &+\phi_{P,i}E_t\left[M^{\$}_{t+1}\left(\frac{(\frac{Z_{i,t}}{Z_{i,t-1}})^{\frac{1}{1-\alpha_i}}\widetilde{Y_{i,t+1}}}{\widetilde{Y_{i,t}}}\right)\left[\frac{\frac{P_{c,t+1}}{P_{c,t}}\frac{Z_{c,t}}{Z_{c,t-1}}(\frac{Z_{i,t}}{Z_{i,t-1}})^{\frac{\alpha_c-1}{1-\alpha_i}}\widetilde{p_{i,t+1}}(n)}{\Pi_i\widetilde{p_{i,t}}(n)}-1\right]\frac{(\frac{P_{c,t+1}}{P_{c,t}}\frac{Z_{c,t}}{Z_{c,t-1}}(\frac{Z_{i,t}}{Z_{i,t-1}})^{\frac{\alpha_c-1}{1-\alpha_i}})^2\widetilde{p_{i,t+1}}^2(n)}{\Pi_i\widetilde{p_{i,t}}^2(n)}\right] \\ &-\phi_{P,i}\left\{\left[\frac{\frac{P_{c,t}}{P_{c,t-1}}\frac{Z_{c,t-1}}{Z_{c,t-2}}(\frac{Z_{i,t-1}}{Z_{i,t-2}})^{\frac{\alpha_c-1}{1-\alpha_i}}\widetilde{p_{i,t}}(n)}{\Pi_i\widetilde{p_{i,t-1}}(n)}-1\right]\frac{\frac{P_{c,t}}{P_{c,t-1}}\frac{Z_{c,t-1}}{Z_{c,t-2}}(\frac{Z_{i,t-1}}{Z_{i,t-2}})^{\frac{\alpha_c-1}{1-\alpha_i}}\widetilde{p_{i,t}}(n)}{\Pi_i\widetilde{p_{i,t-1}}(n)}+\frac{1}{2}\left[\frac{\frac{P_{c,t}}{P_{c,t-1}}\frac{Z_{c,t-1}}{Z_{c,t-2}}(\frac{Z_{i,t-1}}{Z_{i,t-2}})^{\frac{\alpha_c-1}{1-\alpha_i}}\widetilde{p_{i,t}}(n)}{\Pi_i\widetilde{p_{i,t-1}}(n)}-1\right]^2\right\} \end{aligned} \tag{A.14}$$

$$\begin{aligned} 0 = &(1-\mu_c)\left[\frac{p_{c,t}(n)}{P_{c,t}}\right]^{-\mu_c} + \widetilde{\theta_{c,t}}\mu_c\left[\frac{p_{c,t}(n)}{P_{c,t}}\right]^{-\mu_c-1} + \phi_{P,c}E_t\left[M^{\$}_{t+1}\left(\frac{\frac{Z_{c,t}}{Z_{c,t-1}}(\frac{Z_{i,t}}{Z_{i,t-1}})^{\frac{\alpha_c}{1-\alpha_i}}\widetilde{Y_{c,t+1}}}{\widetilde{Y_{c,t}}}\right)\left[\frac{\frac{P_{c,t+1}}{P_{c,t}}}{\Pi_c}-1\right]\frac{(\frac{P_{c,t+1}}{P_{c,t}})^2}{\Pi_c}\right] \\ &-\phi_{P,c}\left\{\left[\frac{\frac{P_{c,t}}{P_{c,t-1}}}{\Pi_c}-1\right]\frac{\frac{P_{c,t}}{P_{c,t-1}}}{\Pi_c}+\frac{1}{2}\left[\frac{\frac{P_{c,t}}{P_{c,t-1}}}{\Pi_c}-1\right]^2\right\} \end{aligned} \tag{A.15}$$

$$0 = \big(\frac{Z_{i,t}}{Z_{i,t-1}}\big)^{\frac{1}{1-\alpha_i}}\widetilde{k_{i,t+1}}(n) - (1-\delta)\,\widetilde{k_{i,t}}(n) - \widetilde{i_{i,t}}(n) \tag{A.16}$$

$$0 = \big(\frac{Z_{i,t}}{Z_{i,t-1}}\big)^{\frac{1}{1-\alpha_i}}\widetilde{k_{c,t+1}}(n) - (1-\delta)\,\widetilde{k_{c,t}}(n) - \widetilde{i_{c,t}}(n) \tag{A.17}$$

$$0 = \widetilde{y_{i,t}}(n) - \frac{Z_{i,t}}{Z_{i,t-1}}\widetilde{k_{i,t}}(n)^{\alpha_i}n_{i,t}(n)^{1-\alpha_i}, \tag{A.18}$$

$$0 = \widetilde{y_{c,t}}(n) - \frac{Z_{c,t}}{Z_{c,t-1}}\widetilde{k_{c,t}}(n)^{\alpha_c}n_{c,t}(n)^{1-\alpha_c}, \tag{A.19}$$

where $\widetilde{q_{j,t}}$ is the detrended price of a marginal unit of installed capital in sector j, the Lagrange multiplier of constraint (8), 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 (12).

The detrended first-order condition of the household

$$0 = \widetilde{W}_t - \frac{\widetilde{C}_t}{1 - \xi N_t^{\eta}} \xi \eta N_t^{\eta - 1}. \tag{A.20}$$

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

$$M_{t+1}^{\$} = \beta\left(\frac{Z_{c,t}}{Z_{c,t-1}}\left(\frac{Z_{i,t}}{Z_{i,t-1}}\right)^{\frac{\alpha_c}{1-\alpha_i}}\right)^{-1/\psi}\left(\frac{\widetilde{C_{t+1}}}{\widetilde{C}_t}\right)^{-1/\psi}\left(\frac{1-\xi N_{t+1}^{\eta}}{1-\xi N_t^{\eta}}\right)^{1-1/\psi}\left(\frac{\widetilde{U_{t+1}}}{(E_t \widetilde{U_{t+1}}^{1-\gamma})^{\frac{1}{1-\gamma}}}\right)^{1/\psi-\gamma}\frac{P_{c,t}}{P_{c,t+1}} \tag{A.21}$$

$$r_t^{\$} = \rho_r r_{t-1}^{\$} + (1-\rho_r)\left(r_{ss}^{\$} + \rho_\pi(\pi_t - \pi_{ss}) + \rho_y(\Delta y_t - \Delta y_{ss})\right) \tag{A.22}$$

$$\widetilde{U}_t = \left\{(1-\beta)\left[\widetilde{C}_t(1-\xi N_t^{\eta})\right]^{1-1/\psi} + \beta(E_t \widetilde{U_{t+1}}^{1-\gamma})^{\frac{1-1/\psi}{1-\gamma}}\left(\frac{Z_{c,t}}{Z_{c,t-1}}\left(\frac{Z_{i,t}}{Z_{i,t-1}}\right)^{\frac{\alpha_c}{1-\alpha_i}}\right)^{1-1/\psi}\right\}^{\frac{1}{1-1/\psi}} \tag{A.23}$$

IA.2 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.4) 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 Calovo 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 $\kappa_i = 0.79$ and $\kappa_c = 0.71$, 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.

IA.3 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 IA.1 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 —

Table IA.1: **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 IA.2: **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 by the q-factors model of Hou et al. (2015) but can be interpreted after augmenting with dp^I.

when augmenting these factors with dp^I. The list of these anomalies is detailed in Table IA.1. Notable anomalies include spreads based on six-month or seasonal momentum and operating leverage.

IA.4 Additional results

Table IA.3: **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($N_t^{\text{surprise}}, R_t^f$)
Realized excess return	0.09	0.09	-0.27	-0.24
agg output growth	0.22	0.15	-0.30	-0.25
nominal interest rate	0.41	0.26	-0.35	-0.28

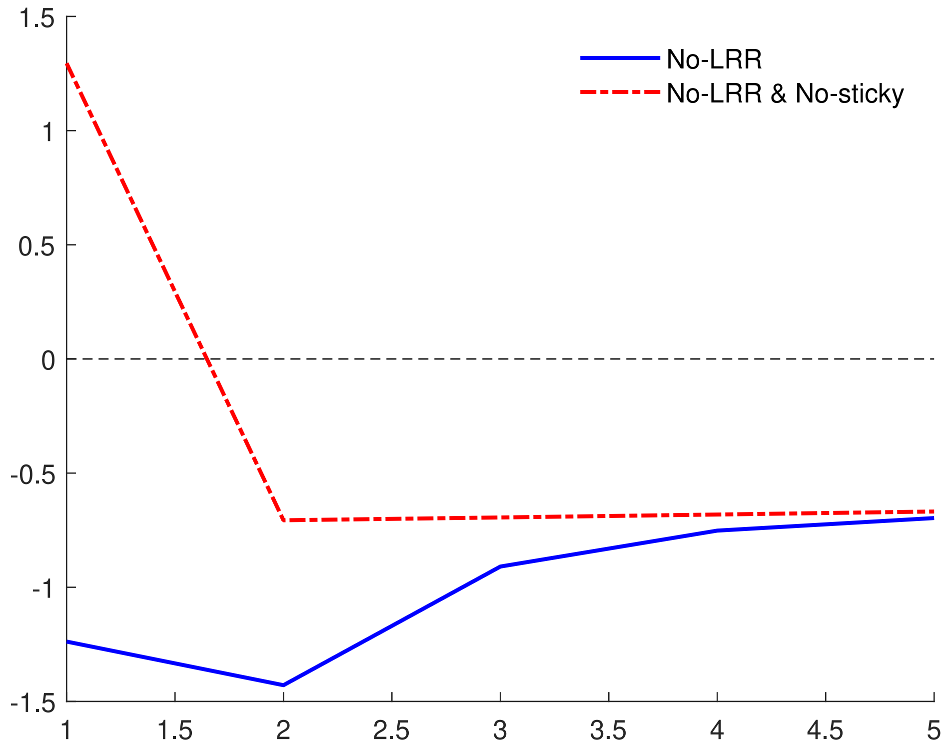
The table shows the model-implied correlation between labor market surprises, N^{surprise}, and the stock market return, R_m^S, or the risk-free interest rate, R_f with stochastic procyclical price stickiness in the 'No-LRR' economy. In the AR(1) process modeling the stickiness, we let $\phi_{p,i}^{ss} = \phi_{p,c}^{ss} = \phi_{p,i} = \phi_{p,c}$ and $\rho_{p,i} = \rho_{p,c} = \rho_{x,i} = \rho_{x,c}$ as the benchmark calibration in Table 2. 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 20th (80th) percentile of the cross-sectional distribution each quarter. Our result is robust to other cutoffs. The correlation is calculated over the next four quarters for each group, where we take the average across finite sample paths.

Table IA.4: Aggregate Earnings-to-Price Ratio, Book-to-Market, and Gross Profitability

	EP (1)	EP (2)	EP (3)
GP	0.76***		0.11
	[4.77]		[1.05]
BM		0.89***	0.80***
		[11.03]	[6.63]
adj. R^2	0.57	0.78	0.78

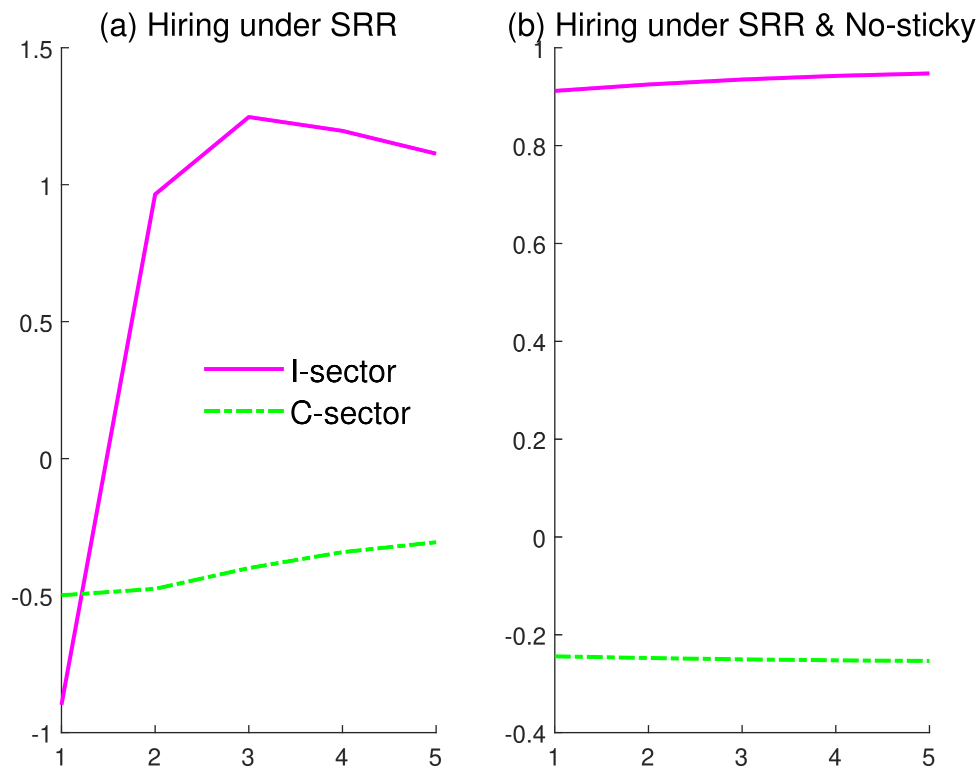
This table shows the how the aggregate book-to-market ratio and aggregate gross profitability affects the aggregate earning-to-price ratio. Data for empirical projections are obtained from Goyal et al. (2024). Each variable is scaled by its unconditional standard deviation. We omit the constant term for brevity. The sample spans the period from 1960 to 2019. Standard errors are computed using the Newey-West estimator with one year lag. We include t-statistics in the brackets. *, **, and *** indicates statistical significance at the 10%, 5%, and 1%, respectively.

Figure IA.1: **Technology Shocks to Wages**



The figure shows impulse responses of model-detrended wage 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.

Figure IA.2: **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) show 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.