

Innovation-Driven Contractions:

A Missing Link for Asset Pricing Puzzles [★]

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Abstract

We provide a unified mechanism for prominent conditional asset-pricing puzzles through “innovation-driven contractions.” Empirically, we document two facts: (1) technological innovations initially cause significant labor contractions and have muted impact on capital growth, and (2) puzzling disconnections—between stock returns and investment growth or hiring surprises—intensify under stickier prices. A New-Keynesian model, interacting two sectors with sticky-price markup dynamics, quantitatively ties these facts, explaining the anomalous negative correlation between stock-returns and investment-returns, the negative market reactions to favorable labor news, and the procyclical equity-yield term-structure slope. We test the mechanism’s new implications for out-of-sample return predictability and labor-market dynamics.

JEL Classification: G12, E32

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

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

Specifically, three foundational puzzles—related to correlations between financial markets and macroeconomic conditions—stand out. First, while expected stock returns and expected investment returns are positively correlated, the contemporaneous correlation between the two *realized* returns is negative in the data (see, e.g., [Liu, Whited, and Zhang \(2009\)](#)). The latter is quite puzzling, since under perfect competition or constant markups, both returns should perfectly comove, as occurs in extant production frameworks. Second, numerous studies show that deteriorating macro conditions, particularly in the labor market, often coincide with high stock valuations (see, e.g., [Boyd, Hu, and Jagannathan \(2005\)](#)), suggesting an ostensible divergence between fundamentals and prices. Third, the slope of the equity yield term structure is positively correlated with the business cycle. While its unconditional magnitude and sign are debated, there is broad agreement that the slope steepens in economic expansions and flattens in recessions (see, e.g., [van Binsbergen, Brandt, and Koijen, 2012](#); [Bansal, Miller, Song, and Yaron, 2021](#); [Gormsen, 2021](#)). Collectively, these conditional ‘disconnection’ puzzles are central: how valuations comove with firms’ invest-

ment and labor decisions is a key discipline for production-based asset pricing models.

At first glance, these puzzles appear unrelated. We argue, however, that they share a common root: transient “innovation-driven contractions.” Technological innovations—spanning from assembly lines to fiber optics, information technology, and artificial intelligence—are essential for sustained economic growth. While their long-term impact is unambiguously positive, prior macroeconomic research revealed that they can surprisingly lead initially to short-term production contractions (see, e.g., [Basu, Fernald, and Kimball \(2006\)](#)). Technological improvements often decrease firms’ input usage in the near term, before subsequent recovery and growth. Despite robust documentation in macro literature, an open question remains: *What are the implications of these short-run, technology-driven contractions for conditional valuation and risk premia in financial markets?* The central thesis of our study is that the apparent macro disconnection between higher technological innovation and lower short-term input usage spills over into financial markets, thereby reconciling the valuation disconnection puzzles with fair pricing.

We start by establishing two stylized facts: (1) We uncover differences compared to the seminal findings of [Basu et al. \(2006\)](#): positive technological innovations initially reduce labor usage significantly. Yet contrary to earlier findings, we find that their immediate effect on capital growth is small and statistically insignificant—an economically important distinction compared to prior literature. While our focus is on the aggregate, complementary firm-level evidence based on the patent metrics of [Kogan, Papanikolaou, Seru, and Stoffman \(2017\)](#) shows lower own employment growth and higher markups after innovation. (2) We go beyond the macro domain into asset prices, and provide new evidence that disconnection puzzles intensify precisely when prices exhibit greater rigidity. The contemporaneous time-series correlation between stock returns and investment growth, and between stock returns and labor market surprises, becomes more negative

in portfolios with stickier prices or during periods characterized by higher aggregate price rigidity.

While many mechanisms could change the comovement between one macro variable and valuations in *isolation*, the two facts jointly discipline different aspects of a specific mechanism. (i) The labor contraction and markup expansion after positive shocks discipline the *transmission*: in standard flexible-price environments, labor expands after favorable technology news. This calls for a model in which innovations can be partially absorbed into monopolistic rents rather than into immediate expansion. (ii) The muted response of capital growth disciplines the *architecture*: Capital is measured in expenditures, so its growth reflects both the quantity of investment and its price. In a one-sector economy the relative price of capital is fixed: capital growth moves one-for-one with the investment rate. When investment is as volatile as in the data, it forces capital growth to move once the shock hits. This calls for a two-sector economy, where a time-varying relative price of investment goods can offset the quantity margin, leaving capital-expenditure growth muted even as investment amount responds. (iii) The state dependence of the correlations disciplines the *source* of rent variation: flexible-price markup shocks do not by themselves imply that disconnections strengthen when price adjustment is less frequent, whereas nominal rigidity delivers that comparative static. Together, the evidence calls for two ingredients: sticky prices that generate endogenous markup fluctuations, and production split between consumption and investment sectors.

Guided by these findings, we develop a general equilibrium model designed to capture these macroeconomic dynamics and explore their financial market implications. It features two sectors: consumption and investment—each composed of monopolistically competitive firms facing nominal price rigidities. The model makes several contributions.

First, we quantitatively reconcile the negative correlation between investment returns and stock

returns using a single type of capital good.¹ Technological innovations enhance firms’ marginal productivities. Without sticky prices, this prompts immediate counterfactual expansions in capital growth and increases the relative price of investment goods. In contrast, empirically disciplined sticky prices introduce more subtle short-term effects of technological shocks. While firms still capitalize on higher productivity by increasing investment rates, price rigidity yields a temporary decline in the output and inflation gaps, which in equilibrium induce a short-lived but pronounced decline in the relative price of capital, thereby decreasing marginal production costs and raising markups. This endogenous markup fluctuation is the central wedge that ‘disconnects’ real economic activity from valuations, setting our mechanism apart from models built on real adjustment-cost shocks, delayed technology adoption, or exogenous markup shocks.

Specifically, these dynamics imply that technological shocks yield transient innovation-driven contractions in investment returns. Following a positive innovation, in our two-sector setup investment returns might rise due to increased investment rates, or they could drop because of a lower relative price of capital goods. Quantitatively, the latter dominates, leading to a drop in investment returns. At the same time, firm valuations and stock returns increase due to enhanced monopolistic rents — negatively comoving with investment returns. Importantly, the negative impact of nominal rigidity on capital prices is transitory, reversing eventually to suggest higher future investment returns. This mechanism explains the observed positive correlation between stock returns and *future* investment returns, as documented in the data.²

¹In relation to this comovement puzzle, [Belo, Deng, and Salomao \(2024\)](#) show that traditional investment-based models with one type of physical capital fail to jointly match the time-series properties of stock returns along with cross-sectional patterns. Furthermore, while introducing intangible capital into a standard model could theoretically generate a negative correlation between measured investment returns and stock returns, this alternative channel falls short empirically. The data feature a negative correlation not only between stock returns and investment returns, but also between stock returns and physical investment *growth*. Our model directly targets this physical growth anomaly, which cannot be resolved merely by adding unmeasured forms of capital.

²The negative contemporaneous correlation between investment returns and stock returns highlighted by [Liu et al.](#)

Our mechanism is not a restatement of market power. While market power is known to break the perfect correlation between investment and stock returns, on its own it does not turn the contemporaneous correlation negative: with constant markups or a constant relative price of investment (as in a one-sector model), the correlation drops below one but remains strongly positive, well above its negative empirical counterpart. The novel margin is the contraction in the relative price of investment after a positive shock, and its ability to overpower a rising investment amount, which is the key to matching the sign. Furthermore, while investment returns are model-specific, we show that our mechanism produces a negative correlation between stock returns and investment growth.

Second, our model explains the anomalous negative market reaction to positive labor market surprises. The common explanation for this inverse relationship often hinges on offsetting monetary or fiscal policies (see, e.g., [Elenev, Law, Song, and Yaron, 2022](#); [Xu and You, 2022](#)). While such policies certainly contribute by softening the negative impact of adverse news on valuations, this rationale may not fully quantitatively explain, in general equilibrium, why these policies would overcompensate to the extent of reversing the sign of the market reaction.³ Moreover, existing research typically interprets spikes in unexpected unemployment as inherently “bad” states. In contrast, we argue that ‘bad’ labor news can be good technology news: unexpected employment changes are endogenous outcomes of innovation-driven contractions and should not be perceived as exogenous negative shocks. Our mechanism demonstrates that a positive shock, under price rigidity, initially reduces wages, leading to higher firm markups. These elevated markups

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

³Online Appendix Section [OA.2](#) shows that even counterfactually aggressive, labor-targeted monetary policy rules move this correlation only marginally — far too small to reverse its sign.

effectively act as higher implicit taxes, rationing short-term hiring. Thus, a single “good” technological innovation endogenously generates both higher firm valuations—driven by increased monopolistic rents—and simultaneous short-run reductions in employment. By incorporating empirically-documented cyclicalities in price rigidity, our model successfully replicates the time-varying nature of this correlation (turning more negative in expansions).

Third, innovation-led contractions affect the term structure of equity yields. While the calibration of the benchmark model deliberately does not target any moment of the term structure, in equilibrium the slope is procyclical, as in the data, whereas in the absence of sticky prices, the slope is countercyclical. Following a positive shock, input usage initially falls but is expected to revert and grow in the short-run. Thus, in good states, the expected dividend growth is larger in shorter-horizons relative to longer-horizons. This turns the equity yield term structure more upward-sloping in expansions, as equity yields vary inversely with expected dividend growth rates.

Fourth, we show that the dynamics of innovation-driven contractions can be used for return predictability. We use our model along with observed paths of utilization-adjusted technological innovations to filter out empirical paths of investment returns and their associated investment-based dividend ‘yields’. These objects capture a nonlinear summary of only past technological innovations. In both the model and the data, investment-based dividend yields predict stock returns negatively. Out of sample, their R^2 is positive at every horizon, ranging from 7% to 15%, while the corresponding values for the conventional dividend yield and the consumption-to-wealth ratio are negative throughout.⁴ These findings demonstrate the empirical applicability of our mechanism.

To validate the mechanism, we show that the model matches untargeted input responses to

⁴For brevity, Section 5 summarizes this analysis, while many of the predictability results are relegated to Online Appendix Sections OA.9 and OA.10.

technology shocks: higher investment quantity is offset by a lower relative price, muting capital expenditure response, as in the data. We also derive and empirically confirm two labor-market predictions: technology shocks lower wages and shift labor from investment toward consumption.

Importantly, our model differs in its *scope* and *ingredients* from previous New-Keynesian and asset pricing models: (1) In the New-Keynesian context, most prior frameworks such as [Galí \(2010\)](#) or [Christiano, Eichenbaum, and Evans \(2005\)](#), feature only a single sector, whereas we emphasize the role of splitting production into two sectors.⁵ Even macro models that include multiple sectors, such as [Basu, Fernald, and Liu \(2013\)](#), overlook asset-pricing implications altogether. We further depart from existing macro setups by employing (i) recursive [Epstein and Zin \(1991\)](#) preferences instead of CRRA or habit formation and (ii) permanent technological shocks with a long-run risk component, contrasting the transitory, mean-reverting shocks previously considered. These departures go a long way toward explaining asset-pricing facts that macro models fail to capture. In particular, (i) is important for obtaining the correct signs of conditional correlations while (ii) is important quantitatively.⁶ (2) In asset-pricing context, numerous studies feature two sectors (e.g., [Papanikolaou, 2011](#); [Garlappi and Song, 2017](#)), but typically with flexible prices. It is the combination of price rigidity *and* the two-sector structure that is critical for the evidence.⁷

More broadly, our work contributes to an extensive literature exploring the relationship between production decisions and asset returns, complementing insights from numerous studies.⁸ While

⁵In such one-sector models, the negative effect of sticky prices is not limited to labor markets; it also leads to a contraction in capital and output growth, contrary to the data. Section 1.1 also presents firm-level evidence that is less consistent with broad displacement as the primary explanation.

⁶In Online Appendix Section OA.1 we provide a comprehensive discussion on the differences between our study and [Basu et al. \(2013\)](#). Importantly, their working paper did not explore any implications for asset prices. Nonetheless, our replication of their structure shows that it cannot fully explain the disconnection puzzles.

⁷In standard two-sector models—lacking sticky prices—aggregate (common) technology shocks have no contractionary effect: they not only 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.

⁸see, for example, [Belo and Lin, 2012](#); [Jones and Tuzel, 2013](#); [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,](#)

these studies primarily focus on *long-term* unconditional aggregate and cross-sectional risk premia, our contribution is to bring the phenomenon of innovation-driven contractions to a financial context, and to show how it affects *short-term* conditional asset-price dynamics. The individual components our model builds on: sector segmentation, monopolistic markups, nominal rigidities, are each well understood. The novelty lies in their interaction: it not only generates innovation-driven contractions quantitatively, but uncovers a new interplay between the relative price of investment and investment quantities that underlies both the macro dynamics (the capital-growth response) and the resolution of the pricing puzzles (the negative comovement between valuations and investment expenditures).⁹

In sum, seemingly unrelated stylized facts, previously viewed as distinct challenges, can be unified through innovation-driven contractions. Integrating these well-established (yet overlooked) macro dynamics into an asset pricing framework enhances production-based asset-pricing models' ability to bridge macro-fundamentals and financial markets. More broadly, our framework provides a methodological contribution: we demonstrate how to successfully bring the New Keynesian model—the workhorse of modern macroeconomics—to bear on conditional asset-pricing puzzles.

and Wu, 2019; Bretscher, Hsu, and Tamoni, 2020; Corhay, Li, and Tong, 2022; Kogan, Li, Zhang, and Zhu, 2023; Anschukov, Bhamra, and Kuehn, 2024, among many others.

⁹Adoption models can also generate valuation–activity disconnections by emphasizing that firms gradually incorporate major innovations in the presence of real growth options (e.g., Garleanu, Panageas, and Yu, 2012; Greenwood and Yorukoglu, 1997). However, three empirical and theoretical distinctions separate our framework from these delayed-adoption mechanisms. First, adoption models tie disconnections to *embodied* innovations whose effects are delayed, whereas standard disembodied shocks in these models still generate positive contemporaneous comovement between valuations and real activity. By contrast, our evidence features a disconnection precisely for *disembodied* technology innovations (utilization-adjusted TFP). Second, because short-run dynamics in adoption models operate through a generalized adoption slowdown, investment and labor move in tandem. Our data instead reveal a sharp asymmetry: labor contracts on impact while capital growth does not, an asymmetry our mechanism explicitly captures. Third, the disconnections in our framework are *state dependent*. They become systematically stronger when prices are stickier. Correspondingly, removing nominal rigidity (even while holding market power fixed) restores high correlations. This confirms that endogenous markup dynamics—rather than constant markups, adoption delays, or long-run risk—are required to qualitatively match the data.

1 Motivating Evidence

We first establish two empirical facts that discipline the mechanism. First, we revisit and extend the seminal evidence on “innovation-driven contractions,” showing that positive aggregate technology shocks are followed by an immediate contraction in labor input, while the corresponding response of capital growth is statistically indistinguishable from zero. Second, we present evidence that salient “disconnection” puzzles are governed by the degree of price stickiness, becoming systematically worse when prices adjust more sluggishly. Jointly, these regularities motivate nominal rigidity and endogenous markup movements within a two-sector economy as the candidate mechanism, and we use them as quantitative discipline.

1.1 Innovation-Driven Contractions Revisited

Stylized Fact 1: Innovation-Driven Contractions. *The short-run response of labor to a positive technology shock is negative, whereas the short-run response of capital growth is statistically muted.*

Aggregate Evidence. To preserve comparability, we directly follow the methodology of [Basu et al. \(2006\)](#) and project the growth rate of production inputs on the contemporaneous value and four lagged values of technological innovations:

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

where Δy_t denotes the log-growth rate of either hours per worker (*dhours*) or capital input (*dk*). We source the former from the Bureau of Labor Statistics (BLS), and the latter from Fernald’s (2014) dataset. Capital growth is measured from capital expenditures, as distributed in

Table 1: Hours and Capital Growth Response to Technological Advancements

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

The table reports OLS slopes and Newey–West t -statistics from regressions of hours or capital-input growth on current technology growth alone (first row) or on current growth and four lags (second row). Within each sample panel the upper block reports annual regressions and the lower block quarterly regressions, each for hours (*dhours*) and capital-input (*dk*) growth. The left panel uses 1953–1996 data; the right extends through 2019. [Basu et al. \(2006\)](#) supply annual technology and hours through 1996; [Fernald \(2014\)](#) supplies all quarterly series, post-1996 annual technology and hours, and capital throughout.

Fernald’s (2014) dataset, so it reflects both the quantity of investment and its price. The independent variable dz represents technological advancements and can be measured in two ways. First, dz could be taken directly from [Basu et al. \(2006\)](#), who use Hall-style regressions to obtain industry-level technological innovations and then aggregate these to form macro-level purified technology shocks. The data are available at the annual frequency from 1953 to 1996. Second, dz could be sourced from [Fernald \(2014\)](#), who uses a similar methodology to [Basu et al. \(2006\)](#), but only uti-

lizes aggregate-level data to estimate technological advancements, captured by utilization-adjusted TFP.¹⁰ The data are available until recent years, at both the annual and the quarterly frequency. Within the overlapping annual sample period of 1953–1996, the correlation between the measure of Basu et al. (2006) and Fernald (2014) is 0.7. Consequently, we employ both measures of dz : for annual projections from 1953 to 1996 we use data from Basu et al. (2006), while for the extended period of 1997–2019 or for quarterly regressions, we use data from Fernald (2014). The extended specifications change the sample period and frequency and, for the extended annual and quarterly results, the technology measure. We therefore do not attribute the change in the capital coefficient to any one of these dimensions.

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

Next, we keep the analysis at the annual frequency but extend the sample to 2019. For hours growth, the loading on dz and its lagged values remain negative, and quantitatively similar to the slope coefficients obtained using the original sample period.¹¹ However, in the new updated sam-

¹⁰We treat utilization-adjusted TFP innovations as the empirical counterpart to the model’s aggregate technology shock. The model abstracts from variable utilization, so this mapping is an approximation rather than a structural identification of the shock.

¹¹Anecdotally, and broadly related, a recent paper by Eisfeldt, Schubert, and Zhang (2023) shows that the introduc-

ple, the response of capital growth to technological advancements is muted, with slope coefficients that are close to zero and statistically *insignificant*.

To examine which empirical pattern is more robust, the bottom panel of Table 1 refines the analysis by considering quarterly frequency regressions. The evidence is consistent with the updated annual data. In the quarterly samples ending either in 1996Q4 or 2019Q4¹², the contractionary effect of technological innovations is confined to the labor markets. For hours growth, the loadings on contemporaneous dz and its first two lags are negative, followed by a partial rebound in the subsequent period. For capital growth, on the other hand, the slope coefficients are statistically insignificant, close to zero and mostly positive. Lastly, the contemporaneous effect of dz on input growth rates remains robust across specifications, even when the lagged values of dz are excluded from the regressions.¹³ We treat the evidence in Table 1—both the significant coefficient on labor and the insignificant coefficient on capital growth—as a quantitative restriction that the model has to replicate (see Section 6), while keeping investment dynamics realistic. This puts substantial discipline on any candidate mechanism: (1) in many setups, if a shock is contractionary for labor it is also contractionary for capital growth; (2) given that investment is highly volatile, a shock that moves the investment rate typically induces an equivalent non-zero effect on capital growth, as the two are synonymous in most models. The mechanism should overcome both challenges.

Firm-Level Evidence. We complement the aggregate analysis above using firm-level projections.

We conduct panel regressions in which we project firm-level variables on firms’ citation-weighted

tion of generative AI has caused a general reduction in job postings for exposed firms.

¹²The sample ends in 2019Q4 by design: we deliberately exclude the COVID-19 period, in which extreme labor-market and output swings reflect pandemic-specific disruptions rather than technology-driven dynamics.

¹³In untabulated results, we repeat projection (1) using only the most recent subsample from 1997 to 2019, at both annual and quarterly frequencies: for capital growth, the loading on dz remains positive but statistically insignificant. This indicates that the data do not show any deep structural change, pre- and post-1996. This suggests that the negative dk coefficient in the original sample is sensitive to the sample period, frequency, lag specification, and technology measure. Even within that sample, changing the frequency of the regression or including additional lags renders the slope on contemporaneous dz insignificant at the 5% level.

patent values from [Kogan et al. \(2017\)](#), as a metric of firm-level innovation.¹⁴ For brevity, the full details are relegated to Online Appendix Section [OA.3](#). Table [OA.2](#) reports the results: we find that a firm’s own innovation predicts lower own employment growth, an insignificant change in capital growth, no decline in competitors’ employment, and higher markups. The first two results are materially consistent with Table [1](#) at the granular level. The other findings differentiate between two possible mechanisms for Stylized Fact 1: displacement versus markup rationing.

A displacement (creative-destruction) narrative posits that “winner” innovators expand while displaced incumbents contract, causing aggregate activity to contract temporarily. However, the documented effect on competitors’ employment is difficult to reconcile with displacement: if the aggregate labor contraction were driven by displacing competitors, the labor decline would show up in industry peers rather than in the innovators’ own hiring.¹⁵ The markup response points to the alternative mechanism: firms absorbing productivity gains into rents rather than into immediate expansion. The theoretical footing for this channel is well established: [Smets and Wouters \(2007\)](#) and [Galí \(2010\)](#), among others, show that under price stickiness, a positive technology shock raises markups and contracts labor — elevated markups acting, in effect, as an implicit tax that rations input demand. As markup variation is endogenously linked to nominal price rigidity, this last finding provides a natural bridge between Stylized Fact 1 and Stylized Fact 2, which connects the asset-pricing disconnections to the same nominal friction. Online Appendix Section [OA.12](#) tests this bridge directly: following positive technology shocks, firms in stickier-price industries exhibit

¹⁴Because the patent measure here may also capture product quality or market-power changes, we view this exercise only as a diagnostic to distinguish among candidate mechanisms for the aggregate findings.

¹⁵Other tensions also help to rule out displacement as a primary driving force here. At the aggregate level, if a sizable mass of incumbents is displaced, both labor and capital growth should be depressed over the same short horizon — whereas Table [1](#) and Table [OA.2](#) show labor contracting sharply while capital growth is indistinguishable from zero. Moreover, creative destruction typically implies a negative risk price for displacing productivity shocks ([Kogan, Papanikolaou, and Stoffman, 2013](#)), in contrast to the positive price of aggregate Hicks-neutral technology in our data.

larger markup increases and weaker employment growth.

1.2 Price Stickiness and Comovement Puzzles

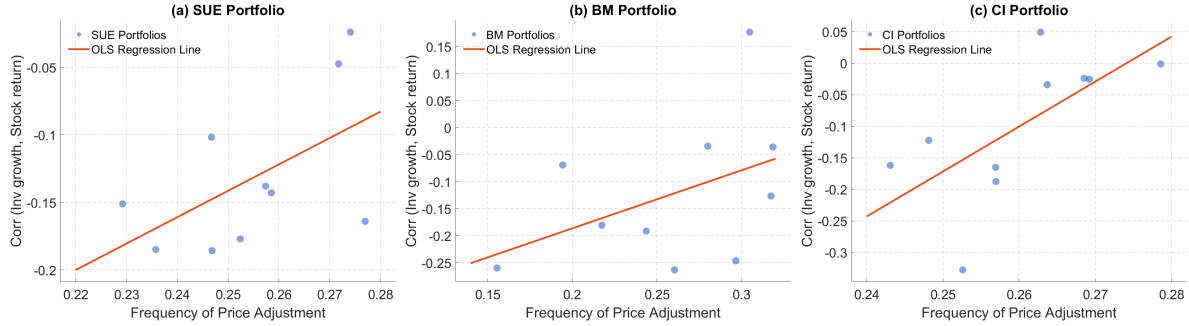
Stylized Fact 2: Comovement puzzles and price rigidity. *When prices are stickier, the contemporaneous correlation between equity returns and either (a) investment growth or (b) hiring news is significantly more negative than it is under flexible prices.*

Establishing this link empirically faces a data challenge. To align with our aggregate theoretical framework, the ideal test would rely entirely on time-series variation in macro-level price-adjustments. Because such direct aggregate measures are confined to a relatively short sample, we overcome this limitation by first exploiting portfolio-level heterogeneity. This variation provides a powerful laboratory to proxy for different regimes of nominal rigidity, allowing us to identify the core prediction before turning to the available aggregate time-series evidence.

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

To materially replicate [Liu et al. \(2009\)](#), we use their original sample and the methodology to create decile portfolios based on the former characteristics. Portfolios sorted on BM and CI are rebalanced annually, while portfolios sorted on SUE are rebalanced monthly. For each of the 30 portfolios, we compute time-series correlation between its value-weighted stock returns and its investment growth. The latter is highly correlated with portfolio-level investment returns, but

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



The panels plot, for SUE-, book-to-market-, and investment-sorted deciles, each portfolio’s time-series correlation between value-weighted stock returns and market-value-weighted investment growth against its market-value-weighted 4-digit NAICS price-adjustment frequency from [Pasten et al. \(2021\)](#). Red lines are OLS fits with heteroskedasticity-robust t -statistics. Samples follow [Liu et al. \(2009\)](#): 1972–2005 for SUE portfolios and 1963–2005 for the book-to-market and investment portfolios.

does not rely on a specific functional form for capital adjustment costs. Portfolio-level investment growth is defined as the value-weighted average of firm-level investment growth rates.¹⁶

We then extend the analysis of [Liu et al. \(2009\)](#) by considering the link to price rigidity. We obtain cross-sectional data on price stickiness from [Pasten, Schoenle, and Weber \(2021\)](#), who measure the frequency of price adjustment at the 4-digit NAICS industry level. We assign each firm a price adjustment frequency based on its granular industry classification. For each of the former 30 portfolios, the portfolio-level metric of price adjustment is defined as the value-weighted average of its underlying constituent firms’ frequencies.

Figure 1 shows a scatter plot of portfolio-level stock return-investment growth correlations against portfolio-level frequency of price adjustment, along the three dimensions of BM, CI and SUE.¹⁷ First, consistent with [Liu et al. \(2009\)](#), for almost all portfolios the time-series correlation

¹⁶A specific challenge arises for the monthly-rebalanced SUE portfolios; to align their investment growth with an annual horizon, we form 12 monthly portfolios for each decile from July of year t to June of year $t + 1$, calculate the investment growth for each, and then average these 12 figures to obtain a single annual investment growth measure for each decile.

¹⁷While Figure 1 displays a cross-section of portfolios, the y-axis values are strictly time-series correlations computed within each portfolio. Because our macroeconomic model features a representative firm in each sector, our focus is on aggregate time-series dynamics rather than cross-sectional asset pricing phenomena. We therefore exploit this cross-sectional variation in stickiness solely to proxy for different regimes of price rigidity.

between stock returns and investment growth rates is negative, as shown on the y-axes of the scatter plots. Second, a pattern emerges across all three sorting dimensions: the lower (higher) the price-adjustment frequency is, the more (less) negative the stock return-investment correlation is. Notably, a lower frequency for price adjustment is equivalent to a higher degree of price stickiness. This pattern is economically meaningful, and the fitted slopes are positive across all three sorting dimensions — statistically significant at the 10% level or better: The red lines in each panel represent the best linear fit for each scatter plot. For SUE-, BM- and CI-sorted portfolios the lines' slope coefficients are 1.85 (t -stat = 1.81), 1.08 (t -stat = 1.95) and 7.13 (t -stat = 3.71), respectively.¹⁸ Online Appendix Section OA.4 repeats this exercise at the granular level of the 48 Fama–French industries for which price rigidity is measured, with similar results (slope 0.35, $t = 2.04$).¹⁹

Notably, portfolio price-adjustment frequency may partly reflect industry composition and correlated characteristics. The next exhibit, Figure 2, provides a complementary aggregate time-series test that does not rely on cross-portfolio composition and points in the same direction.

Labor. Boyd et al. (2005) and subsequent studies show that at the aggregate level, equity valuations typically rise in response to bad labor-market unemployment news. We re-establish this finding in an expanded sample and study how the resulting correlation varies over the business cycle together with the aggregate frequency of price adjustment.

We first obtain quarterly time series on the aggregate frequency of price adjustment from Vavra (2014) and apply a Hodrick-Prescott (HP) filter to isolate its cyclical component.²⁰ Figure OA.6

¹⁸In the interest of space, we confirm that these results hold for alternative specifications, including the use of different weighting schemes, investment return definitions, industry classifications, and an extension of the sample period through 2019.

¹⁹Because the dependent variable is itself an estimated correlation, the appendix also addresses the boundedness of correlations and the differential precision of industries observed over different sample lengths, by computing Fisher-z-transformed and precision-weighted (WLS) estimates; the slope is essentially unchanged under either adjustment or both.

²⁰We apply the HP filter to the series from Vavra (2014) to isolate its cyclical component, as markups rise over time.

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

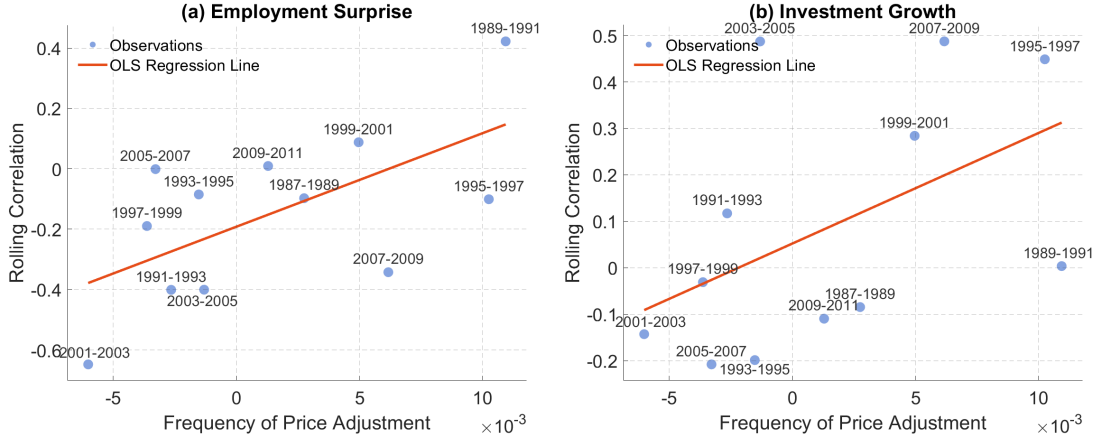
This predictive regression is estimated via a recursive, expanding window.²¹ The fitted value from this regression serves as the out-of-sample forecast for the change in the unemployment rate in quarter t . The unexpected change in unemployment is defined as the difference between its realized value in quarter t and its forecasted value. Following the convention in the literature, the time- t employment surprise is then defined as the negative of this unemployment forecast error.

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

Panel (a) shows that when the frequency of price adjustments is higher — usually in recessions — the correlations between employment surprises and stock returns rise (less negative or even

²¹Following [Boyd et al. \(2005\)](#), we require an initial training period of at least five years. Constrained by the availability of the National Financial Conditions Index (NFCI), which begins in 1971, the estimation window for a forecast for quarter t uses all available data from 1971Q1 up to quarter $t - 1$.

Figure 2: Rolling Correlations and Frequency of Price Adjustment



The panels plot nonoverlapping eight-quarter correlations of stock returns with employment surprises (a) and aggregate investment growth (b) against the HP-filtered frequency of price adjustment. Each point is a two-year window sampled every eight quarters from 1989Q1 to 2011Q1; red lines are OLS fits. Employment surprises follow [Boyd et al. \(2005\)](#); investment growth is market-value weighted from Compustat, stock returns are S&P 500 returns from [Goyal et al. \(2024\)](#), and price-adjustment frequency is from [Vavra \(2014\)](#). All variables are standardized.

positive). The converse happens in expansions, when prices are more rigid: the correlation between employment surprises and stock returns drops (more negative). The correlation between the two dimensions, captured by the slope coefficient of the best linear fit, is 0.62 ($t - stat = 2.03$).

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

In sum, the ‘disconnection’ between stock valuations and real economic activity — investment or hiring — is systematically related to the degree of price stickiness. The force of the evidence

is joint: while estimation error can be present in both the price-adjustment and the correlation measures, the pattern is pervasive in both the time series and the cross-section, and across both economic-activity margins. Sections 4.1–4.2 will show that the same state dependence arises endogenously in the model: when nominal rigidity is removed, these correlations revert toward the neoclassical benchmark, while nominal rigidity and markup movements make them more negative.

2 Model

We present a general equilibrium model to explain prominent asset-pricing disconnection puzzles through innovation-driven contractions, demonstrating how to effectively operationalize the standard New Keynesian macroeconomic workhorse for asset pricing. Motivated jointly by Stylized Facts 1 and 2, the mechanism arises endogenously when technology improvements interact with sticky prices and a two-sector structure, generating fluctuations in markups and the relative price of investment. The resulting comovements follow from these ingredients, rather than from auxiliary adjustment-cost shocks or heterogeneous-firm reallocation.

The model features two sectors, consumption and investment. Intermediate good producers in each sector face monopolistic competition and nominal price rigidity. While these New Keynesian ingredients seem superficially similar to a working paper by [Basu et al. \(2013\)](#), our approach to modeling risk premia is markedly different and leads to distinct outcomes. In particular, our setup features two notable departures: (1) household preferences follow [Epstein and Zin \(1991\)](#) rather than habit formation, and (2) technology shocks have permanent effects (a unit root), accompanied by a long-run-risk component, rather than purely transitory effects.

Economically, these differences go a long way in differentiating the implications of our model, particularly in the asset-pricing domain. In Online Appendix [OA.1](#) we replicate [Basu et al. \(2013\)](#):

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

2.1 Aggregation

In each sector $j \in \{c, i\}$, a competitive final-good producer combines a continuum of differentiated intermediate goods according to the CES aggregator $Y_{j,t} = \left[\int_0^1 y_{j,t}(n)^{(\mu_j-1)/\mu_j} dn \right]^{\mu_j/(\mu_j-1)}$. Here $Y_{c,t}$ and $Y_{i,t}$ are the final consumption and investment goods. The elasticity μ_j governs substitution across varieties and hence the market power of intermediate producers; perfect competition obtains as $\mu_j \rightarrow \infty$. The final-good producer buys variety n at nominal price $p_{j,t}(n)$, sells the composite at $P_{j,t}$, and solves $\max_{\{y_{j,t}(n)\}} \{P_{j,t}Y_{j,t} - \int_0^1 p_{j,t}(n)y_{j,t}(n)dn\}$. Its demand is $y_{j,t}(n) = [p_{j,t}(n)/P_{j,t}]^{-\mu_j}Y_{j,t}$, and zero profits imply $P_{j,t} = [\int_0^1 p_{j,t}(n)^{1-\mu_j}dn]^{1/(1-\mu_j)}$.

2.2 Intermediate good production

2.2.1 Sectoral intermediate good producers

Intermediate goods in sector $j \in \{c, i\}$ are differentiated, and each type is denoted by $n \in [0, 1]$. Each intermediate good producer n in sector j rents labor $n_{j,t}(n)$ from the household and owns a

capital stock $k_{j,t}(n)$. The intermediate good producer n in sector j produces its output $y_{j,t}(n)$ from capital and labor through a constant returns-to-scale Cobb–Douglas technology that is buffeted each period by the sector’s own aggregate technology shock $Z_{j,t}$:

$$y_{j,t}(n) = Z_{j,t} k_{j,t}(n)^{\alpha_j} n_{j,t}(n)^{1-\alpha_j}, \quad j \in \{c, i\}, \quad (2)$$

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

$$\Phi_{j,k}(i_{j,t}(n), k_{j,t}(n)) = \frac{i_{j,t}(n)}{k_{j,t}(n)} + \frac{\phi_{k,j}}{2} \left(\frac{i_{j,t}(n)}{k_{j,t}(n)} - \delta \right)^2 \quad (3)$$

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

$$k_{j,t+1}(n) = (1 - \delta) k_{j,t}(n) + i_{j,t}(n). \quad (4)$$

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

$$\Phi_{P,j}(p_{j,t}(n), p_{j,t-1}(n)) = \frac{\phi_{p,j}}{2} \left[\frac{p_{j,t}(n)}{\Pi_j p_{j,t-1}(n)} - 1 \right]^2 p_{j,t}(n) Y_{j,t}, \quad j \in \{c, i\}, \quad (5)$$

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

$$d_{j,t}^{\$}(n) = p_{j,t}(n) y_{j,t}(n) - W_t n_{j,t}(n) - P_{i,t} \Phi_{j,k} \left(\frac{i_{j,t}(n)}{k_{j,t}(n)} \right) k_{j,t}(n) - \Phi_{P,j}(p_{j,t}(n), p_{j,t-1}(n)). \quad (6)$$

Each intermediate good producer n chooses optimal employment, 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 de-

rived above, and the nominal stochastic discount factor of the household $M_{t,t+1}^{\$}$. Specifically, the intermediate good producers choose these controls to maximize firm value:

$$V_{j,t}^{\$(n)} = \max_{\{n_{j,s}(n), k_{j,s}(n), p_{j,s}(n)\}} E_t \sum_{s=t}^{\infty} M_{t,t+s}^{\$} d_{j,t+s}^{\$(n)}, \quad (7)$$

subject to equation (4), equation (6), and the demand constraint:

$$\left[\frac{p_{j,t}(n)}{P_{j,t}} \right]^{-\mu_j} Y_{j,t} \leq Z_{j,t} k_{j,t}(n)^{\alpha_j} n_{j,t}(n)^{1-\alpha_j}, \quad j \in \{c, i\}. \quad (8)$$

Note that $V_{j,t}^{\$(n)}$ is in nominal consumption units, so the real firm value and real dividend follow by deflating with the consumption price: $V_{j,t}(n) = V_{j,t}^{\$(n)}/P_{c,t}$; $d_{j,t}(n) = d_{j,t}^{\$(n)}/P_{c,t}$. Lastly, we define the real growth rate of aggregate investment expenditures (in terms of real consumption goods) and the growth rate of the relative price of investment 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 $\triangle P_{i,t} = \frac{P_{i,t}/P_{c,t}}{P_{i,t-1}/P_{c,t-1}}$.

2.2.2 Technology

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

$$\frac{Z_{j,t}}{Z_{j,t-1}} = g_z + x_{j,t} + \sigma_{z,j} \varepsilon_{z,t}, \quad j \in \{c, i\} \quad (9)$$

$$x_{j,t} = \rho_x x_{j,t-1} + \sigma_{x,j} \varepsilon_{x,t}, \quad (10)$$

where $\rho_x \in (-1, 1)$ measures the persistence of long-term technology growth, similar to [Croce \(2014\)](#), and $\sigma_{x,j}$ denotes long-run shocks' standard deviation. The shocks $\varepsilon_{z,t}$ and $\varepsilon_{x,t}$ are standard normal and independent over time. Equations (9) and (10) have two key implications: (i) The innovations $\varepsilon_{z,t}$ and $\varepsilon_{x,t}$ are common across sectors, rather than sector-specific. This implies that technological changes in the investment and consumption sectors are perfectly correlated—each responds to the same aggregate technological growth—scaled by sector-specific volatilities $\sigma_{z,j}$ and $\sigma_{x,j}$. This assumption ensures that the model captures a single, economy-wide technological

change (dz) driving both sectors, consistent with the empirical evidence in Section 1.1, which concerns the effects of aggregate technological changes rather than sectoral ones.²² (ii) Despite sharing the same innovation source, the sectors differ in how strongly they react to it, as reflected in the distinct volatility parameters $\sigma_{z,j}$ and $\sigma_{x,j}$. This allows for heterogeneous sensitivity to aggregate technology shocks—a salient feature observed in the data (see Fernald (2014)).²³

2.3 Household

A representative household owns the firms and supplies total labor N_t to the two sectors. Its preferences are recursive, following Epstein and Zin (1991), and are defined over a King–Plosser–Rebelo composite of consumption and leisure:

$$U_t = \left\{ (1 - \beta) [C_t (1 - \xi N_t^\eta)]^{1-1/\psi} + \beta \left(E_t U_{t+1}^{1-\gamma} \right)^{\frac{1-1/\psi}{1-\gamma}} \right\}^{\frac{1}{1-1/\psi}}. \quad (11)$$

Here β is the discount factor, γ is risk aversion, ψ is the intertemporal elasticity of substitution, and ξ and η govern labor disutility. The household prefers early resolution of uncertainty when $\gamma > 1/\psi$ and late resolution when $\gamma < 1/\psi$.²⁴ The household chooses consumption and labor and receives wages and dividends from both sectors. Online Appendix Section OA.5.1 states its budget

²²Recall that the contractionary evidence in Table 1 is based on Fernald’s (2014) utilization-adjusted measure of aggregate, Hicks-neutral technology. In untabulated results, we also repeat the projections using Fernald’s (2014) consumption-sector and investment-sector technology series separately: both yield nearly identical results to the baseline, once again indicating that the effect stems from the sectors’ shared common component rather than from sector-specific variation.

²³In-line with the modeling choice of Papanikolaou (2011) and Garlappi and Song (2017), Z_c and Z_i are not co-integrated. Balanced growth is achieved as consumption and investment expenditures (i.e., investment quantity times its price) grow at the same rate. This also implies that valuations in both sectors—denominated in consumption units—grow at the same rate.

²⁴We use King–Plosser–Rebelo (1988) preferences, in which consumption and leisure are multiplicative. Replacing KPR utility with an additively separable specification, in which leisure does not enter the pricing kernel, leaves every reported sign unchanged (Online Appendix Table OA.15).

constraint. The resulting nominal stochastic discount factor used to value firms is

$$M_{t+1}^{\$} = \beta \left(\frac{C_{t+1}}{C_t} \right)^{-1/\psi} \left(\frac{1 - \xi N_{t+1}^{\eta}}{1 - \xi N_t^{\eta}} \right)^{1-1/\psi} \left(\frac{U_{t+1}}{(E_t U_{t+1}^{1-\gamma})^{\frac{1}{1-\gamma}}} \right)^{1/\psi-\gamma} \frac{P_{c,t}}{P_{c,t+1}}. \quad (12)$$

Closing the model. Online Appendix Sections OA.5 and OA.6 report the monetary-policy rule, market-clearing conditions, and equilibrium first-order conditions.²⁵

2.4 Returns

Stock returns. The real unlevered return in sector j is $R_{j,t+1}^{S(\text{unlevered})} = (d_{j,t+1} + V_{j,t+1})/V_{j,t}$. In nominal consumption units, this is $[d_{j,t+1}^{\$}/P_{c,t+1} + V_{j,t+1}^{\$}/P_{c,t+1}]/[V_{j,t}^{\$}/P_{c,t}]$; the dividend and firm value are defined in equations (6) and (7). Firm value satisfies $V_{j,t}^{\$} = E_t[M_{t,t+1}^{\$}(d_{j,t+1}^{\$} + V_{j,t+1}^{\$})]$.

The unlevered market return is the value-weighted average $R_{M,t}^{S(\text{unlevered})} = [V_{c,t-1}R_{c,t}^{S(\text{unlevered})} + V_{i,t-1}R_{i,t}^{S(\text{unlevered})}]/[V_{c,t-1} + V_{i,t-1}]$. Because the model abstracts from financial debt, operating leverage, and nonsystematic payouts, observed excess returns satisfy

$$R_{j,t}^e = \phi_{lev}(R_{j,t}^{S(\text{unlevered})} - R_t^f) + \sigma_d \varepsilon_{j,d,t} \quad j \in \{c, i, M\}, \quad (13)$$

Here ϕ_{lev} captures total financial and operating leverage and σ_d the volatility of idiosyncratic dividend shocks. Leverage does not affect return cyclicalities, and $\varepsilon_{j,d,t}$ does not covary with the SDF. The levered gross return $R_{j,t}^S$ adds the risk-free rate, where $1/R_t^f = E_t[M_{t+1}]$.

Investment returns. The first-order conditions are reported in Online Appendix Section OA.6.1.

The marginal value of installed capital is $q_{j,t} = P_{i,t} \partial_i \Phi_{j,k}(i_{j,t}, k_{j,t}) k_{j,t}$, where ∂_i denotes differentiation with respect to investment. It depends on the relative investment price and capital installation costs. Let $\theta_{j,t}$ be the marginal cost of producing an additional unit of intermediate good in sector j (i.e., inverse of the markup). Investment returns satisfy $R_{j,t+1}^I = (\partial V_j / \partial k_{j,t+1}) / q_{j,t}$ and admit the

²⁵In what follows, we suppress the variety type (n) from the model's state and control variables, as equilibrium is symmetric.

standard dividend- and capital-gain decomposition:

$$\frac{\overbrace{\alpha_j \theta_{j,t+1} Z_{j,t+1} k_{j,t+1}^{\alpha_j-1} n_{j,t+1}^{1-\alpha_j} - P_{i,t+1} \left(\Phi_{j,k}(i_{j,t+1}, k_{j,t+1}) + \frac{\partial \Phi_{j,k}(i_{j,t+1}, k_{j,t+1})}{\partial k_{j,t+1}} k_{j,t+1} \right)}^{\text{Dividend Gain}} - \delta q_{j,t+1} + \underbrace{q_{j,t+1}}_{\text{Capital Gain}}}_{\underbrace{q_{j,t}}_{\text{Cost}}}, \quad (14)$$

aligning with traditional decompositions of investment return. The market investment return is the value-weighted average $R_{M,t}^I = [V_{c,t-1} R_{c,t}^I + V_{i,t-1} R_{i,t}^I] / [V_{c,t-1} + V_{i,t-1}]$.

In equation (14), the first term is the dividend (cash-flow) component: marginal product scaled by marginal cost, $\theta_{j,t+1}$, less capital installation expenses. The second term is the capital-gain component $q_{j,t+1}/q_{j,t}$, where $q_{j,t+1}$ depends on the relative investment price and installation costs. The key wedge is that sticky prices move θ and P_i jointly, so investment-returns' dividend and capital gains can fall even as stock valuations rise, as we show in section 4.1.

3 Quantification

3.1 Calibration

The model is calibrated at the quarterly frequency. The parameters are detailed in Table 2, grouped into technology, production, preferences, and monetary-policy categories.

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

Table 2: **Model Parametrization**

Symbol	Parameter	Value	Symbol	Parameter	Value
<i>Panel A. Technology</i>			<i>Panel C. Preferences and Rates</i>		
g_z	Technology drift	1.0032	γ	Relative risk aversion	5
$\sigma_{z,i}$	Short-run technology volatility, investment (%)	1.65	ψ	Intertemporal elasticity of substitution	1.4
$\sigma_{z,c}$	Short-run technology volatility, consumption (%)	1.23	ξ	Labor disutility	2
ρ_x	Long-run growth persistence	0.975	η	Working-hours disutility sensitivity	4
$\sigma_{x,i}$	Long-run technology volatility, investment (%)	$0.1\sigma_{z,i}$	β	Time discount factor	0.9955
$\sigma_{x,c}$	Long-run technology volatility, consumption (%)	$0.1\sigma_{z,c}$	ϕ_{lev}	Financial and operating leverage	1.3
<i>Panel B. Production</i>			<i>Panel D. Monetary Policy</i>		
α_i	Capital share, investment	0.33	π_{ss}	Steady-state inflation	0.005
α_c	Capital share, consumption	0.33	ρ_r	Taylor-rule smoothing	0.5
δ	Depreciation rate	0.02	ρ_π	Inflation-gap weight	1.5
$\phi_{k,i}$	Capital adjustment cost, investment	2.9	ρ_y	Output-gap weight	0.5
$\phi_{k,c}$	Capital adjustment cost, consumption	2.9			
μ_i	Substitution elasticity, investment	4			
μ_c	Substitution elasticity, consumption	2.4			
$\phi_{p,i}$	Price adjustment cost, investment	25			
$\phi_{p,c}$	Price adjustment cost, consumption	25			

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

parameters follow [Croce \(2014\)](#). Specifically, we set the persistence of long-run technology, ρ_x , at 0.975 to match the first-order autocorrelation of output growth. The standard deviations of long-run technology shocks are set to 10% of their short-run counterparts, consistent with [Croce \(2014\)](#), which helps pin down the unconditional equity premium.

Production. Capital's share of output in both sectors, $\alpha_c = \alpha_i$, is 33%, as in the data. The capital depreciation rate is 2%, implying an annual depreciation of 8.2%. Capital adjustment costs in both sectors, $\phi_{k,c} = \phi_{k,i}$, are set at 2.9, to match the ratio of investment growth volatility to output growth volatility. These values are also consistent with estimates by [Basu and Bundick \(2017\)](#). We set μ_i and μ_c to 4 and 2.4, respectively. The first implies that the average markup in the investment sector is 33%, close to the value estimated by [Bilbiie, Gironi, 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).²⁶ Thus, the relative sectoral markups are disciplined by external evidence rather than chosen to fit specific moments. The Rotemberg adjustment costs, $\phi_{p,c} = \phi_{p,i} \equiv \phi_p$, are calibrated to match the data on average price duration²⁷, as estimated by Galí, Gertler, and Lopez-Salido (2001) and Sbordone (2002). We set ϕ_p to 25, close to Kung (2015), corresponding to a price duration of about four quarters.²⁸ 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 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. The parameter η governs the curvature of labor disutility and is set to 4. Replacing KPR utility with an additively separable specification, in which leisure does not enter the pricing kernel, leaves every reported sign unchanged (Online Appendix Table OA.15). The time discount factor β is 0.9955, targeting a low real risk-free rate. Consistent with the total degree of leverage (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).

²⁶While the specific values of μ_c and μ_i are disciplined by recent data, the forces at play in Section 4 do not qualitatively depend on the average level of markups. So long as the ratio of the consumption-sector markup to the investment-sector markup is maintained, changing μ_c and μ_i only induces a small quantitative effect on the results to follow.

²⁷Observed adjustment frequencies and quadratic Rotemberg costs are not structurally identical. We use average price duration to discipline the benchmark degree of nominal rigidity, not as a literal one-to-one mapping.

²⁸See Online Appendix section OA.5.4 for details on this mapping.

Monetary Policy. Parameters are from [Basu and Bundick \(2017\)](#). π_{ss} implies an annual inflation of 2%. The inflation and output gap weights are 1.5 and 0.5, respectively. The smoothing of the policy rule, ρ_r , is 0.5. We solve the model using a third-order perturbation method.²⁹

3.2 Unconditional Aggregate Moments

Table 3 shows annual moments in the data and the model. Model entries average 1,000 simulations of 560 quarters, discarding the first 400 quarters; the remaining 160 quarters match the empirical path in projection (1), and quarterly observations are compounded to non-overlapping annual observations. We compare the benchmark with No-LRR ($\sigma_{x,c} = \sigma_{x,i} = 0$), No-LRR & No-Sticky (which also sets $\phi_{p,c} = \phi_{p,i} = 0$), and No-LRR & Perfect-Comp (which also sets $\mu_c = \mu_i \rightarrow \infty$); these nested cases progressively strip out long-run risk, nominal rigidity, and market power.

The benchmark model reproduces the main macroeconomic and asset-pricing moments. Output growth volatility is 3.14% (3.05% in the data), its first-order autocorrelation is 0.40 (0.54), and its correlation with consumption growth is 0.80 (0.88). The consumption- and investment-growth volatility ratios are 0.88 and 2.85, compared with 0.88 and 3.02 in the data. Hours are less volatile unconditionally, although the finite-sample upper bound overlaps the empirical value. More importantly for the mechanism, the model closely matches the untargeted conditional hours response to technology shocks in Section 6.1. The model also closely matches the equity premium (3.97% versus 4.71%), market-return volatility (19.31% versus 20.89%), risk-free rate (1.24% versus 0.65%), and risk-free-rate volatility (1.23% versus 1.86%).

When considering alternative configurations, we deliberately refrain from recalibrating the

²⁹Inflation moments are not calibration targets. Untabulated simulations show that the model reproduces the data's sign pattern: inflation is persistent and comoves negatively with both output growth and technology innovations. Because there are no cost-push or monetary-policy disturbances, the model generates only technology-driven inflation volatility.

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 reports annual moments in the data and the model. ‘Benchmark’ uses the calibration in Table 2. ‘No-LRR’ sets $\sigma_{x,c} = \sigma_{x,i} = 0$; ‘No-LRR & No-Sticky’ also sets $\phi_{p,c} = \phi_{p,i} = 0$; and ‘No-LRR & Perfect-Comp’ additionally sets $\mu_c = \mu_i \rightarrow \infty$. Model entries average 1,000 simulations, retaining 160 quarters after a 400-quarter burn-in and compounding quarterly observations into non-overlapping annual data.

model, so that differences across columns are sequentially attributable to shutting down a particular ingredient rather than to offsetting parameter adjustments. Removing long-run risk leaves most macroeconomic moments broadly similar, but reduces the equity premium to only 0.46% and market-return volatility to 2.67%. As shown here and in subsequent subsections, long-run risk plays an important role for asset-pricing absolute magnitudes, yet never for their sign. The two flexible-price configurations are also quite similar to the benchmark for most unconditional moments, albeit they understate input fluctuations: the investment- and hours-to-output volatility ratios fall to 1.87 and 0.05 under ‘No-LRR & No-Sticky’ and 1.72 and 0.06 under ‘No-LRR & Perfect-Comp,’ against 3.02 and 0.73 in the data. This decline reflects a deeper change in the response of inputs to primitive shocks: while most unconditional moments are only modestly affected by markups and nominal rigidities, the next section uncovers their key qualitative and quantitative role for conditional input and asset-pricing moments.³⁰

³⁰As most unconditional macroeconomic moments do not exhibit substantial variation across columns, all configurations constitute valid laboratories, to be discriminated based on their conditional dynamics (correlations). Nonetheless

4 Resolution of Asset-Pricing Correlation Puzzles

In this section we show that the two-sector New-Keynesian model can explain several disconnection puzzles concerning the comovement of equity markets with cyclical macroeconomic quantities. The reconciliation of these puzzles follows jointly from (i) innovation-driven contractions—technology improvements that contract labor input in the short run (Stylized Fact 1), which the model generates endogenously—and (ii) nominal rigidity, which governs how strongly these disconnections manifest across the various asset-pricing moments (Stylized Fact 2).

4.1 Puzzle I: The comovement of investment and stock returns

We examine the model’s ability to reconcile the comovement puzzle of [Liu et al. \(2009\)](#), whereby stock returns and contemporaneous investment returns are negatively correlated in the data, while their correlation with future investment returns is positive. Table 4 lists the correlations between stock returns and measures of investment as implied by the model.³¹

The benchmark matches the signs and approximate magnitudes of the contemporaneous and lead–lag comovement moments, although none is a calibration target. As shown in the first row of Table 4, the ‘Benchmark’ configuration produces a negative contemporaneous correlation between market stock returns and investment returns. The correlation is -0.1 in the data from [Liu et al. \(2009\)](#), compared to -0.17 in the model. Moreover, the second row of the table shows that the correlation between market returns and one-year-ahead investment returns is positive, at around

less, given the diminished equity premium and return volatility outside the benchmark setting, when judging the success of configurations other than the benchmark, we primarily focus on the signs of comovements rather than their absolute magnitudes.

³¹In the model, investment returns follow standard q -theory and the Euler equation (Online Appendix Section OA.6.1). Because empirical “investment returns” are constructed proxies, we use them mainly to compare the model with [Liu et al. 2009](#). Table 4 also reports comovement with investment growth, which does not depend on a particular return construction.

Table 4: Investment and Stock Returns Correlations

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

The table reports correlations of stock returns with contemporaneous and one-year-ahead investment returns and with current and future investment growth; data moments are from [Liu et al. \(2009\)](#). ‘Benchmark’ uses Table 2; ‘No-LRR’ sets $\sigma_{x,c} = \sigma_{x,i} = 0$; ‘No-LRR & No-Sticky’ also sets $\phi_{p,c} = \phi_{p,i} = 0$; and ‘No-LRR & Perfect-Comp’ additionally sets $\mu_c = \mu_i \rightarrow \infty$. Model moments average annualized finite-sample simulations.

0.1, mirroring the empirical pattern.

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

Long-run productivity risks help quantitatively: in their absence (‘No-LRR’), the signs of the correlations in rows 1–4 are maintained, but the magnitudes are off. Specifically, the correlation between current market returns and contemporaneous investment growth (future investment return) is too low (high) — in absolute value — compared to the data.³²

Conversely, as shown in rows 1 and 3, in configurations without sticky prices — having either constant markup or perfect competition — investment measures and stock returns are (almost) perfectly positively correlated, counterfactually so. The fact that the contemporaneous correlation

³²In Online Appendix Section [OA.1](#) we explain why long-run risks help in this context, by contrasting our setup to [Basu et al. \(2013\)](#) which features habit formation, and consequently, fails to obtain a positive correlation between current stock returns and future investment returns.

between stock- and investment- return/growth is less negative (and even positive) in the absence of sticky prices is consistent with Stylized Fact 2(a). This counterfactual sign is prevalent in the literature (see, e.g., [Jermann, 1998](#); [Zhang, 2005](#); [Kaltenbrunner and Lochstoer, 2010](#); [Croce, 2014](#); [Garlappi and Song, 2017](#), among many others).

The contrast between the benchmark and the constant-markup case is important: under monopolistic competition, stock returns include the value of rents while investment returns are tied to the marginal value of installed capital. Market power indeed breaks the perfect correlation, but not the sign — when markups are invariant, the contemporaneous correlation remains strongly positive (0.90). Turning it negative requires rents to rise precisely when the marginal value of installed capital falls, a joint movement generated endogenously by our mechanism.

Importantly, our model addresses the puzzle with a single type of capital good. While introducing other types of capital could potentially decrease the correlation between stock- and investment-returns, by creating an additional wedge, the model-implied investment returns would not correspond to the empirical evidence of [Liu et al. \(2009\)](#), who only rely on physical capital.³³ Moreover, the puzzle’s resolution is not specific to the investment-return definition in equation (14). Online Appendix Section [OA.7](#) considers four alternative constructions based on [Liu et al. \(2009\)](#); all four produce a negative contemporaneous correlation with stock returns (Table [OA.4](#)).

4.1.1 Inspecting the Mechanism

To explain the core mechanism for the anomaly’s resolution, we shut down long-run risks and plot impulse response functions from technological innovations to macro variables, market stock

³³A recent study by [Gonçalves, Xue, and Zhang \(2020\)](#) suggests that when accounting for multiple types of capital goods, including working capital, the correlation between fundamental returns and stock returns could be mildly positive (around 0.1). Despite the fact that our model features a single type of capital, consistent with [Liu et al. \(2009\)](#), this close-to-zero estimate falls within the model’s confidence interval implied by finite sample simulations.

returns, and investment returns, contrasting the case with sticky prices (represented in blue) against those devoid of such rigidity (in red), as shown in Figure 3.

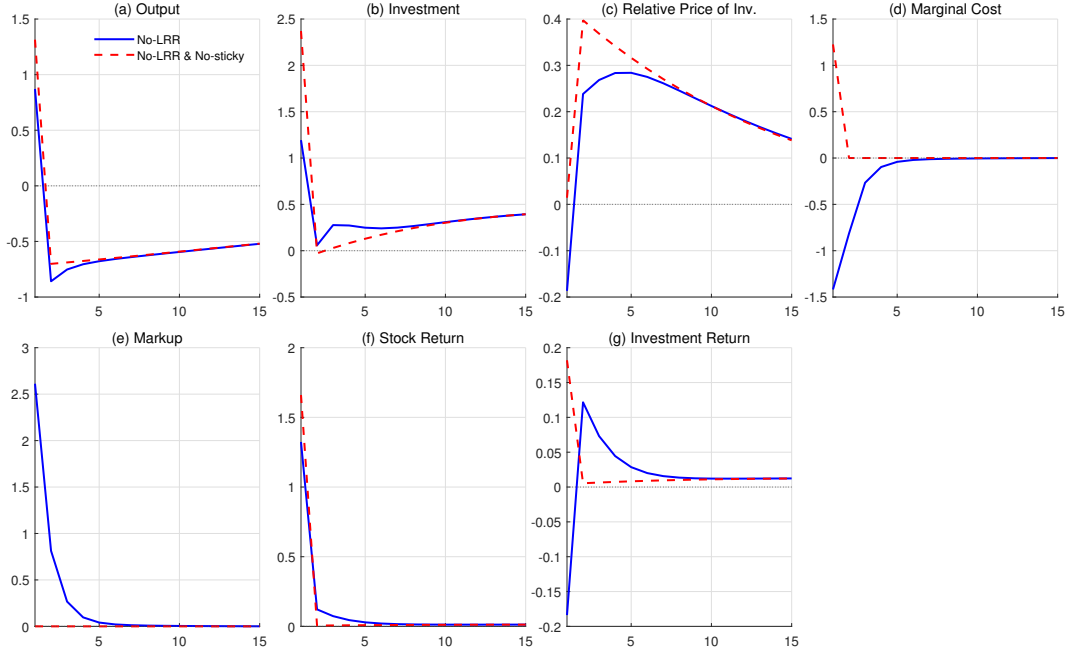
Underlying Macro Dynamics. Without sticky prices, a technological innovation increases firms' contemporaneous and future marginal productivity of capital. This prompts firms to immediately raise their investment, as shown by the red line in panel (b) of Figure 3. The demand for capital raises the relative price of capital goods (red line in panel (c)), and thereby increases firms' marginal production costs in panel (d). Notably, higher investment combined with a higher relative price of capital implies that capital growth strictly increases following the technological innovation, in contrast to Stylized Fact 1(b). We elaborate more on this tension in Section 6.1.

Nominal rigidities change the implications of technological innovations on the relative price of investment, from expansionary to contractionary. After a positive technological innovation, output underreacts to the supply shock, compared to the scenario with flexible prices (panel (a) of Figure 3). This more muted output response occurs as price levels are unable to fully react to the shock because of nominal rigidities, resulting in a contraction in the output gap. The decreased output gap, in turn, implies a decrease in the inflation gap, according to the New-Keynesian Phillips curve (equation (A.9)). Within the New-Keynesian framework, inflation is proportional to the expected discounted value of future marginal costs, which depend on the relative price of investment. Thus, the decline in the inflation gap under sticky prices, in turn, exerts downward pressure on the relative price of investment goods in the short run.

If the degree of price stickiness is sufficiently large — yet, empirically disciplined — the price of capital goods declines after a positive innovation, as illustrated by the blue line in panel (c). As explained later, this is instrumental in reconciling Stylized Fact 1(b). The countercyclical behavior of capital goods' prices is also consistent with the empirical findings of Greenwood et al. (1997)

and [Christiano and Fisher \(2003\)](#). Furthermore, the decrease in the price of capital goods drops the marginal production costs (panel (d)), in sharp contrast to the flexible price case.³⁴

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



Impulse responses to a one-standard-deviation aggregate technology shock. Blue lines show ‘No-LRR’; red dash-dotted lines show the same economy without sticky prices. Panels report output, investment, the relative investment price, marginal cost, markup, stock return, and investment return. The horizontal axis is in quarters and the vertical axis in percent deviations from steady state.

Returns. Under both the flexible and sticky price cases, positive technological shocks raise firms’ valuations and stock returns, as shown in panel (f) of Figure 3. In the sticky-price case, the higher valuation arises due to increased monopolistic rents: The drop in firms’ marginal costs mechanically raises markups (see panel (e)), as output prices are rigid in the short run. It is precisely this endogenous markup variation that breaks the perfect correlation observed in neoclassical settings, translating positive technology shocks into transient, innovation-driven contractions in investment returns. Specifically, within a two-sector New Keynesian framework, stock returns and investment

³⁴The IRFs plot the average marginal cost between the two sectors, each is proportional to $W_t^{1-\alpha_j} R_{K,j,t}^{\alpha_j}$, where W_t denotes the wage—the price of one unit of labor services—and $R_{K,j,t}$ denotes the rental rate (user cost) of one unit of installed capital services in sector j .

returns are not equal state-by-state. Two dominant, yet opposing forces affect investment returns:

On the one hand, technological shocks increase the marginal productivity of capital, thereby increasing investment rates, as in panel (b) of Figure 3. With capital frictions (adjustment costs), higher investment rates should also increase the shadow price of capital (which depends on the relative investment price and installation costs), and consequently, the return on investment. This dynamic, featured in the conventional flexible-price case, operates to induce a counterfactual strong positive correlation between stock and investment returns, as shown by the red line in panel (g).

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

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

4.2 Puzzle II: Labor markets surprises and stock valuations

We explore the ability of the model to resolve the puzzle of [Boyd et al. \(2005\)](#) among others, whereby equity valuations often rise in response to announcements of rising unemployment. The underlying premise is that greater unemployment signals an expected decrease in interest rates (see, e.g., [Elenev et al. \(2022\)](#)). [Xu and You \(2022\)](#) provide empirical evidence during the COVID period

and argue that following increased unemployment, investors anticipate greater fiscal interventions by the Federal Government, resulting in higher stock valuations.

In all of these 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,³⁵ the foundational empirical observations might not inherently be as “anomalous” once we recognize that technological innovations raise stock prices while simultaneously producing transient, innovation-driven contractions in labor demand.

Table 5 shows that our model explains this puzzle without resorting to aggressive exogenous policy shocks. We derive labor surprises within the model by subtracting expected employment from realized employment. Under the ‘Benchmark’ configuration, the correlations between labor surprises and either market stock returns or the risk-free rate are negative, and both are close to the data. This mirrors the average empirical case documented by [Boyd et al. \(2005\)](#).

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

Indeed, the correlation between labor market surprises and the stock market exhibits time variation. In particular, [Boyd et al. \(2005\)](#) find that rising unemployment is good news for equities, particularly during economic expansions, when nominal interest rates are high. Our framework is

³⁵In Online Appendix [OA.2](#) we corroborate that changes to the conduct of monetary policy can decrease the correlation between market returns and labor surprises. However, in general equilibrium, the impact on the correlation — purely from policy expectations — is quantitatively very small, even when the policy rule is counterfactually too aggressive.

Table 5: **Labor Market Surprises and Stock Returns**

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

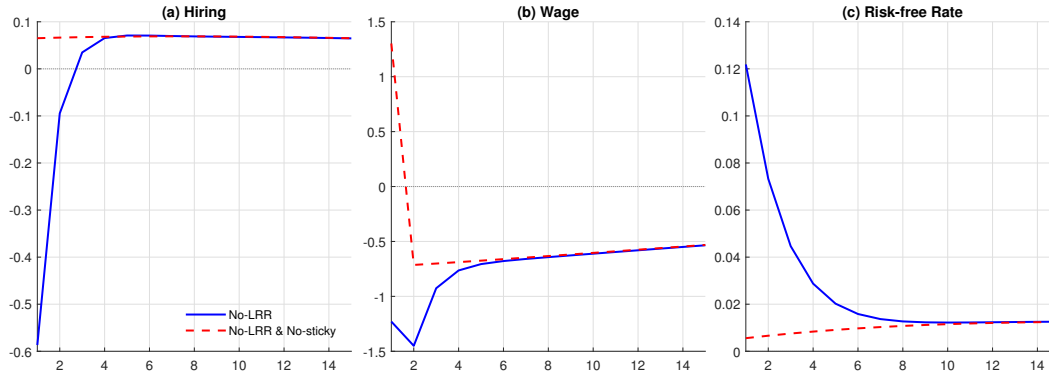
The table reports correlations of labor surprises, $N_t^{\text{surprise}} = N_t - E_{t-1}[N_t]$, with the market return and the real risk-free rate. Columns use the four configurations defined in Table 3; model moments average annualized finite-sample simulations. In the data, labor surprises are AR(1) residuals of aggregate annual employment over 1953–2019. The real rate is the 3-month T-bill rate less one-year-ahead inflation predicted from lagged inflation, the T-bill rate, and the Baa–Aaa spread.

able to replicate this finding when accounting for the findings of Vavra (2014) that the frequency of price changes is countercyclical in the data. In the Online Appendix we incorporate this insight by augmenting the ‘No-LRR’ model configuration with a procyclical degree of price rigidity. The results are reported in Table OA.12. The benchmark holds adjustment costs and Rotemberg parameters fixed; the empirical state-dependence exercise instead asks whether the model’s comparative static is visible across externally observed rigidity states, conditioning on observed price-adjustment frequency rather than treating cyclical rigidity as an endogenous benchmark-model outcome. The data order the disconnections in the same direction as the model counterfactual. During expansions, the nominal interest rate and the nominal price rigidity are both high, leading to a negative correlation between labor surprises and the market. During recessions, when the nominal interest rate is low, the degree of price stickiness falls, decreasing the role of the monetary authority and attenuating markup fluctuations. As in the perfect competition case, the correlation between the stock market and labor market surprises turns positive, in line with Stylized Fact 2(b).

4.2.1 Inspecting the Mechanism

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

Figure 4: **Model-Implied Impulse Responses of Employment, Wages, and the Risk-Free Rate**



Impulse responses of employment, wages, and the real risk-free rate to a one-standard-deviation aggregate technology shock. Blue lines show ‘No-LRR’; red dash-dotted lines show the same economy without sticky prices. The horizontal axis is in quarters and the vertical axis in percent deviations from steady state.

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

However, as discussed in Section 4.1.1, when prices are sticky a positive technological innovation leads to a decline in the output gap, suggesting that hours should decrease in response to the positive technology shock. To see why, the decline in the output gap ultimately leads to a lower wage bill (blue line in panel (b) of Figure 4): an output gap drop exerts a downward pressure on the marginal costs of production — which depend not only on the relative price of capital (as previously discussed) — but also on labor costs. The drop in firms’ marginal costs raises markups as output prices are rigid in the short run (panel (e) of Figure 3).

The higher markups effectively act as an endogenous, implicit tax on production—they induce a rationing effect on desired employment, and, in sharp contrast to flexible prices, total employment

contracts in the short run (blue line in panel (a)). This contractionary effect of positive innovations is consistent with Stylized Fact 1(a). At the same time, the higher markups enhance valuations via higher monopolistic rents, as depicted in panel (f) of Figure 3, generating a negative unconditional comovement between stock returns and labor market surprises.

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

The Role of Expectations. In reality, labor market releases occur in a short window, leaving little time for productivity to affect cash flows. This timing, however, is immaterial for our conceptual mechanism. What matters is that a labor market surprise reveals information about productivity, which in turn, shifts expectations of future profits. In our model, higher productivity raises future markups and the expected value of future dividends, even if no cash-flow change occurs at labor announcement. Put differently, the conventional interpretation of the negative correlation between labor surprises and valuations is that markets *learn* about future monetary easing when labor data are weak, lowering *expected* discount rates. In contrast, our mechanism operates through *expectations* of higher future markups: when employment news is weaker than expected, agents *infer* higher productivity and anticipate greater monopolistic rents ahead.

Table 6: Cyclicity of the Equity Yield Term Structure

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

The table reports ϕ_n from the equity-yield slope regression and β_n from the expected-dividend-growth regression, for $n \in \{8, 12, 16, 20\}$ quarters. The empirical ϕ_{20} is from [Gormsen \(2021\)](#). ‘Benchmark’ uses Table 2; ‘No-LRR’ removes long-run risk, and ‘No-LRR & No-Sticky’ also removes price rigidity. Model entries average 1,000 simulations of 160 quarters after a 400-quarter burn-in; brackets report 90% confidence intervals.

4.3 Puzzle III: The Cyclicity of the Equity-Yield Term Structure

The slope of the equity-yield term structure is procyclical in the data—it is higher in good economic states and lower in bad ones—a pattern that canonical long-run-risk models struggle to reproduce ([Bansal et al., 2021](#)). We show that our mechanism delivers this cyclicity as a further application, not as identifying evidence.³⁶ Let $P_{t,n}$ denote the time- t price of a dividend strip paying d_{t+n} in n periods, defined recursively by $P_{t,0} = d_t$ and $P_{t,n} = \mathbb{E}_t[M_{t,t+1}P_{t+1,n-1}]$. The maturity- n equity yield is $e_{t,n} = \frac{1}{n} \log(d_t/P_{t,n})$, and its slope relative to the one-quarter yield is $\text{Slope}_{t,n} = e_{t,n} - e_{t,1}$. We assess the cyclicity of this slope with the predictive regression

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

where dp_t is the log market dividend yield. Since dp_t is low in good states, a procyclical slope—one that rises in good states—moves opposite to dp_t , corresponding to $\phi_n < 0$.

Table 6 reports $\phi_n < 0$ at every maturity in both the ‘Benchmark’ and ‘No-LRR’ specifications, consistent with the procyclicity documented by [Bansal et al. \(2021\)](#). At 20 quarters, the bench-

³⁶This application is not used for identification, which rests on short-horizon input responses to technology shocks and on the dependence of market-macro comovements on price rigidity.

mark coefficient is -0.22 , close to the empirical value of -0.33 from [Gormsen \(2021\)](#), whereas the No-LRR coefficient is -0.51 . Without sticky prices, ϕ_n is essentially zero and nonnegative, so the slope is acyclical or weakly countercyclical. Thus, nominal rigidity delivers the procyclical sign, while long-run risk brings the magnitude closer to the data.

4.3.1 Inspecting the Mechanism

The procyclical slope follows from the cash-flow dynamics of Sections 4.1.1 and 4.2.1. After a positive technology shock, sticky prices contract labor, so realized dividend growth on impact is lower than in the flexible-price counterfactual. As prices adjust and the contraction dissipates, dividends are expected to catch up toward the flexible-price path, so near-term expected dividend growth is high relative to the depressed current dividend. A negative shock reverses the pattern: current dividends are relatively high and near-term expected growth is low.

This tilts the term structure of expected dividend growth. In good states the short-horizon expected growth rate rises by more than the longer-horizon average, so the gap $E_t[g_{d,t,t+n}] - E_t[g_{d,t,t+1}]$, with $g_{d,t,t+n} = n^{-1} \ln(d_{t+n}/d_t)$ the n -period average dividend growth, becomes more negative. Because good states carry a low dp_t , the dividend-growth regression $E_t[g_{d,t,t+n}] - E_t[g_{d,t,t+1}] = \text{const} + \beta_n \cdot dp_t + \text{error}$ then has $\beta_n > 0$; bad states reverse the tilt. Table 6 confirms $\beta_n > 0$ under ‘Benchmark’ and ‘No-LRR,’ but $\beta_n \leq 0$ without sticky prices.

The maturity structure of equity yields inherits this cash-flow tilt. Higher near-term expected dividends raise the prices of short-maturity dividend strips, which lowers the short-maturity yield $e_{t,1}$ by more than the longer-maturity yield $e_{t,n}$ and therefore raises the slope in good states. The procyclical slope is thus a consequence of the state-dependent cash-flow tilt. Sticky prices are what generate this state-dependent slope: absent them, β_n is about zero or negative and the procyclicality

disappears, as in the ‘No-Sticky’ column. Long-run risk plays a mainly quantitative role, moving the magnitude of ϕ_n toward the data without changing its sign.

Additional Extensions. Online Appendix Section [OA.8](#) shows that the same mechanism reconciles book-to-market and gross profitability as return predictors: a technology shock raises productivity on impact but later lowers annual profits through the ensuing labor contraction, allowing both characteristics to signal high expected returns.

5 Return Predictability

Beyond explaining the three valuation–activity disconnections, the dynamics of innovation-driven contractions generate a model-implied state variable that can be used to forecast returns. This section defines an investment-based dividend yield, recovers its historical path from observed productivity shocks, and evaluates its ability to predict future market excess returns.

Consider a claim on installed capital. For each sector $j \in \{c, i\}$, the claim is priced at its shadow value $q_{j,t}$, and its payout is the marginal value of capital net of that price:

$$P_{j,t}^I = q_{j,t}, \quad \text{Div}_{j,t}^I = \frac{\partial V_{j,t}}{\partial k_{j,t}} - q_{j,t}.$$

Here $q_{j,t}$ is the sectoral claim price, $\text{Div}_{j,t}^I$ the sectoral payout. For each sector j , define the one-year investment-based dividend yield, $dp_{j,t}^I$, as the trailing four-quarter payout sum over the current claim-price denominator $P_{j,t}^I$: $dp_{j,t}^I = \frac{\sum_{\ell=0}^3 \text{Div}_{j,t-\ell}^I}{P_{j,t}^I}$. The aggregate dp_t^I value-weights the two sectoral yields by each sector’s lagged share of total firm value. We use “dividend yield” terminology by analogy: dp_t^I is a model-implied cash-to-price multiple, but not a yield on a traded security.

We build the historical dp_t^I series in two steps. *First, we recover the shock history:* under the benchmark short- and long-run technology restrictions, we back out the quarterly innova-

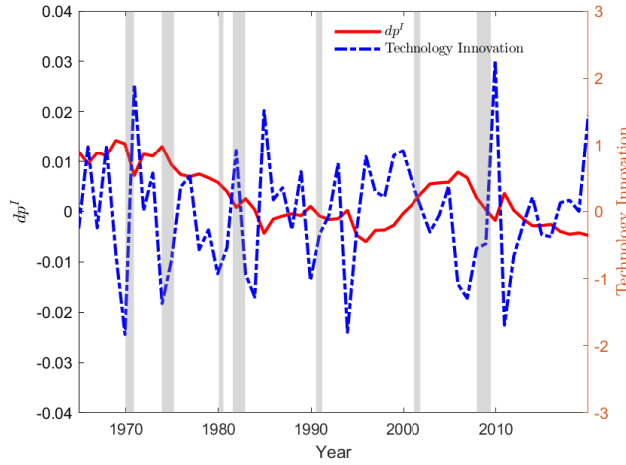


Figure 5: **Technology Innovations and Investment-Based Dividend Yields**

Annualized recovered technology innovations and the model-filtered dp_t^I , 1964–2019. The recovered shock sequence is fed through the benchmark model; Online Appendix Section OA.9 details the construction.

tions $\{\epsilon_t^{Data}\}_{1964Q1}^{2019Q4}$ that make model-implied aggregate technology growth match the utilization-adjusted TFP growth of Fernald (2014). *Second, we generate the yield:* starting from the model’s stochastic steady state, we feed the recovered innovations through the nonlinear equilibrium, which produces the paths of sectoral markups, labor, relative investment prices, the claim prices $q_{j,t}$, the investment payouts, and the sectoral and aggregate dp_t^I . No stock return, market dividend yield, or other financial-market data enter the construction; because the equilibrium mapping is nonlinear, dp_t^I is neither raw TFP nor a linear transform of it.

Figure 5 plots the annualized recovered technology innovations and model-filtered dp_t^I . We then project future market excess returns on dp_t^I . For brevity, Online Appendix Sections OA.9 and OA.10 report the full set of in- and out-of-sample regressions and a cross-sectional extension, while here we summarize the key elements. In both the model and the data, the slope coefficient is negative and statistically significant at every horizon — the opposite of the sign on the conventional stock-market dividend yield dp_t .³⁷ The negative sign is itself informative, indicating that dp_t^I is

³⁷The goal of the exercise is to test an implication that holds inside the model — the filtered dp_t^I should forecast market excess returns with a negative sign — as an additional untargeted restriction on the mechanism, not to establish

a predictor that encapsulates the dynamics of innovation-driven contractions: under perfect competition, the model-implied relation between dp_t^I and future excess returns turns positive, whereas the relation in the data remains negative, echoing the stock–investment comovement failure of Section 4.1. What is even more striking is the forecasting power: empirically, the adjusted R^2 on dp_t^I rises from 11% at one year to 35% at five years, exceeding those for dp_t and the consumption-to-wealth ratio (cay), while the out-of-sample R^2 is positive at every horizon, ranging from 7% to 15% — whereas the corresponding out-of-sample R^2 values for dp_t and cay are negative throughout.

6 Testing the Mechanism

We validate innovation-driven contractions in two ways. Section 6.1 asks whether the calibrated model reproduces the untargeted input responses in Table 1—lower hours and statistically insignificant capital growth—that underpin the asset-pricing mechanisms above. Section 6.2 tests two labor-market predictions generated by the interaction of sticky prices and the two-sector structure.

6.1 Theoretical Test: Matching Inputs Response to Innovations

Using model simulated paths, we run the projections from equation (1) within the context of the model.³⁸ We perform regressions of growth in hours and capital on the aggregate technological change, denoted dz . The duration of model-implied paths is identical to its empirical counterpart. Table 7 shows the median slope coefficient derived from a thousand finite sample simulations, accompanied by the model-implied confidence intervals. It provides a direct model counterpart to the impact restriction in Table 1. Importantly, all slope coefficients are not targeted by our

dp_t^I as a new empirical predictor that passes the fragility tests of the predictability literature (e.g., Goyal and Welch, 2008; Goyal et al., 2024).

³⁸In the model analysis, we do not include lagged values of dz as all shocks are i.i.d.

Table 7: **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, 0.06]	0.06 [0.06, 0.06]
(2) $b_{K,t}$	0.04 [-0.04, 0.10]	0.01 [-0.02, 0.06]	0.15 [0.13, 0.18]	0.16 [0.12, 0.17]

The table reports $b_{y,t}$ from $\Delta y_t = \text{const} + b_{y,t} dz_t + \varepsilon_t$, where dz_t is quarterly aggregate technology growth and $y \in \{N, K\}$ denotes hours (N) and capital (K). Columns use the four configurations defined in Table 3. Entries average over 1,000 simulations of 160 quarters after a 400-quarter burn-in; brackets report 95% confidence intervals.

calibration — providing an over-identification angle to test our framework.

Several insights emerge from Table 7. First, the benchmark model replicates the contractionary or muted reactions of inputs to technological innovations. After a positive shock, there is a marked decline in hours growth, with a slope coefficient of -0.43, compared with -0.38 in the data (Stylized Fact 1(a)). The model’s response of capital growth to technological innovations is 0.04, matching the data. The slope’s *insignificance* within the model aligns with the empirics (Stylized Fact 1(b)). These slope coefficients are not calibration targets, providing an untargeted validation.

Second, long-run risk shocks are not material for these effects. The slope coefficients under the ‘No-LRR’ configuration also exhibit a pronounced decline in hours growth and an even more muted and insignificant capital growth correlation with short-term technological innovations. Lastly, monopolistic competition and sticky prices are crucial to produce contractionary effects. Under both ‘No-LRR & No-Sticky’ and ‘No-LRR & Perfect-Comp’ configurations, the model fails to produce a contraction in the labor and an insignificant response in capital. Hours rise after a positive technology shock, contrasting with Stylized Fact 1(a). Furthermore, the slope coefficient associated with capital growth turns statistically *significant*, contrasting with Stylized Fact 1(b).

While the negative effect of technological innovations on labor was explained in Section 4.2.1, the effect of these shocks on capital growth is more intricate (as hinted in Section 4.1.1), and necessitates the two-sector structure. On the one hand, investment quantity increases following a positive shock (see Figure 3 panel (b)). On the other hand, under sticky prices, the relative price of investment declines (see Figure 3 panel (c)). This counteracting dynamic is absent in a single-sector model.³⁹ The joint impact manifests itself as a muted effect on capital growth, which turns statistically insignificant in finite samples, echoing the data.⁴⁰

6.2 Empirical Test: Labor-Market Predictions

The model yields two labor-market predictions. Both predictions are untargeted by the calibration, yet appear in the data: First, a positive technology shock lowers wages under sticky prices, rather than raising them as in the flexible-price benchmark (Section 4.2.1). Second, because the investment sector responds more strongly to aggregate technology shocks, and the relative price of investment falls on impact, employment contracts more in that sector: the consumption-sector employment share, $n_c/(n_c + n_i)$, therefore rises initially and reverses as the relative price recovers. We test these predictions in an annual VAR analysis over 1964–2019. For brevity, Online Appendix Section OA.11 details the data construction. Figure 6 reports the empirical impulse-responses: wages fall persistently after a positive technology shock,⁴¹ while the consumption-sector employment share rises initially before falling below its steady-state level at longer horizons, as in the

³⁹In untabulated one-sector versions of the model—either with an identical calibration or a perturbed one—we cannot jointly reproduce realistic investment volatility and an insignificant capital-growth response: either the coefficient is indistinguishable from zero but the volatility of investment growth is too small, or the coefficient is strictly positive.

⁴⁰Notably, our model allows labor to adjust freely, while capital faces adjustment costs. Although this asymmetry potentially affects the absolute magnitudes of factor responses, it does not explain their sign. As Table 7 shows, holding the degree of capital adjustment costs fixed across all columns, labor reacts negatively to a productivity innovation only when prices are sticky and markups fluctuate. When prices are flexible, the response of capital growth to a positive innovation is strictly positive despite the presence of adjustment costs.

⁴¹Following Basu et al. (2006), these conditional wage responses need not imply that wages are unconditionally countercyclical. Procyclical demand shocks, which the model abstracts from, can dominate in aggregate data.

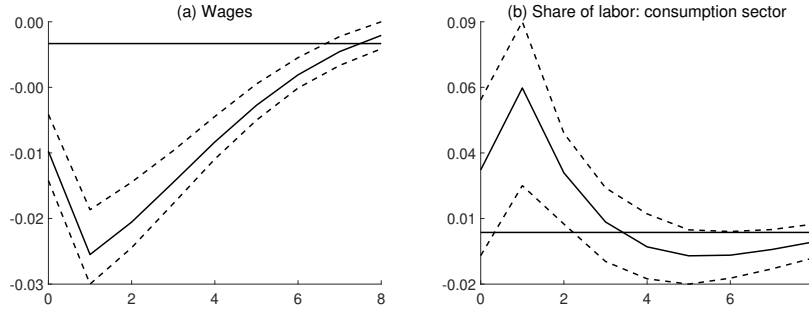


Figure 6: **Empirical Labor-Market Responses to Technology Shocks**

Impulse responses to a one-standard-deviation technology shock from an annual VAR(1) over 1964–2019. Panel (a) shows wages; panel (b) the consumption-sector employment share. Dashed lines are 90% confidence intervals. Online Appendix Section OA.11 reports data construction, variable ordering, and filtering.

model: Figure 4 and Online Appendix Figure OA.5 report the model counterparts. The model also provides a *cross-sectional prediction*: positive technology shocks raise markups by more and employment by less where prices are stickier. Online Appendix Section OA.12 finds direct support for this prediction in firm-level panel data.

7 Conclusion

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

Two facts anchor the analysis: (i) technology shocks contract labor while not affecting capital growth, and (ii) disconnections intensify when prices are stickier. Using the New Keynesian machinery, we show that a two-sector framework with Rotemberg pricing, disciplined by these facts, quantitatively accounts for the negative contemporaneous comovement of investment and stock returns, the “bad labor news is good news for stocks” phenomenon, and the procyclical slope of

the equity-yield term structure. Moreover, investment-based dividend yields, filtered from a model that generates innovation-driven contractions, exhibit strong predictive power for future market excess returns, in and out of sample. The model reproduces input responses to technology shocks without targeting them and delivers auxiliary labor-market predictions borne out in the data.

Future work can benefit from incorporating this channel to better align with both time-series and cross-sectional evidence. Promising directions include studying the implications of the mechanism for the bond term structure, for models with heterogeneous firms and multiple types of capital goods, and for environments with richer financial frictions.

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Online Appendix for

“Innovation-Driven Contractions:

A Missing Link for Asset Pricing Puzzles”

This Online Appendix collects material supporting the main text. Section [OA.1](#) replicates Basu, Fernald, and Liu (2013) and contrasts their model with ours. Section [OA.2](#) evaluates labor-targeted monetary-policy rules and their effect on the stock–labor-surprise correlation. Section [OA.3](#) reports the firm-level evidence distinguishing a markup-rationing channel from broad displacement. Section [OA.4](#) repeats the Stylized Fact 2 analysis at the granular level of the Fama–French 49 industries. Section [OA.5](#) collects further model details—the household problem, the monetary authority, the equilibrium conditions, and the mapping to a Calvo pricing framework. Section [OA.6](#) presents the model’s first-order conditions and their detrended form. Section [OA.7](#) considers alternative constructions of investment returns. Section [OA.8](#) links book-to-market and gross profitability to dividend yields. Section [OA.9](#) constructs the investment-based dividend yield and reports its in- and out-of-sample return-predictability evidence. Section [OA.10](#) examines its cross-sectional implications. Section [OA.11](#) reports the data construction and VAR evidence for the labor-market predictions. Section [OA.12](#) tests the model’s cross-sectional prediction that technology shocks raise markups by more and employment by less where prices are stickier. Section [OA.13](#) reports additional results, including a preference-robustness comparison under additively separable utility.

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

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

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

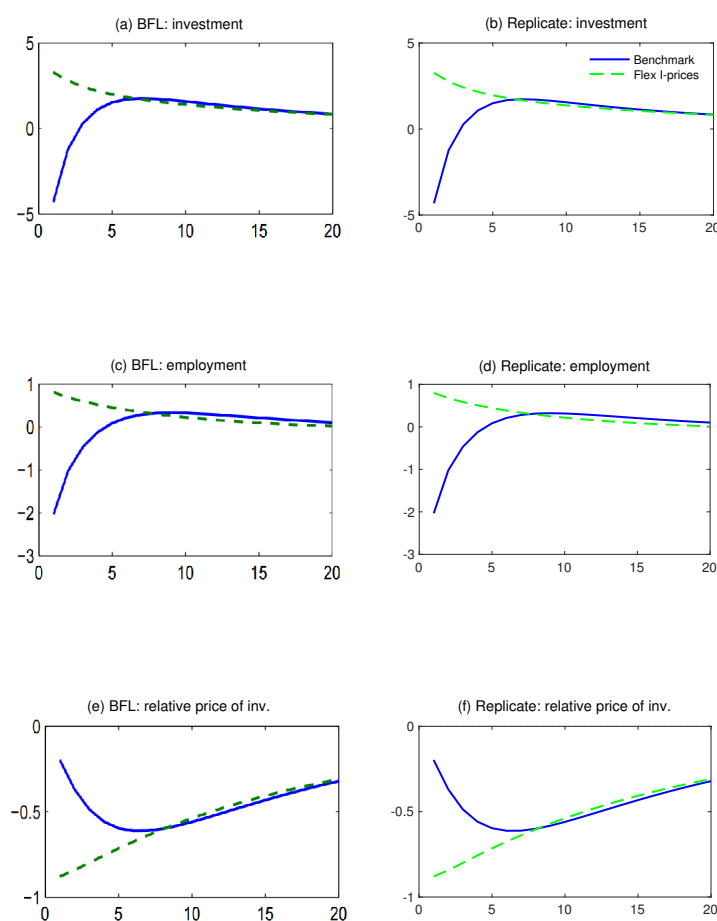
Replication of Macro Dynamics. We begin by solving the quantitative model of BFL. Despite empirical evidence from [Basu et al. \(2006\)](#) that *common* (or aggregate) technological shocks induce labor contractions, the BFL model generates a contraction only from investment-specific technology shocks.¹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

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

confirms successful replication.

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

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



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

This discrepancy arises from the response of the relative price of investment to technology

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

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

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

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

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

Puzzle I. Panel A shows that, similar to our model, BFL can generate a negative contemporaneous correlation between investment and stock returns. The underlying mechanism, involving the drop in the relative price of capital, parallels our framework. Yet, this addresses only one aspect of the comovement puzzle. In the data, the correlation between stock returns and one-year-ahead investment returns turns positive. While our model replicates this feature (see Table 4), Panel A of Table OA.1 shows that in BFL, the correlation between stock returns and future investment returns remains negative, counterfactually, persisting up to four years ahead. This failure traces directly to BFL’s inability to replicate Stylized Fact 1(b), linked to the overly persistent decline in the relative price of investment, which—unlike in our model—does not recover quickly. This reflects a combination of mean reverting productivity shocks coupled with a strong wealth effect. Those inherent features of BFL imply that this counterfactual correlation remains under different calibrations.

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

Moment Description	BFL (2013)
<i>Panel A: Investment and Stock Return Correlations (Ref: Table 4)</i>	
$\text{corr}(R_{M,t}^I, R_{M,t}^S)$	-0.06
$\text{corr}(R_{M,t+1}^I, R_{M,t}^S)$	-0.20
$\text{corr}(R_{M,t+2}^I, R_{M,t}^S)$	-0.12
<i>Panel B: Labor Market Surprises (Ref: Table 5 & Table OA.12)</i>	
$\text{corr}(N^{\text{surprise}}, R_{M,t}^S)$	-0.34
$\text{corr}(N^{\text{surprise}}, R_{M,t}^S)$ under low $r_t^{\$}$	-0.13
$\text{corr}(N^{\text{surprise}}, R_{M,t}^S)$ under high $r_t^{\$}$	0.12
$\text{corr}(N^{\text{surprise}}, R_t^f)$	0.24
<i>Panel C: Cyclicalities and Regression Slopes (Ref: Table 6 & Table 7)</i>	
ϕ_{20} (Equity Yield Slope)	2.99 [-26.82, 5.13]

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

Puzzle II. As the BFL model can generate a labor decline following a positive technology shock,

Panel B indicates it can also produce a negative unconditional correlation between labor surprises and the stock market. However, unlike our model (Table 5), their model generates a counterfactual positive correlation between the risk-free rate and labor surprises. Moreover, when cyclical variation in price stickiness is introduced, their model predicts that the correlation between stock returns and labor surprises turns negative (positive) when the nominal interest rate is low (high), opposing evidence from [Boyd et al. \(2005\)](#) and Table OA.12. Both counterfactuals directly result from habit formation altering the cyclical properties of the risk-free rate. Nonetheless, habit formation is necessary in BFL for achieving a high unconditional risk premium, given their persistent mean-reverting shocks.

Puzzle III. Projecting the equity yield term structure slope on the dividend-price ratio, Panel C shows that BFL generates a statistically insignificant positive slope, implying a countercyclical or at best acyclical relationship, counter to evidence by [Gormsen \(2021\)](#). Two factors explain this result in BFL. First, the relative price of capital persistently declines up to 10 quarters ahead, unlike our model’s immediate overshoot and recovery. Investment rates similarly decline over the medium term. Consequently, short-term dividends do not exhibit the “catch-up” dynamics of our model — they are expected to be lower short-term due to a persistent fall in the capital stock. Second, habit formation transforms the dividend yield from procyclical to countercyclical under mean-reverting shocks. Together, these factors render ambiguous impact of innovation-driven contractions on the slope’s cyclicity in BFL, contrasting sharply with our model.

OA.2 Labor-Targeted Monetary Policy

Several studies argue that the stock market’s response to a negative labor surprise can, counter-intuitively, be positive, as investors expect policymakers to persistently decrease interest rates. In

this section, we show that, in contrast to this common logic, within a general equilibrium New Keynesian model such policy expectations induce only a small effect on the comovement between returns and labor market news. These findings emphasize the central quantitative role of innovation-driven contractions in generating the negative comovement between stock returns and labor surprises, above and beyond policy revisions.

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

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

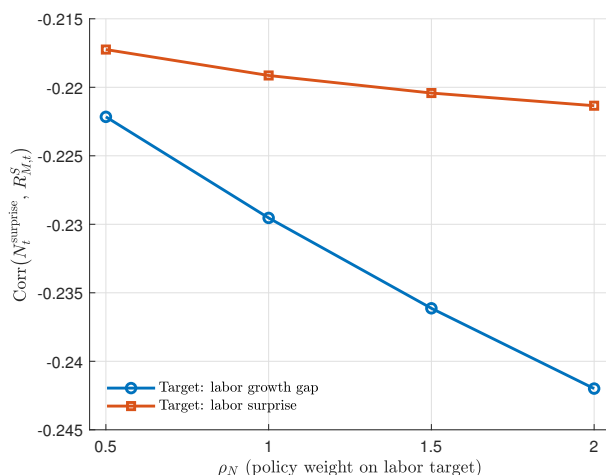
Second, while the dual mandate typically translates to a weight of 0.5 on the output gap (or labor gap) component, we deliberately push the coefficient on the labor gap gradually from 0.5 to 2, making monetary policy potentially very “aggressive.” All other parameters for the policy rule are identical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

Figure OA.2 plots the equilibrium correlation between labor surprises and stock returns under both policy variants above, as a function of the coefficient on the labor gap (ρ_N) on the horizontal axis. First, when ρ_N is 0.5, as in the benchmark model, the correlation is negative and very similar in magnitude to that reported in Table 5. Second, increasing ρ_N —placing more weight on the labor target—makes the correlation qualitatively lower. Intuitively, a higher ρ_N strengthens valuations through the discount-rate channel when labor is low, pushing the stock–labor-surprise correlation

further negative. However, quantitatively, the marginal change in the correlation is small and close to zero. Under policy variant (i), the correlation drops by about -0.02 when ρ_N rises from 0.5 to 2. Under variant (ii), the absolute change in the correlation is even smaller. Consequently, changes in investors' expectations about either monetary policy conduct or the nominal interest rate path produce only a minute effect on the correlation between labor surprises and stock returns.

While interest-rate expectations can cushion bad macroeconomic news, in equilibrium, the absolute drop in the correlation under the most aggressive policy is about 0.02. This effect alone is far too small to flip the sign of the correlation—which, in the absence of innovation-driven contractions, amounts to 0.93 (see Table 5).

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



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

OA.3 Innovation and Firm-Level Analysis

The firm-level analysis is complementary to the aggregate evidence. Citation-weighted patent values capture the private value of innovation for a selected set of firms and are not intended to

identify the aggregate technology shock. Instead, the exercise distinguishes a markup-rationing channel from broad displacement.⁴

For firm i in industry j , we estimate the panel regression

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

following [Kogan et al. \(2017\)](#) and [Huang, Papanikolaou, and Kogan \(2025\)](#). The variable $Acw_{i,t-1}$ is the firm's lagged innovation intensity, constructed from citation-weighted patent values. The vector $X_{i,t}$ contains firm size, book-to-market, and leverage, measured as in [Hou, Mo, Xue, and Zhang \(2019\)](#). The specification includes firm fixed effects α_i and industry-by-year fixed effects $\delta_{j,t}$.

The dependent variables are the log growth rates of the firm's employment, capital, competitors' employment, and markup. Competitors' employment is the employment of all other firms in the same two-digit SIC industry and year. Markup is sales divided by adjusted operating expenses, where operating expenses exclude R&D and 30% of SG&A, following [Ayyagari, Demirgüç-Kunt, and Maksimovic \(2024\)](#). The sample consists of annual Compustat observations from 1953 through 2019.

The markup-rationing channel predicts that innovation raises the innovating firm's markup while reducing its own labor input. Broad displacement instead predicts that innovators expand while competitors contract. The muted aggregate capital response also suggests little change in the innovating firm's capital growth.

Panel A of Table [OA.2](#) shows that innovation is associated with lower own employment growth (coefficient -5.31 , t -statistic -5.22) and no detectable change in capital growth (coefficient -0.25 ,

⁴Measurement error in patent-based innovation intensity tends to attenuate estimated relationships. The main use of Table [OA.2](#) is therefore qualitative: whether employment reductions occur within innovating firms or among their competitors, and whether markups rise after innovation.

Table OA.2: Innovation and Firm-Level Outcomes

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

This table reports panel regressions where the dependent variables are (1) employment growth (EMP_Growth), (2) capital (asset) growth (Cap_Growth), (3) competitors' employment growth (Competitor_Emp_Growth), and (4) markup growth (Markup_Growth), all measured as log-differences. The key independent variable is lagged innovation intensity (Acw_{t-1}), constructed following [Kogan et al. \(2017\)](#). Variable definitions and controls are described in the surrounding text. Coefficients are multiplied by 100. t-statistics (in brackets) are based on heteroskedasticity-robust standard errors clustered by firm and year. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

t -statistic -0.21). The first result is consistent with the labor contraction in Stylized Fact 1, while the second mirrors the muted capital response.

The remaining columns distinguish the markup-rationing channel from broad displacement. If displacement were the first-order source of the aggregate contraction, innovators should expand while competitors contract, and both labor and capital services should weaken over the same short horizon. Instead, competitors' employment is essentially unchanged (coefficient 0.01, t -statistic 0.43). Displacing productivity shocks also typically carry a negative risk price ([Kogan et al., 2013](#)), unlike the positive risk price on aggregate Hicks-neutral technology.

Column (4) shows that innovation is followed by higher own markups (coefficient 0.91, t -

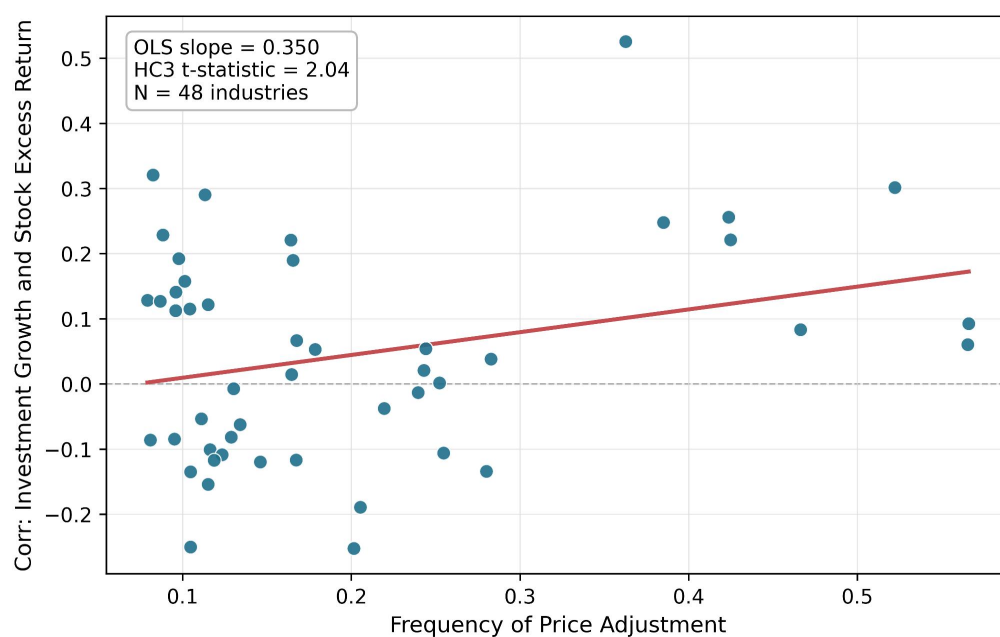
statistic 2.37). Taken together, the decline in own employment, the absence of a competitor-employment response, and the rise in markups are more consistent with a markup-rationing channel than with expansion by innovators at their rivals' expense. This evidence provides a firm-level bridge between the labor response in Stylized Fact 1 and the price-rigidity evidence in Stylized Fact 2.

OA.4 Stylized Fact 2 at the Industry Level

This section repeats the portfolio-level analysis underlying Stylized Fact 2 at the granular level of the Fama–French 49-industry (FF49) classification, for which price-adjustment frequency can be measured. Figure OA.3 plots, for each retained FF49 industry, the time-series correlation between annual industry investment growth and the contemporaneous industry stock excess return against the industry's frequency of price adjustment. The construction follows Figure 1 of the main text: for each year, industry investment growth is paired with the industry's value-weighted excess return, compounded over the twelve months ending in June of that year. Industry investment growth is the total-assets-weighted average of firm-level investment growth rates, and the price-adjustment frequency of Pasten et al. (2021) is measured at the four-digit NAICS level and aggregated to FF49 using total-assets weights. The sample covers 1963–2019, requires at least 20 annual observations per FF49 industry, and excludes four-digit NAICS cells represented by fewer than 25 unique firms.

The estimated slope is 0.350 ($t = 2.04$): investment growth and equity returns comove more positively where prices adjust more often — equivalently, the contemporaneous investment–valuation disconnection is stronger in industries with stickier prices, consistent with Stylized Fact 2. Because the dependent variable in this regression is itself an estimated correlation, two econometric con-

Figure OA.3: **Correlations and Frequency of Price Adjustment (Industry Level)**



The figure plots, for each of 48 FF49 industries, the time-series correlation between annual industry investment growth, $I_{j,t+1}/I_{j,t}$, and the contemporaneous industry stock excess return, $R_{j,t+1}^S$, against the industry's frequency of price adjustment from [Pasten et al. \(2021\)](#). Firm-level investment is capital expenditure net of sales of property, plant, and equipment; firm-level investment growth is aggregated using lagged total assets. Industry stock returns are value weighted and compounded over the July-to-June return year; four-digit NAICS frequencies are aggregated to FF49 using total-assets weights. The sample covers 1963–2019, requires at least 20 annual observations per FF49 industry, and excludes four-digit NAICS cells represented by fewer than 25 unique firms. The red line is the OLS fit. The estimated slope is 0.350, with an HC3 heteroskedasticity-robust t -statistic of 2.04.

cerns arise: correlations are bounded, so their sampling distribution can be skewed, and industries observed over fewer years deliver noisier correlation estimates. Table OA.3 addresses both. The Fisher z transformation maps each correlation to an unbounded scale with approximately normal sampling error, and precision-weighted least squares weights each industry by the inverse sampling variance of its estimated correlation, preventing short-sample industries from driving the fit. Under either adjustment, or both, the slope remains between 0.350 and 0.365 with t -statistics between 2.01 and 2.05: the relation is not an artifact of estimation noise in the industry correlations.

Table OA.3: Robustness of the Industry-Level Frequency–Comovement Relation

	(1)	(2)	(3)	(4)
	Baseline	Fisher z	Precision WLS	WLS + Fisher z
Price-adjustment frequency	0.350** (0.172)	0.365** (0.181)	0.350** (0.171)	0.365** (0.180)
t -statistic	2.04	2.01	2.05	2.02
Industries	48	48	48	48
Fisher transformation	No	Yes	No	Yes
Precision weighting	No	No	Yes	Yes

The table reports the cross-sectional slope of the FF49 industry-level correlation between investment growth and contemporaneous stock excess returns on the industry price-adjustment frequency. Column (2) replaces each raw correlation ρ_j with its Fisher transformation, $z_j = \text{arctanh}(\rho_j)$. Column (3) estimates the raw-correlation regression by weighted least squares using $T_j - 3$ as the precision weight, where T_j is the number of annual observations entering industry j 's correlation; column (4) combines the Fisher transformation and the same precision weights. HC3 robust standard errors are reported in parentheses. Sample construction is as in Figure OA.3. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

OA.5 Further Model Details

OA.5.1 Household Problem

The representative household owns the intermediate-goods firms in both sectors, supplies labor N_t , and chooses consumption and labor to maximize the recursive utility in equation 11.

Its problem is

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

Here $P_{c,t}$ is the nominal price of the consumption good and W_t is the nominal wage. The household receives wage income and the dividends of firms in both sectors. Its labor-supply first-order condition is reported in equation A.12, and equation 12 gives the nominal stochastic discount factor.

We hold the time discount factor fixed and abstract from demand shocks, despite their importance in the macroeconomic literature, to isolate the supply-shock dynamics that motivate the paper.

OA.5.2 Monetary Authority

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

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

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

OA.5.3 Equilibrium

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

- Labor market clearing:

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

- Consumption good market clearing:

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

- Investment good clearing:

$$\int_0^1 \Phi_{c,k} \left(\frac{i_{c,t}(n)}{k_{c,t}(n)} \right) k_{c,t}(n) dn + \int_0^1 \Phi_{i,k} \left(\frac{i_{i,t}(n)}{k_{i,t}(n)} \right) k_{i,t}(n) dn + \int_0^1 \frac{\phi_{p,i}}{2} \left[\frac{p_{i,t}(n)}{\Pi_i p_{i,t-1}(n)} - 1 \right]^2 Y_{i,t} dn = Y_{i,t} \quad (\text{A.4})$$

- Zero net supply of nominal bonds:

$$\frac{1}{R_t^\$} = E_t \left[M_{t+1}^\$ \right] \quad (\text{A.5})$$

An equilibrium consists of prices and allocations such that taking prices as given, (i) the household's allocations solve the problem in Section [OA.5.1](#); (ii) firms' allocations solve equation (7); (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 $p_{j,t}(n) = p_{j,t}$.

OA.5.4 Mapping to 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.9](#)) around the nonstochastic steady state yields

$$\hat{\pi}_{j,t} = \gamma_1 \hat{m}c_{j,t} + \gamma_2 E_t [\hat{\pi}_{j,t+1}], \quad j \in \{c, i\}$$

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

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

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

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

In our calibration, $\beta = 0.9955$, $\mu_i = 4$, $\mu_c = 2.4$, and $\phi_{p,c} = \phi_{p,i} = 25$. It implies $\kappa_i = 0.71$ and

$\kappa_c = 0.79$, suggesting an average price duration of $\frac{1}{1-\kappa_i} = 3.4$ quarters in investment sector and $\frac{1}{1-\kappa_c} = 4.8$ quarters in consumption sector. This is consistent with the empirical evidence in [Gali et al. \(2001\)](#) and [Sbordone \(2002\)](#) that the average price duration is four quarters in the data.

OA.6 Model First-Order Conditions

OA.6.1 First-Order Conditions

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

$$0 = q_{j,t} - P_{it} \frac{\partial \Phi_{j,k}(i_{j,t}(n), k_{j,t}(n))}{\partial i_{j,t}(n)} k_{j,t}(n) \quad (\text{A.6})$$

$$0 = W_t n_{j,t}(n) - (1 - \alpha_j) \theta_{j,t} Z_{j,t} k_{j,t}(n)^{\alpha_j} (n_{j,t}(n))^{1-\alpha_j} \quad (\text{A.7})$$

$$0 = -q_{j,t} + E_t \left[M_{t+1}^{\$} \left\{ -P_{i,t+1} \left(\Phi_{j,k}(i_{j,t+1}(n), k_{j,t+1}(n)) + \frac{\partial \Phi_{j,k}(i_{j,t+1}(n), k_{j,t+1}(n))}{\partial k_{j,t+1}(n)} k_{j,t+1}(n) \right) + q_{j,t+1} (1 - \delta) \right. \right. \\ \left. \left. + \theta_{j,t+1} Z_{j,t+1} \alpha_j k_{j,t+1}(n)^{\alpha_j-1} (n_{j,t+1}(n))^{1-\alpha_j} \right\} \right] \quad (\text{A.8})$$

$$0 = (1 - \mu_j) \left[\frac{p_{j,t}(n)}{P_{j,t}} \right]^{-\mu_j} + \theta_{j,t} \mu_j \left[\frac{p_{j,t}(n)}{P_{j,t}} \right]^{-\mu_j-1} \frac{1}{P_{j,t}} + \phi_{p,j} E_t \left[M_{t+1}^{\$} \left(\frac{Y_{j,t+1}}{Y_{j,t}} \right) \left[\frac{p_{j,t+1}(n)}{\Pi_j p_{j,t}(n)} - 1 \right] \frac{p_{j,t+1}^2(n)}{\Pi_j p_{j,t}^2(n)} \right] \\ - \phi_{p,j} \left\{ \left[\frac{p_{j,t}(n)}{\Pi_j p_{j,t-1}(n)} - 1 \right] \frac{p_{j,t}(n)}{\Pi_j p_{j,t-1}(n)} + \frac{1}{2} \left[\frac{p_{j,t}(n)}{\Pi_j p_{j,t-1}(n)} - 1 \right]^2 \right\} \quad (\text{A.9})$$

$$0 = k_{j,t+1}(n) - (1 - \delta) k_{j,t}(n) - i_{j,t}(n) \quad (\text{A.10})$$

$$0 = y_{j,t}(n) - Z_{j,t} k_{j,t}(n)^{\alpha_j} (n_{j,t}(n))^{1-\alpha_j}, \quad (\text{A.11})$$

where $q_{j,t}$ is the price of a marginal unit of installed capital in sector j , the Lagrange multiplier of constraint (4), 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 (8).

The first-order condition of the household

$$0 = \frac{W_t}{P_{c,t}} - \frac{C_t}{1 - \xi N_t^\eta} \xi \eta N_t^{\eta-1}. \quad (\text{A.12})$$

The nominal SDF, nominal interest rate, as well as the household utility, are given in Eq. (12), (A.1), and (11), respectively. The last equilibrium conditions include four market clearing conditions (labor, investment goods, consumption goods, and bond market) specified in Eq. (A.2), (A.3), (A.4), and (A.5), 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:

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

In turn, there are 32 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 the SDF, utility, and the Taylor rule. Other quantities, such as the real SDF and firm valuations, are derived from the endogenous decision variables, see, e.g., Eq. (7).

OA.6.2 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 $j \in \{c, i\}$:

$$0 = \widetilde{q}_{i,t} - \widetilde{P}_{it} \frac{\partial \Phi_{i,k}(\widetilde{i}_{i,t}(n), \widetilde{k}_{i,t}(n))}{\partial \widetilde{i}_{i,t}(n)} \widetilde{k}_{i,t}(n) \quad (\text{A.13})$$

$$0 = \widetilde{q}_{c,t} - \widetilde{P}_{it} \frac{\partial \Phi_{c,k}(\widetilde{i}_{c,t}(n), \widetilde{k}_{c,t}(n))}{\partial \widetilde{i}_{c,t}(n)} \widetilde{k}_{c,t}(n) \quad (\text{A.14})$$

$$0 = \widetilde{W}_t n_{i,t}(n) - (1 - \alpha_i) \frac{Z_{i,t}}{Z_{i,t-1}} \widetilde{\theta}_{i,t} \widetilde{k}_{i,t}(n)^{\alpha_i} n_{i,t}(n)^{1-\alpha_i} \quad (\text{A.15})$$

$$0 = \widetilde{W}_t n_{c,t}(n) - (1 - \alpha_c) \frac{Z_{c,t}}{Z_{c,t-1}} \widetilde{\theta}_{c,t} \widetilde{k}_{c,t}(n)^{\alpha_c} n_{c,t}(n)^{1-\alpha_c} \quad (\text{A.16})$$

$$0 = -\widetilde{q}_{i,t} + E_t \left[\left(\frac{P_{c,t+1}}{P_{c,t}} \frac{Z_{c,t}}{Z_{c,t-1}} \left(\frac{Z_{i,t}}{Z_{i,t-1}} \right)^{\frac{\alpha_c-1}{1-\alpha_i}} \right) M_{t+1}^S \left\{ -\widetilde{P}_{i,t+1} \Phi_{i,k}(\widetilde{i}_{i,t+1}(n), \widetilde{k}_{i,t+1}(n)) \right. \right. \\ \left. \left. - \widetilde{P}_{i,t+1} \frac{\partial \Phi_{i,k}(\widetilde{i}_{i,t+1}(n), \widetilde{k}_{i,t+1}(n))}{\partial \widetilde{k}_{i,t+1}(n)} \widetilde{k}_{i,t+1}(n) + \widetilde{q}_{i,t+1} (1 - \delta) + \widetilde{\theta}_{i,t+1} \alpha_i \frac{Z_{i,t+1}}{Z_{i,t}} \widetilde{k}_{i,t+1}(n)^{\alpha_i-1} n_{i,t+1}(n)^{1-\alpha_i} \right\} \right] \quad (\text{A.17})$$

$$0 = -\widetilde{q}_{c,t} + E_t \left[\left(\frac{P_{c,t+1}}{P_{c,t}} \frac{Z_{c,t}}{Z_{c,t-1}} \left(\frac{Z_{i,t}}{Z_{i,t-1}} \right)^{\frac{\alpha_c-1}{1-\alpha_i}} \right) M_{t+1}^S \left\{ -\widetilde{P}_{i,t+1} \Phi_{c,k}(\widetilde{i}_{c,t+1}(n), \widetilde{k}_{c,t+1}(n)) \right. \right. \\ \left. \left. - \widetilde{P}_{i,t+1} \frac{\partial \Phi_{c,k}(\widetilde{i}_{c,t+1}(n), \widetilde{k}_{c,t+1}(n))}{\partial \widetilde{k}_{c,t+1}(n)} \widetilde{k}_{c,t+1}(n) + \widetilde{q}_{c,t+1} (1 - \delta) + \widetilde{\theta}_{c,t+1} \alpha_c \frac{Z_{c,t+1}}{Z_{c,t}} \widetilde{k}_{c,t+1}(n)^{\alpha_c-1} n_{c,t+1}(n)^{1-\alpha_c} \right\} \right] \quad (\text{A.18})$$

$$0 = (1 - \mu_i) \left[\frac{\widetilde{p}_{i,t}(n)}{\widetilde{P}_{i,t}} \right]^{-\mu_i} + \widetilde{\theta}_{i,t} \mu_i \left[\frac{\widetilde{p}_{i,t}(n)}{\widetilde{P}_{i,t}} \right]^{-\mu_i-1} \frac{1}{\widetilde{P}_{i,t}} \\ + \phi_{p,i} E_t \left[M_{t+1}^S \left(\frac{\left(\frac{Z_{i,t}}{Z_{i,t-1}} \right)^{\frac{1}{1-\alpha_i}} \widetilde{Y}_{i,t+1}}{\widetilde{Y}_{i,t}} \right) \left[\frac{\frac{P_{c,t+1}}{P_{c,t}} \frac{Z_{c,t}}{Z_{c,t-1}} \left(\frac{Z_{i,t}}{Z_{i,t-1}} \right)^{\frac{\alpha_c-1}{1-\alpha_i}} \widetilde{p}_{i,t+1}(n)}{\Pi_i \widetilde{p}_{i,t}(n)} - 1 \right] \frac{\left(\frac{P_{c,t+1}}{P_{c,t}} \frac{Z_{c,t}}{Z_{c,t-1}} \left(\frac{Z_{i,t}}{Z_{i,t-1}} \right)^{\frac{\alpha_c-1}{1-\alpha_i}} \right)^2 \widetilde{p}_{i,t+1}^2(n)}{\Pi_i \widetilde{p}_{i,t}^2(n)} \right] \\ - \phi_{p,i} \left\{ \left[\frac{\frac{P_{c,t}}{P_{c,t-1}} \frac{Z_{c,t-1}}{Z_{c,t-2}} \left(\frac{Z_{i,t-1}}{Z_{i,t-2}} \right)^{\frac{\alpha_c-1}{1-\alpha_i}} \widetilde{p}_{i,t}(n)}{\Pi_i \widetilde{p}_{i,t-1}(n)} - 1 \right] \frac{\frac{P_{c,t}}{P_{c,t-1}} \frac{Z_{c,t-1}}{Z_{c,t-2}} \left(\frac{Z_{i,t-1}}{Z_{i,t-2}} \right)^{\frac{\alpha_c-1}{1-\alpha_i}} \widetilde{p}_{i,t}(n)}{\Pi_i \widetilde{p}_{i,t-1}(n)} + \frac{1}{2} \left[\frac{\frac{P_{c,t}}{P_{c,t-1}} \frac{Z_{c,t-1}}{Z_{c,t-2}} \left(\frac{Z_{i,t-1}}{Z_{i,t-2}} \right)^{\frac{\alpha_c-1}{1-\alpha_i}} \widetilde{p}_{i,t}(n)}{\Pi_i \widetilde{p}_{i,t-1}(n)} - 1 \right]^2 \right\} \quad (\text{A.19})$$

$$0 = (1 - \mu_c) \left[\frac{p_{c,t}(n)}{P_{c,t}} \right]^{-\mu_c} + \widetilde{\theta}_{c,t} \mu_c \left[\frac{p_{c,t}(n)}{P_{c,t}} \right]^{-\mu_c-1} + \phi_{p,c} E_t \left[M_{t+1}^S \left(\frac{\frac{Z_{c,t}}{Z_{c,t-1}} \left(\frac{Z_{i,t}}{Z_{i,t-1}} \right)^{\frac{\alpha_c}{1-\alpha_i}} \widetilde{Y}_{c,t+1}}{\widetilde{Y}_{c,t}} \right) \left[\frac{\frac{P_{c,t+1}}{P_{c,t}}}{\Pi_c} - 1 \right] \frac{\left(\frac{P_{c,t+1}}{P_{c,t}} \right)^2}{\Pi_c} \right] \\ - \phi_{p,c} \left\{ \left[\frac{\frac{P_{c,t}}{P_{c,t-1}}}{\Pi_c} - 1 \right] \frac{\frac{P_{c,t}}{P_{c,t-1}}}{\Pi_c} + \frac{1}{2} \left[\frac{\frac{P_{c,t}}{P_{c,t-1}}}{\Pi_c} - 1 \right]^2 \right\} \quad (\text{A.20})$$

$$0 = \left(\frac{Z_{i,t}}{Z_{i,t-1}} \right)^{\frac{1}{1-\alpha_i}} \widetilde{k}_{i,t+1}(n) - (1 - \delta) \widetilde{k}_{i,t}(n) - \widetilde{i}_{i,t}(n) \quad (\text{A.21})$$

$$0 = \left(\frac{Z_{i,t}}{Z_{i,t-1}} \right)^{\frac{1}{1-\alpha_i}} \widetilde{k}_{c,t+1}(n) - (1 - \delta) \widetilde{k}_{c,t}(n) - \widetilde{i}_{c,t}(n) \quad (\text{A.22})$$

$$0 = \widetilde{y}_{i,t}(n) - \frac{Z_{i,t}}{Z_{i,t-1}} \widetilde{k}_{i,t}(n)^{\alpha_i} n_{i,t}(n)^{1-\alpha_i}, \quad (\text{A.23})$$

$$0 = \widetilde{y}_{c,t}(n) - \frac{Z_{c,t}}{Z_{c,t-1}} \widetilde{k}_{c,t}(n)^{\alpha_c} n_{c,t}(n)^{1-\alpha_c}, \quad (\text{A.24})$$

where $\widetilde{q}_{j,t}$ is the detrended price of a marginal unit of installed capital in sector j , the Lagrange multiplier of constraint (4), 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 (8).

The detrended first-order condition of the household

$$0 = \widetilde{W}_t - \frac{\widetilde{C}_t}{1 - \xi N_t^\eta} \xi \eta N_t^{\eta-1}. \quad (\text{A.25})$$

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

$$M_{t+1}^\$ = \beta \left(\frac{Z_{c,t}}{Z_{c,t-1}} \left(\frac{Z_{i,t}}{Z_{i,t-1}} \right)^{\frac{\alpha_c}{1-\alpha_i}} \right)^{-1/\psi} \left(\frac{\widetilde{C}_{t+1}}{\widetilde{C}_t} \right)^{-1/\psi} \left(\frac{1 - \xi N_{t+1}^\eta}{1 - \xi N_t^\eta} \right)^{1-1/\psi} \left(\frac{\widetilde{U}_{t+1}}{(E_t \widetilde{U}_{t+1})^{1-\gamma}} \right)^{1/\psi-\gamma} \frac{P_{c,t}}{P_{c,t+1}} \quad (\text{A.26})$$

$$r_t^\$ = \rho_r r_{t-1}^\$ + (1 - \rho_r) \left(r_{ss}^\$ + \rho_\pi (\pi_t - \pi_{ss}) + \rho_y (\Delta y_t - \Delta y_{ss}) \right) \quad (\text{A.27})$$

$$\widetilde{U}_t = \left\{ (1 - \beta) \left[\widetilde{C}_t (1 - \xi N_t^\eta) \right]^{1-1/\psi} + \beta (E_t \widetilde{U}_{t+1})^{1-\gamma} \left(\frac{Z_{c,t}}{Z_{c,t-1}} \left(\frac{Z_{i,t}}{Z_{i,t-1}} \right)^{\frac{\alpha_c}{1-\alpha_i}} \right)^{1-1/\psi} \right\}^{\frac{1}{1-1/\psi}} \quad (\text{A.28})$$

OA.7 Alternative Investment-Return Constructions

Table 4 shows that the benchmark model generates a negative comovement between stock returns and either investment growth or investment returns, when the latter are defined using equation (14) and the same market-value weights used in Section 2. In Table OA.4, we demonstrate that this negative correlation is not contingent on the specific functional forms underlying the Euler

equations. We consider an alternative definition of sectoral investment returns that generalizes the metric employed empirically by [Liu et al. \(2009\)](#) and is consistent with standard one-sector perfect-competition setups:

$$R_{j,t+1}^{I,(\text{Alt})} = \frac{\alpha_j \widetilde{YK}_{j,t+1} + \frac{\phi_{k,j}}{2} \left(\widetilde{IK}_{j,t+1}^2 - \widetilde{\delta}^2 \right)}{1 + \phi_{k,j} \left(\widetilde{IK}_{j,t} - \widetilde{\delta} \right)} + (1 - \delta) \frac{1 + \phi_{k,j} \left(\widetilde{IK}_{j,t+1} - \widetilde{\delta} \right)}{1 + \phi_{k,j} \left(\widetilde{IK}_{j,t} - \widetilde{\delta} \right)}, \quad j \in \{c, i\}, \quad (\text{A.29})$$

where $\widetilde{YK}_{j,t}$ represents an empirical equivalent for the marginal product of capital in sector j , and $\widetilde{IK}_{j,t}$ represents observed paths of sectoral investment rates. The rate $\widetilde{\delta}$ is equal to δ , if the quadratic adjustment costs are defined over net investment (as in our model) or 0, if the adjustment costs are defined over gross investment (as in [Liu et al. \(2009\)](#)).⁵ The market-wide return on investment uses the same market-value weights as in Section 2, replacing R_j^I by $R_j^{I,(\text{Alt})}$.

To be consistent with the empirical construction of $\widetilde{YK}$ by [Liu et al. \(2009\)](#), we simulate detrended model paths and divide firms' sales revenue by their capital stock, expressed in dollar amounts (i.e., in consumption units).⁶ Similarly, to measure $\widetilde{IK}$, we use the same simulations of detrended model paths and divide firms' investment expenditures by the lagged value of their end-of-period capital stock, also expressed in dollar amounts.

We examine four different configurations for the parameter values, suggesting four different time series of investment returns: (i) $R^{I,(\text{Alt i})}$: Setting $\widetilde{\delta} = 0$, and where the values of α and ϕ_k are identical to those of Table 2; (ii) $R^{I,(\text{Alt ii})}$: Setting $\widetilde{\delta} = \delta$, and where the values of α and ϕ_k are identical to those of Table 2; (iii) $R^{I,(\text{Alt iii})}$: Setting $\widetilde{\delta} = 0$, and where the values of α and ϕ_k are identical to their average estimates from [Liu et al. \(2009\)](#), amounting to 0.33 and 10.3, respectively. (iv) $R^{I,(\text{Alt iv})}$: Setting $\widetilde{\delta} = \delta$, where the values of α and ϕ_k are taken from [Liu et al. \(2009\)](#).

⁵That is, definition (A.29) is identical to equation (3) in [Liu et al. \(2009\)](#), when $\widetilde{\delta} = 0$, and the tax rate, τ , is also set to 0.

⁶Firms' sales revenue is equal to the amount produced Y_j times the sell-price P_j . Firms' end-of-period capital stock in dollar amount equals the amount of their machines K_j multiplied by the machines' market price P_I .

Table OA.4: Investment and Stock Returns Correlation: Alternative Measures

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

The table report the simultaneous correlation between investment returns (R^I) and stock returns (R^S) in the simulated model. We show four alternative specifications of investment returns: (1) $R^{I,(\text{Alt i})}$: Setting $\tilde{\delta} = 0$ in equation (A.29), and where the values of α and ϕ_k are identical to those of Table 2; (2) $R^{I,(\text{Alt ii})}$: Setting $\tilde{\delta} = \delta$ in equation (A.29), and where the values of α and ϕ_k are identical to those of Table 2; (3) $R^{I,(\text{Alt iii})}$: Setting $\tilde{\delta} = 0$ in equation (A.29), and where the values of α and ϕ_k are taken from Liu et al. (2009), amounting to 0.33 and 10.3, respectively; (4) $R^{I,(\text{Alt iv})}$: Setting $\tilde{\delta} = \delta$ in equation (A.29), where the values of α and ϕ_k are taken from Liu et al. (2009).

Columns (1)—(4) of Table OA.4 show that the population correlation between stock returns and the alternative investment returns remains negative, and even closer to the point estimate reported by Liu et al. (2009).

OA.8 The relation of B/M and profits to dividend-yields

Firms with higher book-to-market and higher profitability have higher expected returns. Studies such as Zhang (2005) and İmrohoroglu and Tüzel (2014) offer a reconciliation of the former observation. Specifically, value firms, characterized by lower productivity, face increased capital adjustment costs, thus amplifying their risk profile. However, this rationale poses a puzzle when trying to explain why high gross profits, associated with higher productivity in standard production models, are also associated with a higher risk premium.

A full quantitative reconciliation of the gross profitability premium entails a model with a cross section of firms. This, admittedly, is beyond the scope and focus of our model. Rather than using a cross section, we show a key novel insight: low productivity — associated with greater risk — can produce not only high book-to-market ratios but also *low* gross profits under the mechanism of innovation-driven contractions. To demonstrate this point, we focus on the time series association

of both characteristics with the risk premium. As discussed below, aggregate-level data shows that both book-to-market and gross profits have a positive association with discount rates, and our model is able to replicate this empirical pattern.

We start by augmenting our benchmark model with stochastic volatility, allowing for variation in risk premia.⁷ The incorporation of stochastic volatility into our model framework is important only for generating temporal variations in the risk premium and dividend yield, but not for cash flow dynamics. As shown in Panel B of Table OA.5, the model, once augmented with this volatility component, continues to produce macro moments that align closely with the data, while preserving the previously established correlations between stock returns, investment returns, and labor surprises.

Next, we perform regressions using model-simulated paths and the data. We project the annualized aggregate dividend yield (i.e., dividend-to-price ratio), which commonly proxies for the discount rate, on current annual aggregate gross profits or/and aggregate book-to-market ratios. Both the dependent and the independent variables are standardized. In both the model and the data, all slope coefficients are positive and significant, as shown in Panel A of Table OA.5. 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.⁸

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

⁷In 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.

⁸Supplemental table OA.14 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.

Table OA.5: **Dividend-price ratio, Risk Premia, B/M, and Gross Profits**

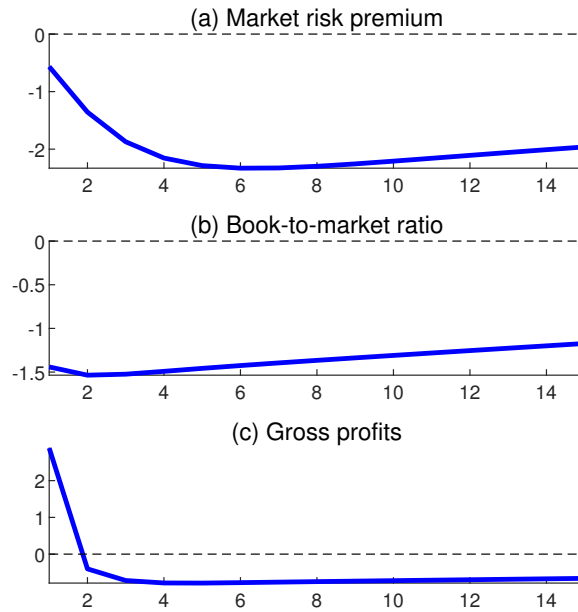
Panel A: Time series comovement with aggregate dividend-price ratio						
	Data			Model		
	(1)	(2)	(3)	(1)	(3)	
GP_t^M	0.82		0.23	0.94	0.74	
t -stat	[8.55]		[3.51]	[22.64]	[16.81]	
BM_t^M		0.93	0.74		0.81	
t -stat		[12.57]	[11.36]		[13.64]	
Panel B: Other moments						
	Moments	Value	Moments	Value	Moments	Value
	$E(\Delta C)(\%)$	1.93	$b_{N,t}$	-0.36	$\text{Corr}(R_{M,t}^I, R_{M,t}^S)$	-0.11
	$\sigma(\Delta Y)(\%)$	3.57	$b_{K,t}$	0.04	$\text{Corr}(R_{M,t+1}^I, R_{M,t}^S)$	0.08
	$\sigma(\Delta C)/\sigma(\Delta Y)$	0.93			$\text{Corr}(\frac{I_{t+1}}{I_t}, R_{M,t}^S)$	0.12
	$\sigma(\Delta I)/\sigma(\Delta Y)$	2.73			$\text{Corr}(R_{c,t}^I, R_{c,t}^S)$	-0.11
	$\sigma(\Delta N)/\sigma(\Delta Y)$	0.40			$\text{Corr}(R_{c,t+1}^I, R_{c,t}^S)$	0.09
	$E(R_M^e)(\%)$	4.49			$\text{Corr}(R_{i,t}^I, R_{i,t}^S)$	-0.18
	$\sigma(R_M^e)(\%)$	19.68			$\text{Corr}(R_{i,t+1}^I, R_{i,t}^S)$	0.07
	$E(r^f)(\%)$	1.30			$\text{Corr}(N_t^{\text{surprise}}, R_{M,t}^S)$	-0.29
	$\sigma(r^f)(\%)$	1.44			$\text{Corr}(N_t^{\text{surprise}}, R_t^f)$	-0.05

The table shows model-implied moments for the framework augmented with stochastic countercyclical volatility. In Panel A, we report the slope coefficients and the t -statistics (in brackets) from regressions, performed in both the model and the data, where the dependent variable is the annualized aggregate dividend-to-price ratio and the independent variables are the aggregate book-to-market ratio or aggregate gross-profits. Data for empirical projections are obtained from [Goyal et al. \(2024\)](#). Each variable is scaled by its unconditional standard deviation. The sample spans the period from 1953 to 2019. In Panel B, we report other model-implied moments as in Table 3 - Table 5, under the augmented model.

OA.4 the impulse responses originating from technological innovations, to aggregate gross profits, book-to-market ratios, and the market risk premium. A positive technological innovation leads to a decrease in the risk premium (and lowers the dividend-yield), an immediate consequence of countercyclical volatility, as illustrated in panel (a). At the same time, this innovation amplifies firm valuations by increasing monopolistic rents while leaving the predetermined capital stock unaffected. This suggests a persistent reduction in the book-to-market ratio, as shown in panel (b), thereby yielding a positive correlation with the conditional risk premium.

Furthermore, the technological shock exerts an immediate and positive impact on gross profits due to enhanced productivity. In a standard flexible-price model, these gross profits would persis-

Figure OA.4: **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.

tently remain high, leading to a counterfactual negative correlation between profitability and risk premia (or dividend yields).

However, within our model, a counteracting dynamic emerges that suppresses gross profits after the initial shock, as shown in panel (c). Specifically, technological innovations trigger a transient contraction in labor, which, in subsequent periods, outweighs the benefits of increased productivity, resulting in below trend profitability, starting one quarter after the initial shock. Consequently, technological innovations are related to reduced (annual) gross profits. This dynamic suggests that the correlation between profitability and the risk premium turns positive, in line with the data.⁹

⁹Incorporating this mechanism into future cross-sectional models can assist in producing both the value and the profitability spreads in a parsimonious manner.

OA.9 Return Predictability

This section uses the model as a measurement device. The mechanism implies that the history of technology innovations maps nonlinearly into the shadow value of installed capital, and therefore into a model-implied investment-based valuation ratio. Constructed using only the history of technology shocks—ensuring no return data is used in its formulation—this disciplined state variable contains economically meaningful information about expected returns. We show that it predicts future excess returns both in- and out-of-sample, outperforming standard valuation ratios.

OA.9.1 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 $P_{j,t}^I = q_{j,t}$. Sector j 's quarterly investment-return's dividend is defined as $Div_{j,t}^I = \partial V_{j,t} / \partial k_{j,t} - q_{j,t}$. These definitions imply that $R_{j,t+1}^I = \frac{Div_{j,t+1}^I + P_{j,t+1}^I}{P_{j,t}^I}$, where $R_{j,t+1}^I$ is the investment return of sector j . The one-year investment-based dividend yield is set to the sum of the investment-return dividends over the last four quarters divided by their current price: $dp_{j,t}^I = \frac{\sum_{k=0}^3 Div_{j,t-k}^I}{P_{j,t}^I}$. Consequently, the economy-wide investment-based dividend yield is:

$$dp_t^I = \frac{V_{c,t-1}}{V_{c,t-1} + V_{i,t-1}} dp_{c,t}^I + \frac{V_{i,t-1}}{V_{c,t-1} + V_{i,t-1}} dp_{i,t}^I.$$

We use the “dividend yield” terminology by analogy to equity markets. We do not interpret this object as a literal yield on a traded financial claim; rather, it is a disciplined state variable representing the investment cash-flow component implied by the model's equilibrium mapping.

Empirical Path Extraction. Using equations (9) and (10), and imposing the restriction that short- and long- run technology shocks are perfectly correlated we extract a path of technology innovations $\{\varepsilon_t^{\text{Data}}\}$ such that the model-implied path of aggregate technology growth (i.e.,

Table OA.6: **Investment-Based Dividend Yield and Risk Premia**

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

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

dz_t) matches the observed quarterly utilization-adjusted TFP growth rates of [Fernald \(2014\)](#) from 1964Q1 to 2019Q4. The start year is based on the availability of factor data from [Chen and Velikov \(2023\)](#). We 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 in the main paper plots the recovered technology innovations and the resulting model-filtered investment-based dividend yield.

Investment-Based Dividend Yield and Risk Premia. We compute the correlation between investment-based dividend yields and one-year-ahead market excess returns in both the data and the model. The model estimates are based on the median values of the correlation implied by simulating finite paths – having the same length as the data – of investment-based dividend yields and stock market returns. Data estimates are obtained from the filtered time series of dp_t^I and the observed market excess returns. Table OA.6 shows that under the benchmark, investment-based dividend yields correlate negatively with risk premia, with a correlation of about -0.35, which is consistent with the data.

We repeat the same exercise when we shut down our core mechanism for contractionary innovations, under the assumption of perfect competition. Specifically, we set $\mu_j \rightarrow \infty$ and use the

same technological innovations to extract dp_t^I from the model without markups. Using the same procedure described above, we recompute the correlation between perfect-competition investment-based dividend yields and future market excess returns. Table OA.6 shows that the model-implied correlation is positive, whereas the empirical counterpart is negative. This mismatch mirrors the comovement puzzle of investment and stock returns, addressed in Section 4.1.

OA.9.2 Investment-based dividend yield and predictability

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

$$R_{t \rightarrow t+k}^e = \text{const} + \beta x_t + \text{error}, \quad (\text{A.30})$$

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

Panel A of Table OA.7 shows that within our full sample period, both dp and cay struggle to explain future excess return variation. While the slope coefficients on dp and cay are positive, in line with existing studies, they are statistically insignificant. Across all horizons, the average R^2 s produced by dp (cay) alone is about 0.0% (4.3%).

In contrast, the investment-based dividend yield, dp^I , generates economically large R^2 s which increase with the predictive horizons. These range from 11% at the one-year-ahead horizon to 35% at the five-year-ahead horizon. This is quite remarkable, given that the dp^I time series, which is structured by the model, depends only on historical data of technology shocks up to time t , in a

non-linear way, but not on any financial market data.¹⁰

In the bottom two rows of each sub-panel I, II and III in Table OA.7 we examine the ability of investment-based dividend yield to predict future excess returns jointly with the other predictors. The statistical significance of the slope coefficient on dp^I remains robust. The adjusted R^2 s 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 OA.7 we repeat the analysis for a sub-sample starting in 1980. In this time frame, dp and cay produce substantially larger R^2 s, 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 the dynamics of innovation-driven contractions, contains valuable information for equity markets, above and beyond market-based valuation ratios.

Out-of-Sample Analysis. We split our full sample period into two equal parts, ranging from 1964 to 1991, and from 1992 to 2019. We estimate equation (A.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 $MSE_{OOS} = \frac{1}{T_{Test}} \sum_{t \in Test} (R_{t \rightarrow t+k}^e - \hat{R}_{t \rightarrow t+k}^e)^2$, where T_{Test} is the number of years between 1992 and 2019 and $\hat{R}_{t \rightarrow t+k}^e$ is the model's prediction. The OOS- R^2 is computed by $R_{OOS}^2 = 1 - \frac{\sum_{t \in [1992, 2019]} (R_{t \rightarrow t+k}^e - \hat{R}_{t \rightarrow t+k}^e)^2}{\sum_{t \in [1992, 2019]} (R_{t \rightarrow t+k}^e - \bar{R}_{t \rightarrow t+k}^e)^2}$. The results are reported in Table OA.8.

Whereas both dp and cay produce a negative OOS- R^2 , dp^I stands out by producing lower MSE s and positive OOS- R^2 s. Its out-of-sample explanatory power is positive at every horizon and ranges from 7% to 15%.

Cross-Sectional Analysis. In Online Appendix Section OA.10 we explore whether the dy-

¹⁰The literature has shown that investment rates themselves negatively predict market returns, and dp^I is conceptually correlated with investment. Nonetheless, the predictive power of dp^I remains unchanged after controlling for investment rates (see Table OA.13 in the Online Appendix).

Table OA.7: **Return Predictability using Investment-Based Dividend Yields**

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

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

Table OA.8: **Out-of-Sample Predictive Power of Investment-Based Dividend Yields**

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

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

namics 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.

OA.10 Investment-Based Dividend Yield and the Cross-Section

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

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

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

Table [OA.9](#) reports the average abnormal return, α , along with the average adjusted R^2 across all anomalies using both sets of factors. When dp^I is appended to the q-factors, the adjusted R^2 increase by about 1%. In addition, we find that there are 12 anomalies whose alpha changes from being statistically significant — using only the q-factors — to insignificant — when augmenting these factors with dp^I . The list of these anomalies is detailed in Table [OA.10](#). Notable anomalies include spreads based on six-month or seasonal momentum and operating leverage.

Table OA.9: Cross-sectional Implications of Investment-Based Dividend Yields

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

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

Table OA.10: List of Factors and Their Descriptions

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

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

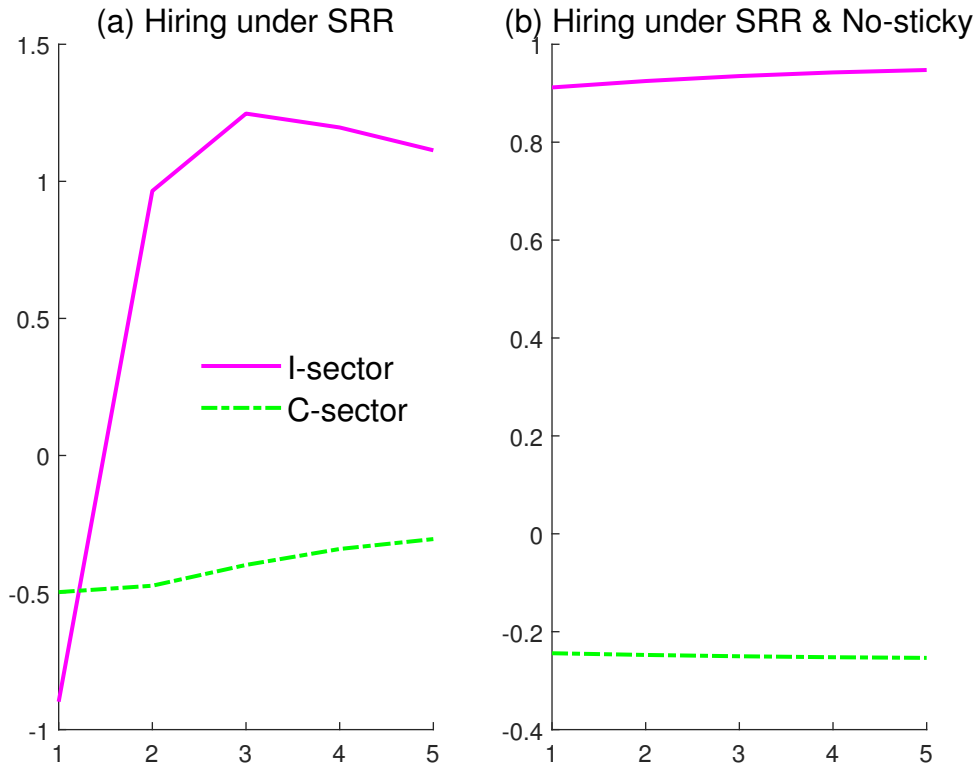
OA.11 Labor-Market Predictions: Data and VAR Evidence

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

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

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

Figure OA.5: Sectoral Employment Responses to Technology Shocks



The figure shows impulse responses of model-detrended employment in both the investment sector (the solid magenta line) and consumption sector (the dash-dotted green line) to one standard deviation shock of aggregate technology. Panel (a) shows impulse responses under the SRR shock. Panel (b) shows 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.

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

capital growth, and the relative price of capital are obtained from [Fernald \(2014\)](#).

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

Figure 6 presents the impulse response functions for a one-standard-deviation structural technology shock on wages (panel (a)) and the relative share of labor in the consumption sector (panel (b)).¹¹ In that figure, the vertical axes denote standard-deviation changes relative to the steady state, and dashed lines represent 90% confidence intervals. Consistent with our model's implications, technological shocks lead to a persistent decrease in wages, confirming our first prediction.¹² 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.

OA.12 Cross-Sectional Model Predictions: Markups, Employment, and Price Rigidity

In the model, nominal rigidity converts a positive technology shock into a markup expansion that rations input demand: where prices are stickier, markups rise by more and employment responds by less. This comparative static underlies the state dependence documented in Stylized

¹¹The model counterparts for these objects are shown in Figures 4 and OA.5; the key comparison is the sign and timing on impact—wages fall and labor reallocates toward the consumption sector in the short run.

¹²Following [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.

Fact 2, and it provides another testable cross-sectional prediction. This section tests it directly in firm-level panel data, complementing the aggregate labor-market evidence of the previous section.

For firm i in year t , we estimate

$$\Delta y_{i,t} = \beta (dz_t \times \text{Frequency}_{i,t-1}) + \alpha_i + \gamma_{j(i),t} + \varepsilon_{i,t}, \quad (\text{A.31})$$

where $\Delta y_{i,t}$ is markup growth or employment growth, dz_t is annual utilization-adjusted TFP growth from [Fernald \(2014\)](#), $\text{Frequency}_{i,t-1}$ is the price-adjustment frequency assigned from firm i 's lagged four-digit NAICS industry using [Pasten et al. \(2021\)](#), α_i is a firm fixed effect, and $\gamma_{j(i),t}$ is an FF49-industry-by-year fixed effect. The accounting markup proxy is the ratio of sales to adjusted operating expenses, where adjusted operating expenses exclude R&D and 30 percent of SG&A, following [Ayyagari et al. \(2024\)](#). This is the same markup construction used in the paper's firm-level evidence. The FF49-by-year fixed effects absorb the aggregate shock level and all broad-industry-by-year conditions. The firm fixed effects absorb time-invariant firm heterogeneity, including persistent differences in firms' usual price-frequency exposure. The coefficient β is therefore identified from differential responses across firms assigned to more versus less sticky-price industries within the same FF49 industry and year.

Table [OA.11](#) reports the estimates. Both interactions carry the sign predicted by the model. Because a lower frequency denotes stickier prices, the negative markup coefficient means that a positive technology innovation is associated with a larger increase in the accounting markup proxy among firms in stickier-price industries. The positive employment coefficient means that employment growth responds more strongly where prices are flexible and, equivalently, is weaker under greater rigidity. Thus, the two outcomes satisfy the model's predictions.

For scale, the standard deviation of annual dz_t over 1963–2019 is approximately 1.43 percent-

Table OA.11: **Firm-Level Responses to Technology Shocks across Price-Adjustment Frequencies**

	(1)	(2)
	Markup Growth	Employment Growth
$dz_t \times \text{Frequency}_{i,t-1}$	-0.0294** (-2.05)	0.0159*** (2.77)
Observations	267,335	232,563
Firms	20,973	19,000
Firm FE	Yes	Yes
FF49 $\times$ Year FE	Yes	Yes
Two-way clustering: NAICS4 and Year	Yes	Yes

The table reports estimates of equation (A.31). The dependent variable is markup growth, $\Delta \log(\mu_{i,t})$, in column (1) and employment growth, $\Delta \log(\text{EMP}_{i,t})$, in column (2). The sample covers 1963–2019 and requires consecutive fiscal years. Outcomes are winsorized at the 1st and 99th percentiles within fiscal year. t -statistics in parentheses are based on CR1 standard errors two-way clustered by lagged four-digit NAICS industry and year. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

age points, and the interquartile range of the common lagged NAICS4 frequency distribution is approximately 0.25 (about 0.09 at the 25th percentile and 0.34 at the 75th percentile). The point estimates therefore imply that, following a one-standard-deviation increase in dz_t , a firm in the 25th-percentile-frequency industry has approximately 1.0 percentage point higher markup growth and 0.6 percentage point lower employment growth than an otherwise comparable firm in the 75th-percentile-frequency industry.

OA.13 Additional results

Table OA.12: **Conditional Labor Market Surprises and Stock Returns**

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

The table shows the model-implied correlation between labor market surprises, N_t^{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 30th (70th) percentile of the cross-sectional distribution each quarter. Our result is robust to other cutoffs. The correlation is calculated over the next 12 quarters for each group, where we take the average across finite sample paths.

Table OA.13: **Return Predictability using Investment-Based Dividend Yields (Control Investment Rates)**

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

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

Table OA.14: Aggregate Earnings-to-Price Ratio, Book-to-Market, and Gross Profitability

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

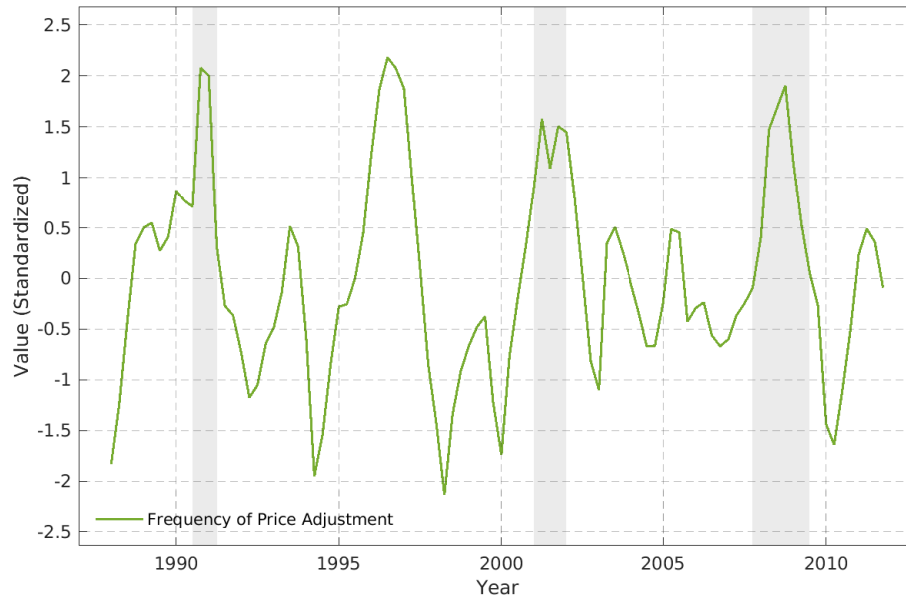
This table shows how the aggregate book-to-market ratio and aggregate gross profitability affect the aggregate earning-to-price ratio. *EP* is the earnings-to-price ratio, which is computed as the 12-month sum of earnings on the S&P 500 index divided by the price index of the S&P 500. *BM* is the aggregate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

Table OA.15: **Preference Robustness: Additively Separable Utility**

	Data	Benchmark	Separable Utility
<i>Aggregate moments</i>			
$\sigma(\Delta Y)(\%)$	3.05	3.14	3.03
$\sigma(\Delta I)/\sigma(\Delta Y)$	3.02	2.85	3.20
$\sigma(\Delta N)/\sigma(\Delta Y)$	0.73	0.41	0.82
$E(R^e)(\%)$	4.71	3.97	4.07
$\sigma(R^e)(\%)$	20.89	19.31	19.09
$E(r^f)(\%)$	0.65	1.24	1.57
<i>Comovements</i>			
$\text{Corr}(R_{M,t}^I, R_{M,t}^S)$	-0.10	-0.17	-0.16
$\text{Corr}(R_{M,t+1}^I, R_{M,t}^S)$	0.20	0.08	0.09
$\text{Corr}(I_t/I_{t-1}, R_{M,t}^S)$	-0.20	-0.22	-0.03
$\text{Corr}(I_{t+1}/I_t, R_{M,t}^S)$	0.10	0.14	0.15
$\text{Corr}(N_t^{\text{surprise}}, R_{M,t}^S)$	-0.27	-0.27	-0.24
$\text{Corr}(N_t^{\text{surprise}}, R_t^f)$	-0.11	-0.10	-0.03
<i>Input responses to technology shocks</i>			
b_N	—	-0.43	-0.81
		$[-0.56, -0.28]$	$[-0.94, -0.66]$
b_K	—	0.04	0.02
		$[-0.04, 0.10]$	$[-0.04, 0.13]$

The table compares the data, the paper’s benchmark, and an economy identical to the benchmark except that King–Plosser–Rebelo utility is replaced by the additively separable recursive specification of Corhay, Kung, and Schmid (2020, *Review of Financial Studies*), in which leisure does not enter the pricing kernel; the disutility of labor is scaled by trend productivity so that it remains stationary along the balanced growth path. All parameters are held at their benchmark values, so differences are attributable solely to the utility specification. Model moments average one hundred simulations of 160 quarters each, after a 400-quarter burn-in, aggregated to annual frequency. The bottom panel reports the slope coefficients b_y from $\Delta y_t = \text{const} + b_y dZ_{\text{agg},t} + \varepsilon_t$ for hours (b_N) and capital growth (b_K), with model-implied confidence intervals in brackets; empirical counterparts appear in Table 1 of the main text.

Figure OA.6: **Frequency of Price Adjustment (Time Series)**



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