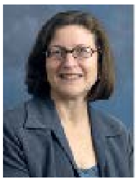
2015 FIRN Asset Pricing Research Group Meeting

University of Melbourne Finance Department
28-29 October, 2015



Professor Jean Helwege (University of California, Riverside)
Keynote Presenter and Discussant

Samuel Hartzmark (Chicago)

Howard Kung (LBS)

Michael Weber (Chicago)

Wednesday – October 28 Program

12:00 - 13:30	**Lunch at Dean's Boardroom**, Level 12, The Spot.
13:30 – 14:45	**Michael Weber session** – "Nominal Rigidities and Asset Pricing".
13:30 – 14:00	Presentation – Michael Weber.
14:00 – 14:45	Panel & group discussion Qi Zeng (University of Melbourne), Oleg Chuprinin (UNSW), and Philip Gharghori (Monash).
14:45 – 15:15	**Coffee break**
15:15 – 16:30	**Sam Hartzmark session** – "A Tough Act to Follow: Contrast Effects in Financial Markets".
15:15 – 15:45	Presentation – Sam Hartzmark.
15:45 – 16:30	Panel & group discussion – Bruce Grundy (University of Melbourne), Pedro Barroso (UNSW) and Doug Foster (University of Sydney).
16:30 – 17:00	**Coffee break**
17:00 – 18:00	**New ideas session 1**
17:00 – 17:20	Albert Chun (University of Queensland).
17:20 – 17:40	Tze Chuan Ang (Deakin University).
17:40 – 18:00	Oleg Chuprinin (University of New South Wales).
19:00	**Dinner at Lord Cardigan**, 59 Cardigan Pl, Albert Park, VIC 3206.

Thursday – October 29

9:30 – 10:00	**Breakfast**
10:00 – 11:15	**Howard Kung session** – "Competition, Markups, and Predictable Returns".
10:00 – 10:30	Presentation – Howard Kung.
10:30 – 11:15	Panel & group discussion – Garry Twite (University of Melbourne), Albert Chun (University of Queensland), and Robert Xiao (Deakin University).
11:15 – 11:45	**Coffee break**
11:45 – 12:25	**New ideas session 2**
11:45 – 12:05	Li Ge (Monash University)
12:05 – 12:25	David Feldman (University of New South Wales)

Participants

Jamie	Alcock	SYDNEY
Chewie (Tze Chuan)	Ang	DEAKIN
Pedro	Barroso	UNSW
James	Brugler	MELBOURNE
Albert	Chun	UQ
Carole	Comerton-Forde	MELBOURNE
David	Feldman	UNSW
Doug	Foster	SYDNEY
Li	Ge	MONASH
Philip	Gharghori	MONASH
Vincent	Gregoire	MELBOURNE
Bruce	Grundy	MELBOURNE
Samuel	Hartzmark	University of Chicago
Jean	Helwege	University of California, Riverside
Henny	Jung	MELBOURNE
Howard	Kung	London Business School
Andrea	Lu	MELBOURNE
Spencer	Martin	MELBOURNE
Steven	Riddiough	MELBOURNE
Juan	Sotes-Paladino	MELBOURNE
Garry	Twite	MELBOURNE
Michael	Weber	University of Chicago
Robert	Xiao	DEAKIN
Qi	Zeng	MELBOURNE
Zhuo	Zhong	MELBOURNE
Frederico	Nardari	MELBOURNE

Competition, Markups, and Predictable Returns

Alexandre Corhay * Howard Kung† Lukas Schmid‡§

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Imperfect competition is an important channel for time-varying risk premia in asset markets. We build a general equilibrium model with monopolistic competition and endogenous firm entry and exit. Endogenous variation in industry concentration generates countercyclical markups, which amplifies macroeconomic risk. The nonlinear relation between the measure of firms and markups endogenously generates countercyclical macroeconomic volatility. With recursive preferences, the volatility dynamics lead to countercyclical risk premia forecastable with measures of competition. Also, the model produces a U-shaped term structure of equity returns.

Keywords: Imperfect competition, markups, entry and exit, productivity, business cycle propagation, asset pricing, return predictability, recursive preferences

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1 Introduction

Economists have long argued that the creation of new businesses is an important engine of growth. In fact, careful measurement reveals that the vast majority of productivity growth occurs as new establishments enter product markets (for recent evidence, see, e.g. Gourio, Messer and Siemer (2014)). The flipside of entry is that old establishments face increased competitive pressure that may eventually drive them out of business. Going back at least to Schumpeter, economists have referred to this process as 'creative destruction'. One striking stylized fact about the intensity of net business creation is that it is highly procyclical.[1] While procyclical variation in the number of competitors is related to changes in profit opportunities, it also suggests that competitive pressure and the price elasticity of demand, should adjust accordingly. Indeed, a long list of contributions documents empirically that markups are countercyclical[2] and that the degree of competitiveness in industries is strongly procyclical.[3]

In this paper, we quantitatively link variation in industry concentration to the predictable component in equity risk premia. We show theoretically and empirically that measures of net business formation and markups forecast the equity premium. To this end, we build a general equilibrium asset pricing model with monopolistic competition and endogenous firm entry and exit. There are two endogenous components of measured productivity in the model, *product innovation* and *process innovation*. Product innovation refers to resources expended for the creation of new products and firms (e.g., Atkeson and Burstein (2014)). Process innovation refers to incumbent firms investing to upgrade their technology in response to the entry threat. Due to spillover effects from process innovation, process innovation provides a powerful low-frequency growth propagation mechanism that leads to sizable endogenous long-run risks as in Kung (2015) and Kung and Schmid (2015).

Product innovation, on the other hand, implies a novel amplification mechanism for shocks at business cycle frequencies. A positive technology shock raises profits and increases firm creation, and vice versa (e.g., firm creation is procyclical). Also, the price elasticity of demand is positively related to the number of competitors in a particular industry. Thus, markups are countercyclical, which magnifies short-run risks. In booms (downturns), markups fall which expands (contracts) production more. Consequently, short-run dividends are very risky and the model produces a U-

[1]See, e.g., Cooper and Chatterjee (1993), Portier (1995), Devereux, Head and Lapham (1996), Floetotto and Jaimovich (2008), Bilbiie, Ghironi and Melitz (2012)

[2]See, for example, Bils (1987), Rotemberg and Woodford (1991, 1999), Chevalier, Kashyap and Rossi (2003).

[3]Some examples include Bresnahan and Reiss (1991) and Campbell and Hopenhayn (2005)

shaped term structure of equity returns, consistent with the empirical evidence from Binsbergen, Brandt, and Koijen (2012).

We show that in equilibrium the relation between the number of firms and markups is nonlinear. In economic downturns, profits fall, firms exit and industry concentration rises. As a consequence, surviving producers enjoy elevated market power and face steeper demand curves. While this allows firms to charge higher markups in our model, it also makes them more sensitive to aggregate shocks and implies that the amplification mechanism is asymmetric. Markups increase more in recessions than it decreases in booms. Consequently, the model endogenously produces countercyclical macroeconomic volatility. With recursive preferences, these volatility dynamics generate a countercyclical equity premium that can be forecasted by measures of industry concentration.

The calibrated model generates an equity premium of around 5% on an annual basis, while simultaneously fitting a wide-range of macroeconomic moments, including those relating to markup and business creation dynamics. The sizable equity premium is primarily compensation for the endogenous long-run risks (e.g., Bansal and Yaron (2004) and Croce (2014)) generated by the process innovation channel as in Kung (2015) and Kung and Schmid (2015). The countercyclical equity premium is attributed to the product innovation channel due to nonlinearities in markup dynamics. The model generates quantitatively significant endogenous variation in risk premia. For example, excess stock return forecasting regressions using the price-dividend ratio produces a R^2 of 0.22 at a five-year horizon. The model also predicts that excess stock returns can be forecasted by markups, profit shares, and net business formation, which we find strong empirical support for. In short, our paper highlights how fluctuations in competitive pressure are an important source of time-varying risk premia.

1.1 Literature

Our work belongs to several strands of literature. First, the paper is related to the emerging literature linking risk premia and imperfect competition. Second, it connects to research on sources of endogenous return predictability. Third, it contributes to the literature on general equilibrium asset pricing with production.

Our starting point is an innovation-driven model of stochastic endogenous growth following Kung (2015) and Kung and Schmid (2015). Also, Ward (2014) uses a similar framework as Kung and Schmid (2015) to estimate the transition dynamics of the IT revolution. Methodologically, this work builds on the literature on medium-term cycles pioneered by Comin and Gertler (2006) and Comin, Gertler and Santacreu (2009). More generally, these papers are a stochastic extension of the endogenous growth models developed by Romer (1990), Aghion and Howitt (1992), and Peretto (1999). We extend the framework from Kung (2015) and Kung and Schmid (2015) to account for entry and exit along the lines of Bilbiie, Ghironi and Melitz (2012) and Floetotto and Jaimovich (2008), and examine the asset pricing implications. We follow the multisector approach from Floetotto and Jaimovich, which yields endogenous countercyclical markups. Opp, Parlour and Walden (2014) obtain time-varying markups in a model of strategic interactions at the industry level.

Our paper is related to a growing literature studying the link between product market competition and stock returns. Hou and Robinson (2006), Bustamante and Donangelo (2014), van Binsbergen (2014), and Loualiche (2014) examine the impact of competition on the cross section of stock returns. Our paper is closely related to Loualiche (2014) who also considers a general equilibrium asset pricing model with recursive preferences and entry and exit. He finds that aggregate shocks to entry rates are an important factor priced in the cross-section of returns. Our work differs from these papers by focusing on the time-series implications and especially on how changes in competition endogenously generate time-varying risk premia. Our approach therefore provides distinct and novel empirical predictions.

Our paper shares its focus with the growing literature on asset pricing in general equilibrium models with production. Papers that use habit preferences include Jermann (1998) and Boldrin, Christiano, and Fisher (2001). More recently, Tallarini (2000), Campanale, Castro, and Clementi (2008), Kuehn (2008, 2009), Ai (2010) and Kaltenbrunner and Lochstoer (2010) explore endogenous long-run consumption risks in real business cycle models with recursive preferences. Gourio (2012, 2013) examines disaster risks. Particularly closely related are recent papers by Croce (2012), Backus, Routledge, and Zin (2007, 2010), Gomes, Kogan, and Yogo (2009), Kogan and Papanikolaou (2010), Garleanu, Kogan, and Panageas (2012), Papanikolaou (2011), and Ai, Croce, and Li (2013) who examine the implications of long-run productivity risk and technological innovation for equity market returns. Our approach differs from their work as technological progress and productivity growth is endogenous in our model through process and product innovation. Furthermore, these papers focus on unconditional asset pricing moments, while we consider return predictability.

Our work is related to papers examining mechanisms that generate return predictability. Dew-Becker (2012) and Kung (2015) generate return predictability by assuming exogenous time-varying processes in risk aversion and the volatility of productivity, respectively. A number of papers show how predictability can be generated endogenously. Favilukis and Lin (2014a, 2014b), Kuehn, Petrosky-Nadeau and Zhang (2014), Santos and Veronesi (2006) work through frictions in the labor markets. In these papers, wages effectively generate operating leverage and they identify variables related to labor market conditions that can forecast stock returns. Gomes and Schmid (2014) explicitly model financial leverage in general equilibrium and find that credit spreads forecast stock returns through countercyclical leverage. Our channel, which operates through endogenous time-varying markups, is novel and allows us to empirically identify a new set of predictive variables for stock returns linked to time-varying competitive pressure.

Finally, our paper relates to models that try to explain the declining term structure of equity returns documented in Binsbergen, Brandt, and Koijen (2012) and Binsbergen, Hueskes, Koijen, and Vrugt (2012). Belo, Collin-Dusfresne, and Goldstein (2014) show, in an endowment economy, that imposing a stationary and procyclical leverage ratio amplifies short-run risks and increases the procyclicality of short-term dividends, which leads to a downward sloping term structure. Croce, Lettau, and Ludvigson (2014) also generate this result using an endowment economy with limited information. Ai, Croce, Diercks and Li (2014) and Favilukis and Lin (2014a) show how vintage capital and wage rigidities, respectively, are alternative channels in a production-based framework. In contrast to these papers, endogenous countercyclical markups in our model provide a distinct but complimentary amplification mechanism for short-run risks that helps to explain the equity term structure.

The paper is organized as follows. We describe our model in section 2 and examine the main economic mechanisms in section 3. The next section discusses quantitative implications by means of a calibration, and presents empirical evidence supporting our model predictions. Section 5 offers a few concluding remarks.

2 Model

In this section, we present a general equilibrium asset pricing model with imperfect competition and endogenous productivity growth. Endogenous innovation impacts productivity growth because of imperfect competition, as markups and the associated profit opportunities provide incentives for new firms to enter (product innovation) and for incumbent firms to invest in their own production technology (process innovation). Cyclical movements in profit opportunities affect the mass of active firms and thus competitive pressure and markups. We also assume a representative household with recursive preferences.

Overall the model is a real version of the endogenous growth framework of Kung (2014), extended to allow for entry and exit with multiple industries and time-varying markups. We start by briefly describing the household sector, which is quite standard. Then we explain in detail the production sector and the innovation process in our economy, and define the general equilibrium. Also, note that we use calligraphic letters to denote aggregate variables.

2.1 Household

The representative agent is assumed to have Epstein-Zin preferences over aggregate consumption $\mathcal{C}_t$ and labor $\mathcal{L}_t$[4]

$$U_t = u\left(\mathcal{C}_t, \mathcal{L}_t\right) + \beta\left(E_t[U_{t+1}^{1-\theta}]\right)^{\frac{1}{1-\theta}}$$

where $\theta = 1 - \frac{1-\gamma}{1-1/\psi}$, γ captures the degree of risk aversion, ψ is the elasticity of intertemporal substitution, and β is the subjective discount rate. The utility kernel is assumed to be additively separable in consumption and leisure,

$$u\left(\mathcal{C}_t, \mathcal{L}_t\right) = \frac{\mathcal{C}_t^{1-1/\psi}}{1-1/\psi} + \mathcal{Z}_t^{1-1/\psi}\chi_0\frac{(1-\mathcal{L}_t)^{1-\chi}}{1-\chi}$$

where χ captures the Frisch elasticity of labor[5], and χ_0 is a scaling parameter. Note that we multiply the second term by an aggregate productivity trend $\mathcal{Z}_t^{1-1/\psi}$ to ensure that utility for leisure does not become trivially small along the balanced growth path.

When $\psi \neq \frac{1}{\gamma}$, the agent cares about news regarding long-run growth prospects. We will assume that $\psi > \frac{1}{\gamma}$ so that the agent has a preference for early resolution of uncertainty and dislikes uncertainty about long-run growth rates.

The household maximizes utility by participating in financial markets and by supplying labor. Specifically, the household can take positions Ω_t in the stock market, which pays an aggregate dividend $\mathcal{D}_t$, and in the bond market $\mathcal{B}_t$. Accordingly, the budget constraint of the household

[4]Traditionally, Epstein-Zin preference are defined as $\tilde{U}_t = \left\{u\left(\mathcal{C}_t, \mathcal{L}_t\right)^{1-1/\psi} + \beta\left(E_t[\tilde{U}_{t+1}^{1-\gamma}]\right)^{\frac{1-1/\psi}{1-\gamma}}\right\}^{\frac{1}{1-1/\psi}}$ where γ is the coefficient of relative risk aversion and ψ is the intertemporal elasticity of substitution. The functional form above is equivalent when we define $U_t = \tilde{U}_t^{1-1/\psi}$ and $\theta = 1 - \frac{1-\gamma}{1-1/\psi}$ but has the advantage of admiting more general utility kernels $u\left(\mathcal{C}_t, \mathcal{L}_t\right)$ (see Rudebusch and Swanson (2012)).

[5]Given our assumption that the household works 1/3 of his time endowment in the steady state, the steady state Frisch labor supply elasticity is $2/\chi$.

becomes

$$\mathcal{C}_t + \mathcal{Q}_t\Omega_{t+1} + \mathcal{B}_{t+1} = \mathcal{W}_t\mathcal{L}_t + (\mathcal{Q}_t + \mathcal{D}_t)\Omega_t + \mathcal{R}_{f,t}\mathcal{B}_t, \tag{1}$$

where $\mathcal{Q}_t$ is the stock price, $\mathcal{R}_{f,t}$ is the gross risk free rate and $\mathcal{W}_t$ is the wage rate.

These preferences imply the stochastic discount factor (intertemporal marginal rate of substitution)

$$\mathcal{M}_{t+1} = \beta \left(\frac{U_{t+1}}{E_t(U_{t+1}^{1-\theta})^{\frac{1}{1-\theta}}} \right)^{-\theta} \left(\frac{\mathcal{C}_{t+1}}{\mathcal{C}_t} \right)^{-\frac{1}{\psi}}$$

Additionally, the labor supply condition states that at the optimum the household trades off the wage rate against the marginal disutility of providing labor, so that

$$\mathcal{W}_t = \frac{\chi_0(1-\mathcal{L}_t)^{-\chi}}{\mathcal{C}_t^{-1/\psi}} \mathcal{Z}_t^{1-1/\psi}.$$

2.2 Production Sector

The production sector is composed of three entities: final goods production, intermediate goods production, and the capital producers. The final good aggregates inputs from a continuum of industries, and each industry uses a finite measure of differentiated intermediate goods as inputs. Stationary shocks drive stochastic fluctuations in the profits on intermediate goods. Higher profit opportunities induce new intermediate goods producers to enter (product innovation) and incumbent firms respond by upgrading their technology through R&D (process innovation). The capital sector produces and accumulates both physical and intangible capital and rents it out to the intermediate goods firms.

Final Goods The final goods sector is modeled following Jaimovich and Floetotto (2008). The final good is produced by aggregating sectoral goods which are themselves composites of intermediate goods. We think of each sector as a particular industry and use these labels interchangeably.

More specifically, a representative firm produces the final (consumption) goods in a perfectly competitive market. The firm uses a continuum of sectorial goods $Y_{i,t}$ as inputs in the following CES production technology

$$\mathcal{Y}_t = \left(\int_0^1 Y_{i,t}^{\frac{\nu_1-1}{\nu_1}} \, di \right)^{\frac{\nu_1}{\nu_1-1}}$$

where ν_1 is the elasticity of substitution between sectorial goods. The profit maximization problem of the firm yields the isoelastic demand for sector j goods,

$$Y_{j,t} = \mathcal{Y}_t \left(\frac{P_{j,t}}{P_{Y,t}} \right)^{-\nu_1}$$

where $P_{Y,t} = \left(\int_0^1 P_{j,t}^{1-\nu_1} \, dj \right)^{\frac{1}{1-\nu_1}}$ is the final goods price index (and the numeraire). We provide the derivations in the appendix.

In turn, each industry j produces sectoral goods using a finite number $N_{j,t}$ of differentiated goods $X_{i,j,t}$. Importantly, the number of differentiated goods in each industry is allowed to vary over time. Because each industry is atomistic, sectorial firms face an isoelastic demand curve with constant price elasticity ν_1. The sectoral goods are aggregated using a CES production technology

$$Y_{j,t} = N_{j,t}^{1-\frac{\nu_2}{\nu_2-1}} \left(\sum_{i=1}^{N_{j,t}} X_{i,j,t}^{\frac{\nu_2-1}{\nu_2}} \right)^{\frac{\nu_2}{\nu_2-1}}$$

where $N_{j,t}$ is the number of firms and ν_2 is the elasticity of substitution between intermediate goods. The multiplicative term $N_{j,t}^{1-\frac{\nu_2}{\nu_2-1}}$ is added to eliminate the variety effect in aggregation.

The profit maximization problem of the firm yields the following demand schedule for intermediate firms in industry j (see the appendix for derivations):

$$X_{i,j,t} = \frac{Y_{j,t}}{N_{j,t}} \left(\frac{P_{i,j,t}}{P_{j,t}} \right)^{-\nu_2}$$

where $P_{i,j,t}$ is the price of intermediate good i in industry j and $P_{j,t} = N_{j,t}^{\frac{-1}{1-\nu_2}} \left(\sum_{i=1}^{N_{j,t}} P_{i,j,t}^{1-\nu_2} \right)^{\frac{1}{1-\nu_2}}$ is the sector j price index. In the following, we assume that the elasticity of substitution within industry is higher than across industries, i.e. $\nu_2 > \nu_1$.

Intermediate Goods Intermediate goods production in each industry is characterized by monopolistic competition. In each period, a proportion δ_n of existing firms becomes obsolete and leaves the economy. The specification of the production technology is similar to Kung (2014). Intermediate goods firms produce $X_{i,j,t}$ using a Cobb-Douglas technology defined over physical capital $K_{i,j,t}$, labor $L_{i,j,t}$, and technology $Z_{i,j,t}$. We think of technology as intangible capital, such as patents. Firms rent their physical and technology from capital producers at a period rental rate of $r_{j,t}^k$ and $r_{j,t}^z$, respectively. Labor input is supplied by the household. We assume that technology is only partially appropriable and that there are spillovers across firms. The production technology is

$$X_{i,j,t} = K_{i,j,t}^{\alpha} \left(A_t Z_{i,j,t}^{\eta} \mathcal{Z}_t^{1-\eta} L_{i,j,t} \right)^{1-\alpha}$$

where $\mathcal{Z}_t \equiv \int_0^1 \left(\sum_{i=1}^{N_{j,t}} Z_{i,j,t} \right) dj$ is the aggregate stock of technology in the economy and the parameter $\eta \in [0,1]$ captures the degree of technological appropriability. These spillover effects are crucial for generating sustained growth in the economy (e.g. Romer (1990)). Technology increases the efficiency of intermediate good production, so that we interpret that input as process innovation. The variable A_t represents an aggregate technology shock that is common across firms and evolves in logs as an AR(1) process:

$$a_t = (1-\rho)a^{\star} + \rho a_{t-1} + \sigma \epsilon_t$$

where $a_t \equiv \log(A_t)$, $\epsilon_t \sim N(0,1)$ is i.i.d., and $a^{\star}$ is the unconditional mean of a_t.

Dividends for an intermediate goods firm is then given by

$$D_{i,j,t} = \frac{P_{i,j,t}}{P_{Y,t}} X_{i,j,t} - W_{j,t} L_{i,j,t} - r_{j,t}^{k} K_{i,j,t} - r_{j,t}^{z} Z_{i,j,t}.$$

The demand faced by an individual firm depends on its relative price and the sectoral demand which in turn depends on the final goods sector. Expressing the inverse demand as a function of final goods variables,

$$X_{i,j,t} = \frac{\mathcal{Y}_t}{N_{j,t}} \left(\tilde{P}_{i,j,t} \right)^{-\nu_2} \left(\tilde{P}_{j,t} \right)^{\nu_2 - \nu_1}$$

where tilde-prices are normalized by the numeraire, i.e. $\tilde{P}_{i,j,t} \equiv \frac{P_{i,j,t}}{P_{Y,t}}$ and $\tilde{P}_{j,t} \equiv \frac{P_{j,t}}{P_{Y,t}}$.

The objective of the intermediate goods firm is to maximize shareholder's wealth, taking input prices and the stochastic discount factor as given:

$$\begin{aligned} V_{i,j,t} = & \max_{\left\{L_{i,j,t}, K_{i,j,t}, Z_{i,j,t}, \tilde{P}_{i,j,t}\right\}_{t \geqslant 0}} E_0 \left[\sum_{s=0}^{\infty} \mathcal{M}_{t,t+s} (1-\delta_n)^s D_{i,j,s} \right] \\ \text{s.t.} \quad & X_{i,j,t} = \frac{\mathcal{Y}_t}{N_{j,t}} \left(\tilde{P}_{i,j,t} \right)^{-\nu_2} \left(\tilde{P}_{j,t} \right)^{\nu_2 - \nu_1} \end{aligned}$$

where $\mathcal{M}_{t,t+s}$ is the marginal rate of substitution between time t and time $t+s$.

This market structure yields a symmetric equilibrium in the intermediate goods sector. Hence, we can drop the i subscripts in the equations above. As derived in the appendix, the corresponding first order necessary conditions are

$$\begin{aligned} r^k_{j,t} &= \frac{\alpha}{\text{ø}_{j,t}} \frac{X_{j,t}}{K_{j,t}} \\ r^z_{j,t} &= \frac{\eta(1-\alpha)}{\text{ø}_{j,t}} \frac{X_{j,t}}{Z_{j,t}} \\ W_{j,t} &= \frac{(1-\alpha)}{\text{ø}_{j,t}} \frac{X_{j,t}}{L_{j,t}} \\ \text{ø}_{j,t} &= \frac{-\nu_2 \, N_{j,t} + (\nu_2 - \nu_1)}{-(\nu_2 - 1)\, N_{j,t} + (\nu_2 - \nu_1)} \end{aligned}$$

where $\text{ø}_{j,t}$ is the price markup reflecting monopolistic competition. Note that the price markup depends on the number of active firms $N_{j,t}$ in each industry, and so can be time-varying. We describe how the evolution of the mass of active firms is endogenously determined below.

Capital producers Capital producers operate in a perfectly competitive environment and produce industry-specific capital goods. They specialize in the production of either physical capital or technology.

Physical capital producers lease capital $K^c_{j,t}$ to sector j for production in period t at a rental rate of $r^k_{j,t}$. At the end of the period, they retrieve $(1-\delta_k)K^c_{j,t}$ of depreciated capital. They produce new capital by transforming $I_{j,t}$ units of output bought from the final goods producers into new capital via the technology[6]:

$$\Phi_{k,j,t} K^c_{j,t} = \left(\frac{\alpha_{1,k}}{1 - \frac{1}{\zeta_k}} \left(\frac{I_{j,t}}{K^c_{j,t}} \right)^{1-\frac{1}{\zeta_k}} + \alpha_{2,k} \right) K^c_{j,t}$$

Therefore, the evolution of aggregate physical capital in industry j is

$$K^c_{j,t+1} = (1-\delta_k) K^c_{j,t} + \Phi_{k,j,t} K^c_{j,t}$$

and the dividend is defined as $r^k_{j,t} K^c_{j,t} - I_{j,t}$.

[6]This functional form for the capital adjustment costs is borrowed from Jermann(1998). The parameters $\alpha_{1,k}$ and $\alpha_{2,k}$ are set to values so that there are no adjustment costs in the deterministic steady state. Specifically, $\alpha_{1,k} = (\Delta\mathcal{Z} - 1 + \delta_k)^{\frac{1}{\zeta_k}}$ and $\alpha_{2,k} = \frac{1}{\zeta_k - 1}(1 - \delta_k - \Delta\mathcal{Z})$.

The optimization problem faced by the representative physical capital producer is to choose $K^c_{j,t+1}$ and $I_{j,t}$ in order to maximize shareholder value:

$$\begin{aligned} V^k_{j,t} = & \max_{\{I_{j,t},K^c_{j,t+1}\}_{t\geqslant 0}} E_0\left[\sum_{s=0}^{\infty}\mathcal{M}_{t,t+s}(r^k_{j,s}K^c_{j,s}-I_{j,s})\right] \\ \text{s.t.}\;\; & K^c_{j,t+1} = (1-\delta_k)K^c_{j,t}+\Phi_{k,j,t}K^c_{j,t} \end{aligned}$$

As shown in the appendix, this optimization problem yields the following first order conditions:

$$\begin{aligned} Q^k_{j,t} &= \Phi'^{-1}_{k,j,t} \\ Q^k_{j,t} &= E_t\left[\mathcal{M}_{t,t+1}\left(r^k_{j,t+1}+Q^k_{j,t+1}\left(1-\delta_k-\Phi'_{k,j,t+1}\left(\frac{I_{j,t}}{K^c_{j,t}}\right)+\Phi_{k,j,t+1}\right)\right)\right] \end{aligned}$$

where Q^k_t is the Lagrange multiplier on the capital accumulation constraint.

The structure of the technology capital producer is similar. More specifically, this sector produces new intangible capital by transforming $S_{j,t}$ units of output bought from the final goods producers into new technology via the technology[7]:

$$\Phi_{k,j,t}Z^c_{j,t} = \left(\frac{\alpha_{1,z}}{1-\frac{1}{\zeta_z}}\left(\frac{S_{j,t}}{Z^c_{j,t}}\right)^{1-\frac{1}{\zeta_z}}+\alpha_{2,z}\right)Z^c_{j,t}.$$

We think of $S_{j,t}$ as investment in R&D. In the model, therefore, technology accumulates endogenously.

As with physical capital producers, the optimization problem of the representative technology producer is to maximize shareholder value, so that the first conditions are,

$$\begin{aligned} Q^z_{j,t} &= \Phi'^{-1}_{z,j,t} \\ Q^z_{j,t} &= E_t\left[\mathcal{M}_{t,t+1}\left(r^z_{j,t+1}+Q^z_{j,t+1}\left(1-\delta_z-\left(\frac{S_{j,t+1}}{Z^c_{j,t+1}}\right)\Phi'_{z,j,t+1}+\Phi_{z,j,t+1}\right)\right)\right] \\ Z^c_{j,t+1} &= (1-\delta_z)Z^c_{j,t}+\Phi_{z,j,t}Z^c_{j,t}. \end{aligned}$$

[7]Similarly, the parameters $\alpha_{1,z}$ and $\alpha_{2,z}$ are set to values so that there are no adjustment costs in the deterministic steady state. Specifically, $\alpha_{1,z} = (\Delta\mathcal{Z}-1+\delta_z)^{\frac{1}{\zeta_z}}$ and $\alpha_{2,z} = \frac{1}{\zeta_z-1}(1-\delta_z-\Delta\mathcal{Z})$.

2.3 Entry & Exit

Each period, new firms contemplate entering the intermediate goods sector. Entry into the intermediate goods sector entails the fixed cost $F_{E,j,t} \equiv \kappa_j \mathcal{Z}_t$. A newly created firm will start producing in the following period. Note that these costs are multiplied by the aggregate trend in technology to ensure that the entry costs do not become trivially small along the balanced growth path.

The evolution equation for the number of firms in the intermediate goods sector is

$$N_{j,t+1} = (1-\delta_n)N_{j,t} + N_{E,j,t}$$

where $N_{E,j,t}$ is the number of new entrants and δ_n is the fraction of firms, randomly chosen, that become obsolete after each period. The entry condition is:

$$E_t[\mathcal{M}_{t+1}V_{j,t+1}] = F_{E,j,t} \tag{2}$$

where $V_{j,t} = D_{j,t} + (1-\delta_n)E_t[\mathcal{M}_{t+1}V_{j,t+1}]$ is the market value of the representative firm in sector j. Movements in profit opportunities and valuations thus lead to fluctuations in the mass of entering firms.

2.4 Equilibrium

Symmetric Equilibrium We focus on a symmetric equilibrium, in which all sectors and intermediate firms make identical decisions, so that the i and j subscripts can be dropped. Given the symmetric equilibrium, we can express aggregate output as

$$\begin{aligned} \mathcal{Y}_t &= \mathcal{N}_t X_t \\ X_t &= K_t^{\alpha}(A_t Z_t^{\eta} \mathcal{Z}_t^{1-\eta} L_t)^{1-\alpha} \end{aligned}$$

Aggregation Aggregate macro quantities are defined as: $\mathcal{I}_t \equiv \int_0^1 I_{j,t}\, dj = I_t$, $\mathcal{S}_t \equiv \int_0^1 S_{j,t}\, dj = S_t$, $\mathcal{Z}_t \equiv \int_0^1 \sum_{i=1}^{\mathcal{N}_t} Z_{i,j,t}\, dj = \mathcal{N}_t Z_t$, $\mathcal{K}_t \equiv \int_0^1 \sum_{i=1}^{\mathcal{N}_t} K_{i,j,t}\, dj = \mathcal{N}_t K_t$. The aggregate dividend coming from the production sector is defined as

$$\mathcal{D}_t = \mathcal{N}_t D_t + (r_t^k \mathcal{K}_t - \mathcal{I}_t) + (r_t^z \mathcal{Z}_t - \mathcal{S}_t)$$

Note that the aggregate dividend includes dividends from the capital and technology sectors.

Market Clearing Imposing the symmetric equilibrium conditions, the market clearing condition for the final goods market is:

$$\mathcal{Y}_t = \mathcal{C}_t + \mathcal{I}_t + \mathcal{S}_t + \mathcal{N}_{E,t} \cdot \mathcal{F}_{E,t}$$

The market clearing condition for the labor market is:

$$\mathcal{L}_t = \sum_{j=1}^{\mathcal{N}_t} L_{j,t}$$

Imposing symmetry, the equation above implies

$$L_t = \frac{\mathcal{L}_t}{\mathcal{N}_t}$$

The market clearing condition for the capital markets implies that the amount of capital rented by firms equals the aggregate supply of capital:

$$\mathcal{K}_t = \mathcal{K}_t^c$$
$$\mathcal{Z}_t = \mathcal{Z}_t^c$$

Equilibrium We can thus define an equilibrium for our economy in a standard way. In a symmetric equilibrium, there is one exogenous state variable, A_t, and three endogenous state variables, the physical capital stock $\mathcal{K}_t$, the intangible capital stock $\mathcal{Z}_t$, and the number of intermediate good firms, $\mathcal{N}_t$. Given an initial condition $\{A_0, \mathcal{K}_0, \mathcal{Z}_0, \mathcal{N}_0\}$ and the law of motion for the exogenous state variable A_t, an equilibrium is a set of sequences of quantities and prices such that (i) quantities solve producers' and the household's optimization problems and (ii) prices clear markets.

We interpret the stock market return as the claim to the entire stream of future aggregate dividends, $\mathcal{D}_t$.

3 Economic mechanisms

Our model departs in two significant ways from the workhorse stochastic growth model in macroeconomics. First, our setup incorporates imperfect competition and the entry and exit of intermediate goods firms. Product innovation, or the variation in the number of firms in a particular sector, changes the degree of industry competitiveness. Second, rather than assuming an exogenous trend in aggregate productivity, the long-run growth is endogenously determined by firms' investment in their technology, which we refer as process innovation.

In this section, we qualitatively examine how both product and process innovation produce rich model dynamics with only a single homoscedastic technology shock. In particular, in the language of Bansal and Yaron (2004), we document that product innovation provides an *amplification* mechanism for short-run risks while process innovation provides a growth *propagation* mechanism that generates long-run risks. Further, the product innovation channel generates conditional heteroscedasticity in macroeconomic quantities due to nonlinearities in markups.

While we focus on a qualitative examination of our setup here, we provide a detailed quantitative analysis of the model in the next section.

3.1 Product Innovation

This subsection describes how business creation combined with imperfect competition provides an short-run amplification mechanism that is asymmetric. This channel is important for generating return predictability and a U-shaped term structure of equity returns.

Entry & Exit We start by examining the business creation process through the free entry condition, equation (2). Suppose there is a positive technology shock. As firms become more productive, the value of intermediate goods firms increases. Attracted by higher profit opportunities, new firms enter the market. Firms will enter the market up until the entry condition is satisfied, implying procyclical entry. On the other hand, as the number of firms in the economy grows, product market competition intensifies. Thus, the model is consistent with the empirical evidence that the degree of competitiveness in industries is procyclical, as documented, for example, in Bresnahan and Reiss (1991) and Campbell and Hopenhayn (2005).

Next, we show that in our model how changes in the number of competitors in an industry lead to time-varying markups.

Markups In the classic Dixit-Stiglitz CES aggregator, an individual firm is atomistic. Therefore, a single firm will not affect the sectoral price level, $P_{j,t}$. The firm faces a constant price elasticity of demand and charges a constant markup equal to $\frac{\nu_2}{\nu_2-1}$.

In contrast, in our model the measure of firms within each sector is finite. Consequently, the intermediate producer takes into account its effect on the sectoral price index. This implies that the price elasticity of demand in a sector depends on the number of firms. As we show in the appendix, intermediate firms' cost minimization problem implies that the price markup is[8]

$$\varnothing_t \quad = \quad \frac{-\nu_2 \mathcal{N}_t + (\nu_2 - \nu_1)}{-(\nu_2 - 1)\mathcal{N}_t + (\nu_2 - \nu_1)}.$$

Thus, equilibrium markups depend on the number of active firms and thus, the degree of competition. Taking the derivative of the markup with respect to $\mathcal{N}_t$, we find

$$\frac{\partial \varnothing_t}{\partial \mathcal{N}_t} = \frac{\nu_1 - \nu_2}{\left[-(\nu_2 - 1)\mathcal{N}_t + (\nu_2 - \nu_1)\right]^2} < 0. \tag{3}$$

Assuming that the elasticity of substitution within industries is higher than across sectors ($\nu_2 > \nu_1$) implies that markups decrease as the number of firms increases, and thus are countercyclical in the model. This implication is consistent with the empirical evidence documented e.g. in Bils (1987), Rotemberg and Woodford (1991, 1999) and Chevalier, Kashyap and Rossi (2003). Moreover, countercyclical markups amplifiy short-run risks as in booms (downturns), markups are higher which expands (contracts) production more. Riskier short-run cash flows allows the model to generate a downward sloping equity term structure initially.

The expression for the derivative of the markup with respect to the number of firms $\mathcal{N}_t$ implies that the sensitivity of markups to a marginal entrant depends on the number of firms in the industry. The nonlinear relation between markups and $\mathcal{N}_t$ is illustrated in figure 1. Adding a new firm to an already highly competitive industry (high $\mathcal{N}_t$) will have little impact on product market competition. In contrast, a marginal entrant will have a large impact on markups when the number of firms are low. Consequently, markups will rise more recessions than it falls in booms, which leads to countercyclical macroeconomic volatility.

3.2 Process Innovation

This subsection illustrates the long-run growth propagation mechanism through process innovation. This channel generates endogenous long-run risks.

[8]The standard constant markup specification is a particular case in which $N_t \to \infty$.

Endogenous Productivity The aggregate production technology can be expressed as

$$\begin{aligned}
\mathcal{Y}_t &= \mathcal{N}_t K_t^{\alpha}(A_t Z_t^{\eta} \mathcal{Z}_t^{1-\eta} L_t)^{1-\alpha} \\
&= \mathcal{N}_t \left(\frac{\mathcal{K}_t}{\mathcal{N}_t}\right)^{\alpha} \left[A_t \left(\frac{\mathcal{Z}_t}{\mathcal{N}_t}\right)^{\eta} \mathcal{Z}_t^{1-\eta} \left(\frac{\mathcal{L}_t}{\mathcal{N}_t}\right)\right]^{1-\alpha} \\
&= \mathcal{K}_t{}^{\alpha} \left[\mathcal{Z}_{p,t}\mathcal{L}_t\right]^{1-\alpha}
\end{aligned}$$

where $\mathcal{Z}_{p,t} \equiv A_t \mathcal{Z}_t \mathcal{N}_t^{-\eta}$ is measured TFP, which is composed of three components. A_t is an exogenous component while $\mathcal{Z}_t$, the stock of intangible capital, is endogenously accumulated through process innovation (i.e., R&D), and the mass of active firms $\mathcal{N}_t$, endogenously created through product innovation. Due to the spillover effect from process innovation, $\mathcal{Z}_t$ grows and is the endogenous trend component.

To filter out the cyclical components of productivity, we can take conditional expectations of the log TFP growth rate:

$$\begin{aligned}
E_t[\Delta z_{p,t+1}] &= E[\Delta a_{t+1} + \Delta z_{t+1} - \eta\, \Delta n_{t+1}] \\
&\approx \Delta z_{t+1},
\end{aligned}$$

where the second approximation is recognizing that a_{t+1} and n_{t+1} are persistent stationary processes, so Δa_{t+1} and Δn_{t+1} are approximately iid. Thus, as in Kung (2015) and Kung and Schmid (2015), low-frequency components in growth are driven by the accumulation of intangible capital, which they also find strong empirical support for. With recursive preferences, these low-frequency movements in productivity lead to sizable risk premia in asset markets.

4 Quantitative Implications

In this section, we present quantitative results from a calibrated version of our model. We calibrate it to the replicate salient features of industry and business cycles and use it to gauge the quantitative significance of our mechanisms for risk premia. We also provide empirical evidence supporting the model predictions.

In order to quantitatively isolate the contributions of process innovation, product innovation and time-varying markups on aggregate risk and risk premia, we find it instructive to compare our benchmark model to another nested model. In the following, we refer to the benchmark model as model A. Model B features a CES aggregator, and abstracts away from entry and exit, so that the mass of firms and hence markups are constant.

The models are calibrated at quarterly frequency. The empirical moments correspond to the U.S. postwar sample from 1948 to 2013. The model is solved using third-order perturbation methods.[9]

Calibration We begin with a description of the calibration and the construction of the key empirical data series, such as entry rates, markups, R&D, and intangible capital stock.

Following Bils (1987), Rotemberg and Woodford (1999) and Campello (2003), we construct an empirical price markup series by exploiting firms' first order condition with respect to L_t, imposing the symmetry condition,

$$\o_t \quad = \quad (1-\alpha)\frac{\mathcal{Y}_t}{\mathcal{L}_t W_t} = (1-\alpha)\frac{1}{\mathcal{S}_{L,t}}$$

and adjusting for potential nonlinearities in the empirical counterparts. Here, $\mathcal{S}_{L,t}$ is the labor share in the model. We discuss further details about the construction of the markup measure in the appendix.

For entry rates, we use two empirical counterparts. First, we use the index of net business formation (NBF). This index is one of the two series published by the BEA to measure the dynamics of firm entry and exit at the aggregate level. It combines a variety of indicators into an approximate index and is a good proxy for n_t. The other is the number of new business incorporations (INC), obtained from the U.S. Basic Economics Database. Both series have similar dyanmics. Below, we provide a number of robustness checks with respect to both measures.

Finally, our empirical series for $\mathcal{S}_t$ measures private business R&D investment and comes from the National Science Foundation (NSF). The Bureau of Labor Statistics (BLS) constructs the R&D stock by accumulating these R&D expenditures and allowing for depreciation, much in the same way as the physical capital stock is constructed. We thus use the R&D stock as our empirical counterpart for the stock of technology $\mathcal{Z}_t$. For consistency, we use the same depreciation rate δ_n in our calibration as does the BLS in its calculations. The remaining empirical series are standard in the macroeconomics and growth literature. Additional details are collected in the appendix.

Table 1 presents the quarterly calibration. Panel A reports the values for the preference parameters. The elasticity of intertemporal substitution ψ is set to 1.8 and the coefficient of relative

[9]We prune simulations using the Kim, Kim, Schaumburg and Sims (2008) procedure to avoid generating explosive paths in simulations.

risk aversion γ is set to 10.0, both of which are standard values in the long-run risks literature (e.g. Bansal, Kiku, and Yaron (2008)). The labor elasticity parameter χ, is set to 3. This implies a Frisch elasticity of labor supply of 2/3, which is consistent with estimates from the microeconomics literature (e.g. Pistaferri (2003)). χ_0 is set so that the representative household works 1/3 of her time endowment in the steady state. The subjective discount factor β is calibrated to 0.995 to be consistent with the level of the real risk-free rate.

Panel B reports the calibration of the technological parameters. The capital share α is set to 0.33, and the depreciation rate of capital δ_k is set to 2.0%. These two parameters are calibrated to standard values in the macroeconomics literature (e.g. Comin, and Gertler (2006)). The parameters related to R&D are calibrated following Kung (2014). The depreciation rate of the R&D capital stock δ_z is set to 3.75%, implying an annualized depreciation rate of 15%. The physical and R&D capital adjustment cost parameters ζ_k and ζ_z are both set at 0.738 to be consistent with the relative volatility of R&D investment growth to physical investment growth. The degree of technological appropriability η is calibrated to 0.065, in line with Kung (2014). The exogenous firm exit shock δ_n is set to 1%, slightly lower than in Bilbiie, Ghironi, and Melitz (2012). The price elasticity accross (ν_1) and within (ν_2) industries are calibrated to 1.05 and 75, respectively to be consistent with estimates from Jaimovich and Floetotto (2008). κ is set to ensure an aggregate price markup of 20% in the deterministic steady state.

Panel C reports the parameter values for the exogenous technology process. The volatility parameter σ is set at 1.24% to match the unconditional volatility of measured productivity growth. The persistence parameter ρ is calibrated to 0.985 to match the first autocorrelation of expected productivity growth. $a^\star$ is chosen to generate an average output growth of 2.0%.

4.1 Quantitative Results

We now report quantitative results based on our calibration. We start by discussing the nature of macroeconomic dynamics and then present quantitative predictions for asset returns and empirical tests.

4.1.1 Implications for Growth and Cycles

Aggregate cycles in the model reflect movements at the industry level. New firms enter, obsolete products exit, competitive pressure and markups adjust, and measured productivity fluctuates. Productivity dynamics in turn shape macroeconomic cycles.

Industry Cycles Table 2 reports basic industry moments from the benchmark model. The average markup and the mean profit share are broadly consistent with the data. Similarly, the model quantitatively captures industry cycles well by closely matching the volatilities and first autocorrelations of markups, intangible capital growth, profit shares and net entry rates. The last panel confirms the negative relation between the mass of firms and entry rates.

Figure 2 illustrates the underlying dynamics by plotting the responses of key variables to a positive one standard deviation exogenous technology shock. We focus on two model specifications, namely the benchmark model and model B (constant mass of firms and a constant markup). In the benchmark model, a positive technology shock raises valuations and thus triggers entry, as shown in the top left panel, and the mass of firms increases, as documented in the top right panel. In our benchmark model, firms take their effect on competitor firms into account when setting prices, so that increasing competitive pressure leads to falling markups, as shown in the lower left panel. Importantly, as the lower right panel illustrates, the entry margin significantly amplifies investment in technology. This is because in response to falling markups, demand for intermediate goods increase. To satisfy the higher demand, firms produce more and increase demand for both physical and technology capital.

In table 3, we report results from predictive regressions of aggregate growth rates on entry rates. Qualitatively, the model predicts that a rise in entry rates forecasts higher growth. Indeed, we empirically find that entry positively forecasts higher growth rates of output, consumption, and investment. While the signs are consistent with the model prediction throughout, statistical significance obtains only for shorter horizons, consistent with the notion that entry rates are highly cyclical. This suggests that variations in entry rates are an important determinant of business cycles fluctuations, which we examine next.

Business Cycles Table 4 reports the main business cycle statistics for models A, and B. While all of them are calibrated to match the mean and volatility of consumption growth, the cyclical behavior across models differs considerably.

The benchmark model quantitatively captures basic features of macroeconomic fluctuations in the data well. It produces consumption volatility, investment volatility and R&D volatility that are similar to their empirical counterparts. While investment volatility falls a bit short of the empirical analogue, Kung (2014) shows that incorporating sticky nominal prices and interest rate shocks in such a framework can help to explain the remaining volatility. The model generates volatile movements in labor markets, even overshooting the volatility of hours worked slightly. This is noteworthy, as standard macroeconomic models typically find it challenging to generate labor market fluctuations of the orders of magnitude observed in the data.

The quantitative success of the benchmark model contrasts starkly to the simulated moments from the nested model B. Without entry and exit investment and R&D volatility are significantly reduced. Thus, entry and exit combined with countercyclical markups serve as a quantitatively significant amplification mechanism for shocks at business cycle frequencies.

The amplification mechanism is illustrated in figure 3, which plots the impulse response functions of aggregate quantities. Upon impact of a positive exogenous productivity shock, output, investment and consumption all rise, and significantly more so than in a specification without the entry margin. The lower two panels show that both the responses of realized and and expected consumption growth are amplified in the benchmark model. Accordingly, the amplification mechanism increases the quantity of priced risk in the economy, since the stochastic discount factor in the model reflects both realized and predictable movements in consumption growth, given the assumption of Epstein-Zin preferences.

The intuition for the amplification result is as follows. With procyclical entry, the model predicts countercyclical markups, so that falling markups in expansions triggers higher demand for intermediate goods from the final good producer, further stimulating investment in capital and technology, and thus output. Similarly, rising markups in downturns dampen the demand for intermediate goods, and deepens recessions further.

Table 5 provides empirical support for the model predictions regarding the cyclical behavior of entry rates, number of firms, and markups. The correlation of aggregate quantities and our empirical markup series is negative while the number of firms and entry rates are procyclical.

Asymmetric Cycles Fig. 4 plots the *difference* between the response of quantities to a positive shock and to a negative shock of the same magnitude. Any deviation from a zero difference reflects an asymmetry in responses at some horizon. Observe that model B, with constant firm mass and markups, generates no differential response at any horizon. That specification thus predicts symmetric cycles. This is quite different in our benchmark model. It features differential responses at all horizons. The number of firms increases relatively more in expansions than it falls in recessions. Similarly, markups fall relatively more in upswings than they rise in downturns. On the other hand, investment, consumption and output rise by relatively less in good times than they fall in bad times, so that recessions are deeper in our benchmark economy.

The source of asymmetry in the model comes from the nonlinear relation between markups and the number of firms, which is highlighted in figure 5. This figure plots responses of quantities in the benchmark conditional on high and low number of firms. Note that the figure shows that both realized and expected consumption growth fall by relatively more in a scenario with a low mass of incumbent firms (i.e., during a recession). Consequently, this asymmetry implies conditional heteroscedasticity in fundamentals, including consumption growth. If we fit our simulated data to the consumption process of Bansal and Yaron (2004), we obtain:

$$\begin{aligned} z_{t+1} &= 0.961\ z_t + 0.433\ \sigma_t e_{t+1} \\ g_{t+1} &= z_t + \sigma_t \eta_{t+1} \\ \sigma^2_{t+1} &= 0.0046^2 + 0.975\ (\sigma^2_t - 0.0046^2) + 0.184 \times 10^{-6}\ w_{t+1} \end{aligned}$$

where g_{t+1} is the realized consumption growth, z_t is the expected consumption growth, σ_t is the conditional volatility of g_{t+1} and e_{t+1}, η_{t+1}, and w_{t+1} are i.i.d. shocks. To compare with Bansal and Yaron (2004), we time aggregate their model to a quarterly frequency, and obtain:

$$\begin{aligned} z_{t+1} &= 0.939\ z_t + 0.151\ \sigma_t e_{t+1} \\ g_{t+1} &= z_t + \sigma_t \eta_{t+1} \\ \sigma^2_{t+1} &= 0.0022^2 + 0.962\ (\sigma^2_t - 0.0022^2) + 8.282 \times 10^{-6}\ w_{t+1} \end{aligned}$$

Note that our endogenous consumption volatility dynamics closely matches the exogenous specification of Bansal and Yaron (2004). Quantitatively, our model generates significant time-varying volatility. Consistent with Kung (2015) and Kung and Schmid (2015), the model also generates significant long-run risks through the process innovation channel.

Table 6 highlights that our time-varying macroeconomic volatility is also countercyclical. Using our markup series, we split the data sample into high and low markup episodes. This procedure allows us to compute moments conditional on markups. Given the countercyclicality of our markup measure, it is perhaps not surprising that average output, consumption and investment is lower in high markup episodes. More interestingly, however, we find that the volatilities conditional on high markups are also higher. In line with the discussion above, the model is consistent with these findings.

4.1.2 Asset Pricing Implications

In our production economy, the endogenous consumption and cash flow dynamics will be reflected in aggregate risk premia and their dynamics. Intuitively, we expect two effects. First, the entry margin endogenously amplifies movements in realized consumption growth. Second, R&D decisions of firms propagates technology shocks to long-run consumption growth, which generates endogenous persistence in expected consumption growth. With Epstein-Zin preferences, both shocks to realized and expected consumption growth are priced, hence we expect that the amplification and propagation mechanisms will give rise to a sizable *unconditional* equity premium. Second, since quantity of risk is time-varying and depends negatively on the mass of firms, we expect a countercyclical *conditional* equity premium.

We now use our calibration to assess the quantitative significance of these dynamics for risk premia and to generate empirical predictions. We discuss and quantify these implications in turn and present empirical evidence supporting the model predictions.

Equity Premium Table 7 reports the basic asset pricing implications of the benchmark model and the alternative specification. Absent entry and exit, the risk free rate is about double its empirical counterpart (model B), while the benchmark model (model A) replicates a low and stable risk free rate. While we calibrate the endogenous average growth rate to coincide across all models, the amplification mechanism working through the entry margin coupled with countercyclical markups creates higher persistent uncertainty. Higher uncertainty increases the precautionary savings motive, driving down interest rates to realistic levels in our benchmark economy.

The higher uncertainty also leads to a significantly higher and realistic equity premium. This is because product innovation provides an amplification mechanism for short-run risks while process innovation provides a growth propagation mechanism that generates endogenous long-run risks. While stock return volatility falls short of the empirical target, Ai, Croce and Li (2013) report that empirically, the productivity driven fraction of return volatility is around just 6%, which is close to our quantitative finding.

Consistent with the existence of sizeable risk premia, the benchmark model also generates quantitatively realistic implications for the level and the volatility of the price-dividend ratio.

Competition and asset prices Imperfect competition and variations in competitive pressure is a key mechanism driving risk premia in our setup. We now provide some comparative statics of risk and risk premia with respect to average competitive pressure. We do this by reporting some sensitivity analysis of simulated data with respect to the sectoral elasticity of substitution between goods, ν_2. Fig. 6 reports the results by plotting key industry, macro and asset pricing moments for different values of ν_2.

Raising the sectoral elasticity of substitution between goods, ν_2, has two main effects on markups. First, by facilitating substitution between intermediate goods, it increases competition and therefore, holding all else constant, lowers markups. Second, by the virtue of our expression for the markup, equation (3), it raises the sensitivity of markups with respect to the number of incumbent firms, and thus, all else equal, makes markups more volatile. The first effect is an important determinant of the average growth rate of the economy, while the latter affects the volatility of growth.

With respect to the first effect, increasing ν_2 has two opposing implications. First, decreasing the average markup, holding all else equal, lowers monopoly profits in the intermediate sector. Second, a lower average markup increases the demand for intermediate goods inputs, which raises monopoly profits. In our benchmark calibration, the second effect dominates, and therefore more intense competition, and a higher average markup raises steady-state growth. On the other hand, a more volatile demand for intermediate goods inputs triggered by increasingly volatile markups leads to a more volatile growth path. This effect is exacerbated by increasingly cyclical entry as profit opportunities become more sensitive to aggregate conditions. The net effect is a riskier economy, which translates into a higher risk premium.

Term structure of equity returns An emerging literature starting with van Binsbergen, Brandt, and Koijen (2012) provides evidence that the term structure of expected equity returns is downward sloping, at least in the short-run. This is in contrast to the implications of the baseline long-run risks model (Bansal and Yaron (2004)) or the habits model (Campbell and Cochrane (1999)). The empirical finding reflects the notion that dividends are very risky in the short-run.

Our benchmark model is qualitatively consistent with these findings. We compute the current price $\mathcal{Q}_{t,t+k}$ of a claim to the aggregate dividend at horizon k as $\mathcal{Q}_{t,t+k} = E[\mathcal{M}_{t,t+k}\mathcal{D}_{t+k}]$ and compute its unconditional expected return accordingly.

The left panel of figure 7 shows that the term structures of (unlevered) equity returns for the benchmark model and the model without entry and exit. Consistent with the standard long-run risks model, the model absent entry and exit produces an upward sloping term structure. In the benchmark model, countercyclical markups substantially amplify short-run risks and increase the procyclicality of short-term cash flows, which leads to a downward-sloping equity term structure for roughly the first five years. Note also that the risk premia on the very short-term strips are significantly higher than those at medium to long horizons, consistent with the data.

These cash flow dynamics are illustrated in the right panel of figure 7, which plots the impulse response function of the aggregate dividend growth rate to a positive exogenous technology shock in the benchmark model and the model without entry and exit. Both models generate a persistent increase in dividend growth at longer maturities through the process innovation channel. Thus, long-run cash flows are risky as reflected by the high long-horizon risk premia. On the other hand, industry and markup dynamics render short-run dividends significantly more risky in the benchmark model. Intuitively, dividends spike upwards on impact as new firms enter more slowly in response to attractive profit opportunities. When competitive pressure rises, markups and dividends start falling until the aggregate demand for capital and R&D increases, triggering low-frequency movements in productivity that drive up dividends again.

Return predictibility The previous sections establish how the endogenous short- and long-run risks in our benchmark model produce a realistic unconditional equity premium. This section documents that the endogenous countercyclical volatility due to nonlinearities in markups implies countercyclical variation in the conditional equity premium consistent with the data. We show that excess equity returns are forecastable by measures of markups and net business formation, which we verify empirically.

Table 8 presents our main predictability results. Panel A first verifies standard long-horizon predictability regressions projecting future aggregate returns on current log price-dividend ratios in our data sample, and shows statistically significant and negative slope coefficients, and R^2's increasing with horizons up to five years. Perhaps more interestingly, we run the same regressions with simulated data from our benchmark model using a sample of equal length as the empirical counterpart. The top right panel reports the results. Consistent with the data, we find statistically significant and negative slope coefficients, with R^2's increasing with horizons up to five years and of similar magnitude as the data. Notably, the R^2's in our model simulations match their empirical counterparts remarkably well.

These predictability results in the model imply that the model generates endogenous conditional heteroscedasticity, as shocks to the forcing process, A_t, are assumed to be homoscedastic. Figure

8 confirms this. It shows the impulse response functions of the conditional risk premium and the conditional variance of excess returns to a positive exogenous technology shock, both in the benchmark model and in model absent entry and exit. While in model B neither the risk premium nor the conditional variance respond, they both persistently fall on impact in the benchmark model. With the entry margin and countercyclical markups, the risk premium and its variance are countercyclical, mirroring the endogenous countercyclical consumption volatility.

Our predictability results are related to the degree of competition, which we confirm in the remaining panels in table 8. Moreover, we present novel empirical evidence supporting this prediction. We use two measures of entry, our markup series, and the profit share as predictive variables. Panels B to E report the results from projecting future aggregate returns on these variables for horizons up to 5 years, in the model and in the data. In the model, the proxies for entry forecast aggregate returns with a statistically significant negative sign, while markups and profit shares forecast them with a statistically significant positive sign. We verify this empirical prediction in the data. The empirically estimated slope coefficients all have the predicted sign, and except for the profit share regressions, are statistically significant. We thus provide novel evidence on return predictability related to time-varying competitive pressure.

It is well-known that statistical inference in predictive regressions is complicated through small sample biases. To illustrate that the sources of predictability in our model is robust to these concerns, we repeat the predictability regressions in a long sample of 200,000 quarters. For simplicity, we only report evidence from projecting returns on log price-dividend ratios. Table 9 shows the results from these regressions across model specifications. In case of the model without entry and exit, the explanatory power of the regressions are identically equal to zero. In contrast, the benchmark model produces R^2 that are still sizeable and increasing with horizon.

4.2 Extensions

Given the importance of markup dynamics for our asset pricing results, we next consider two extensions of the model that address properties of markups recently emphasized in the literature. Countercyclical movements in both price and wage markups are often recognized as the main source of fluctuations at higher frequency (e.g. Christiano, Eichenbaum and Evans (2005)). The objective of this section is to investigate which features of markups appear relevant through the lens of asset pricing. In a first extension, we consider price markup shocks, in a way often considered in the DSGE literature (e.g. Smets and Wouters (2003), Justiniano, Primiceri, and Tambalotti (2010)).

Second, in addition to price markups, we consider wage markups, whose relevance has recently been pointed out in the context of New Keynesian macroeconomic models (e.g. Gali, Gertler, and Lopez-Salido (2007)). The two extensions also allow us to gain further intuition about the mechanisms underlying the risk premia and predictability results in the benchmark model.

4.2.1 Markup Shocks

In this section, we show that we need two ingredients to jointly generate a countercyclical risk premium: markups need to be countercyclical and conditionally heteroskedastic.

We start by considering exogenously stochastic price markups. To that end, we solve the version of the model without entry and exit and specify the markup process as

$$\log(\o_t) = (1-\rho_{\o})\log(\o) + \rho_{\o}\log(\o_{t-1}) + \sigma_{\o} u_t$$

where u_t is a standard normal i.i.d. shock that has a contemporaneous correlation of ϱ with ϵ_t. We investigate three cases, (i) constant price markups, (ii) uncorrelated time-varying markups, and (iii) countercyclical markups. We set $\o$, $\rho_{\o}$, and $\sigma_{\o}$ to match the unconditional mean, first autocorrelation, and unconditional standard deviation of $\o_t$ in the benchmark model.

Panels A, B, and C in table 10 report the main quantitative implications for asset returns and price-dividend ratios. The results are instructive. Panel B shows that introducing uncorrelated stochastic markups has a 40 bps impact on the risk premia and increases significantly the volatility of the price dividend ratio. Consistent with the intuition developed earlier, the additional risk raises the precautionary savings motive and lowers the risk-free rate. When markups are exogenously countercyclical, panel C shows that the risk premium goes up by close to one percent. In line with the intuition explained in the benchmark case, countercyclical markups amplifiy uncertainty.

While countercyclical markups increase uncertainty, it does not generate predictability if the dynamics are symmetric. Table 11 illustrates this point by reporting the results from projecting future returns on log price-dividend ratios in models with exogenous markups. The results in panels A, B, and C show that none of these specifications generate any predictability. The missing ingredient is the asymmetry or conditional heteroscedasticity in markups that is generated endogenously in our benchmark model.

To illustrate the importance of this asymmetry for predictibility, we solve a version of the model where the volatility of technology shocks is affected by the level of markups. In particular, we assume

$$
\begin{aligned}
a_t &= (1-\rho_a)a^\star + \rho_a a_{t-1} + \sigma_t \epsilon_t \\
\sigma_t &= \sigma(1+\kappa_\text{ø}\hat{\text{ø}}_t)
\end{aligned}
$$

where $\kappa_\text{ø} > 0$ captures the effects of markups on the conditional volatility of productivity shocks. We choose $\kappa_\text{ø}$ to approximately replicate the asymmetry generated by the benchmark model. Results from the simulation are reported in Tables 10 and 11, panel D. While the average risk premium is barely affected, markup induced heteroskedasticity generates excess stock return predictability.

4.2.2 Wage Markups

In addition to price markups, imperfect competition in labor markets reflected in wage markups plays an important role in current DSGE models. The dynamics of wage markups is currently subject to a debate after an influential paper by Gali, Gertler, and Lopez-Salido (2007) which argues that they should be countercyclical. In this section, we quantitatively explore the implications of dynamic wage markups for asset returns.

Formally, the wage markup is defined as the ratio of the real wage to the households marginal rate of substitution between labor and consumption,

$$
\log(\text{ø}^w_t) = \log(W_t) - \log\left(\frac{\chi_0(1-\mathcal{L}_t)^{-\chi}}{\mathcal{C}_t^{-1/\psi}}\mathcal{Z}_t^{1-1/\psi}\right)
$$

reflecting imperfect competition in the labor supply market. We specify the wage markup process exogenously as an AR(1) process in logs

$$
\log(\text{ø}^w_t) = (1-\rho^w_\text{ø})\log(\text{ø}^w) + \rho^w_\text{ø}\log(\text{ø}^w_{t-1}) + \sigma^w_\text{ø} u^w_t
$$

where u^w_t is a standard normal i.i.d. shock that has a contemporaneous correlation of ϱ^w with ϵ_t.

We augment the benchmark model with wage markups and compare asset pricing moments and predictability results for two additional specifications: (i) uncorrelated time-varying markups, and (ii) countercyclical wage markup. We calibrate the markup process to match the standard deviation and first autocorrelation of the wage markup reported in Gali, Jordi, Gertler, and Lopez-Salido (2007): $\rho^w_\text{ø} = 0.96$, and $\sigma^w_\text{ø} = 2.88\%$. Whenever applicable, we set $\varrho^w = -0.45$ in order to replicate the -0.79 correlation between wage markups and output documented in Gali, Jordi, Gertler, and

Lopez-Salido (2007). The steady state markup is set to 1.2 (see e.g., Comin and Gertler, 2006).

The main asset pricing implications are collected in table 12 and predictability results are reported in table 13. Accounting for wage markups in addition to endogenous countercyclical price markups amplifies priced risk and raises risk premia. On the other hand, introducing wage markups only sharpens predictability when the dynamics are countercyclical.

5 Conclusion

We build a general equilibrium model with monopolistic competition and endogenous firm entry and exit. Endogenous R&D accumulation (process innovation) generates substantial long-run risks and therefore, a sizable equity premium. Also, our model structure implies a negative and nonlinear relation between the number of firms and markups. Consequently, variation in entry and exit of firms (product innovation), generates countercyclical and asymmetric markups. Countercyclical markups amplifiy short-run risks, which allows the model to generate a downward sloping equity term structure up to roughly five years. Asymmetric markup dynamics produce countercyclical consumption volatility, and with recursive preferences, this implies a countercyclical equity premium. The model also predicts that the equity premium is forecastable with measures of markups and the intensity of new firm creation, which we verify in the data. In short, our paper highlights how fluctuations in competitive pressure is an important source of time-varying risk premia.

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7 Appendix A: Data Sources

Quarterly data for consumption, capital investment, and GDP are from the Bureau of Economic Analysis (BEA). Annual data on private business R&D investment are from the survey conducted by the National Science Foundation. Annual data on the stock of private business R&D are from the Bureau of Labor Statistics. Real annual capital stock data is obtained from the Penn World Table. Quarterly productivity data are from Fernald (2009) (Federal Reserve Bank of San Francisco) and is measured as Business sector total factor productivity. The labor share and average weekly hours are obtained from the Bureau of Labor Statistics (BLS). The monthly index of net business formation (NBF) and number of new business incorporations (INC) are from the U.S. Basic Economics Database. Consumption is measured as expenditures on nondurable goods and services. Capital investment is measured as private fixed investment. Output is measured as GDP. The labor share is defined as the business sector labor share. Average weekly hours is measured for production and nonsupervisory employees of the total private sector. The variables are converted to real using the Consumer Price Index (CPI), which is obtained from the Center for Research in Security Prices (CRSP). Annual data are converted into quarterly data by linear interpolation. The inflation rate is computed by taking the log return on the CPI index. The sample period is for 1948-2013, except for the average weekly hours series which starts in 1964 and the NBF and INC series that were discontinued in 1993.

Monthly nominal return and yield data are from CRSP. The real market return is constructed by taking the nominal value-weighted return on the New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) and deflating it using the CPI. The real risk-free rate is constructed by using the nominal average one-month yields on treasury bills and taking out expected inflation[10]. Aggregate market and dividend values are from CRSP. The price dividend ratio is constructed by dividing the current aggregate stock market value by the sum of the dividends paid over the preceding 12 months.

[10]The monthly time series for expected inflation is obtained using an AR(4).

7.1 Markup measure

Solving the intermediate producer problem links the price markup to the inverse of the marginal cost of production MC_t,

$$\o_t = \frac{1}{MC_t}$$

In equilibrium, MC_t is equal to the ratio of marginal cost over marginal product of each production input (see the cost mininization problem). Since data on wages are available at the aggregate level, the labor input margin has been the preferred choice in the literature. Using the first order condition with respect to L_t and imposing the symmetry condition,

$$\o_t = (1-\alpha)\frac{\mathcal{Y}_t}{\mathcal{L}_t W_t} = (1-\alpha)\frac{1}{\mathcal{S}_{L,t}}$$

where $\mathcal{S}_{L,t}$ is the labor share.

The inverse of the labor share should thus be a good proxy for the price markup. However, there are many reasons why standard assumptions may lead to biased estimates of the markup (see Rotemberg and Woodford (1999)). In this paper, we follow Campello (2003) by focusing on non-linearities in the cost of labor[11]. More specifically, when deriving the cost function, we assumed that the firm was able to hire all workers at the marginal wage. In practice however, the total wage paid $W(L_t)$, is likely to be convex in hours (e.g. Bils (1987)). This creates a wedge between the average and marginal wage that makes the labor share a biased estimate of the real marginal cost. Denoting this wedge by $\omega_t = W'(L_t)/(W(L_t)/L_t)$, the markup becomes,

$$\o_t = (1-\alpha)\frac{1}{S_{L,t}}\,\omega_t^{-1}$$

Log-linearizing this expression around the steady state,

$$\hat{\o}_t = -\hat{s}_{L,t} - \omega_L \hat{l}_t$$

where ω_L is the steady state elacticity of ω_t with respect to average hours. Bils (1987) proposes a

[11]Rotemberg and Woodford (1999) presents several other reasons that makes marginal costs more procyclical than the labor share (e.g. non-Cobb-Douglas production technology, overhead labor, etc.). For robustness, we tried additional corrections. Overall, they make markups even more countercyclical, and further strengthen our empirical results.

simple model of overtime. Assuming a 50% overtime premium[12] he estimates the elasticity ω_L to be 1.4. We use this value to build our overtime measure of the price markups. We set the steady state values for L_t and $S_{L,t}$ to 40 hours and 100[13], respectively and linearly detrend the series.

8 Appendix B: Derivation of demand schedule

Final goods sector The final goods firm solves the following profit maximization problem

$$\max_{\{Y_{j,t}\}_{j\in[0,1]}} P_{Y,t}\left(\int_0^1 Y_{j,t}^{\frac{\nu_1-1}{\nu_1}}\,dj\right)^{\frac{\nu_1}{\nu_1-1}} - \int_0^1 P_{j,t}Y_{j,t}\,dj$$

where $P_{Y,t}$ is the price of the final good (taken as given), $Y_{j,t}$ is the input bought from sector j and $P_{j,t}$ is the price of that input $j \in [0,1]$,

The first-order condition with respect to $Y_{j,t}$ is

$$P_{Y,t}\left(\int_0^1 Y_{j,t}^{\frac{\nu_1-1}{\nu_1}}\,dj\right)^{\frac{\nu_1}{\nu_1-1}-1} Y_{j,t}^{-\frac{1}{\nu_1}} - P_{j,t} = 0$$

which can be rewritten as

$$Y_{j,t} = \mathcal{Y}_t\left(\frac{P_{j,t}}{P_{Y,t}}\right)^{-\nu_1} \tag{4}$$

Using the expression above, for any two intermediate goods $j,k \in [0,1]$,

$$Y_{j,t} = Y_{k,t}\left(\frac{P_{j,t}}{P_{k,t}}\right)^{-\nu_1} \tag{5}$$

Since markets are perfectly competitive in the final goods sector, the zero profit condition must hold:

$$P_{Y,t}Y_t = \int_0^1 P_{j,t}Y_{j,t}\,dj \tag{6}$$

[12]This is the statutory premium in the United States.

[13]The Bureau of labor statistics use 100 as the index for the labor share in 2009. Our results stay robust to change in this value.

Substituting (9) into (6) gives

$$Y_{j,t} = P_{Y,t}\mathcal{Y}_t \frac{P_{j,t}^{-\nu_1}}{\int_0^1 P_{j,t}^{1-\nu_1}\, dj} \tag{7}$$

Substitute (8) into (7) to obtain the price index

$$P_{Y,t} = \left(\int_0^1 P_{j,t}^{1-\nu_1}\, dj\right)^{\frac{1}{1-\nu_1}}$$

Since each sector is atomistic, their actions will not affect $\mathcal{Y}_t$ nor $P_{Y,t}$. Thus, each of these sectors will face an isoelastic demand curve with price elasticity ν_1.

Sectorial goods sector The representative sectorial firm j solves the following profit maximization problem

$$\max_{\{X_{i,j,t}\}_{i=1,N_{j,t}}} P_{j,t} N_{j,t}^{1-\frac{\nu_2}{\nu_2-1}} \left(\sum_{i=1}^{N_{j,t}} X_{i,j,t}^{\frac{\nu_2-1}{\nu_2}}\right)^{\frac{\nu_2}{\nu_2-1}} - \sum_{i=1}^{N_{j,t}} P_{i,j,t} X_{i,j,t}$$

where $P_{j,t}$ is the aggregate price in sector j (taken as given by the firm), $X_{i,j,t}$ is intermediate good input produced by firm i in sector j, and $N_{j,t}$ is the number of firms in sector j.

The first-order condition with respect to $X_{i,j,t}$ is

$$P_{j,t} N_{j,t}^{1-\frac{\nu_2}{\nu_2-1}} \left(\sum_{i=1}^{N_{j,t}} X_{i,j,t}^{\frac{\nu_2-1}{\nu_2}}\right)^{\frac{\nu_2}{\nu_2-1}-1} X_{i,j,t}^{-\frac{1}{\nu_2}} - P_{i,j,t} = 0$$

which can be rewritten as

$$X_{i,j,t} = \frac{Y_{j,t}}{N_{j,t}} \left(\frac{P_{i,j,t}}{P_{j,t}}\right)^{-\nu_2} \tag{8}$$

Using the expression above, for any two intermediate goods i, and k,

$$X_{i,j,t} = X_{k,j,t} \left(\frac{P_{i,j,t}}{P_{k,j,t}}\right)^{-\nu_2} \tag{9}$$

Now, raising both sides of the equation to the power of $\frac{\nu_2-1}{\nu_2}$, summing over i and raising both sides to the power of $\frac{\nu_2}{\nu_2-1}$, we get

$$\left(\sum_{i=1}^{N_{j,t}} X_{i,j,t}^{\frac{\nu_2-1}{\nu_2}}\right)^{\frac{\nu_2}{\nu_2-1}} = X_{k,j,t}\frac{\left(\sum_{i=1}^{N_{j,t}} P_{i,j,t}^{1-\nu_2}\right)^{\frac{\nu_2}{\nu_2-1}}}{P_{k,j,t}^{-\nu_2}} \tag{10}$$

Substituting for the production function in the left-hand side and rearranging the terms,

$$\frac{Y_{j,t}}{\mathcal{N}_t}\frac{P_{k,j,t}^{-\nu_2}}{X_{k,j,t}} = \mathcal{N}_t^{-\frac{\nu_2}{\nu_2-1}}\left(\sum_{i=1}^{N_{j,t}} P_{i,j,t}^{1-\nu_2}\right)^{\frac{-\nu_2}{\nu_2-1}} \tag{11}$$

Using the first order condition with respect to $X_{i,j,t}$, the left-hand side is equal to $P_{j,t}^{-\nu_2}$. Therefore, the sectoral price index is

$$P_{j,t} = N_{j,t}^{\frac{-1}{1-\nu_2}}\left(\sum_{i=1}^{N_{j,t}} P_{i,j,t}^{1-\nu_2}\right)^{\frac{1}{1-\nu_2}}$$

8.1 Individual firm problem

Using the demand faced by an individual firm i in sector j, and the demand faced by sector j, the demand faced by firm (i,j) can be expressed as

$$X_{i,j,t} = \frac{\mathcal{Y}_t}{N_{j,t}}\left(\frac{P_{i,j,t}}{P_{j,t}}\right)^{-\nu_2}\left(\frac{P_{j,t}}{P_{Y,t}}\right)^{-\nu_1} \tag{12}$$

$$= \frac{\mathcal{Y}_t}{N_{j,t}}\left(\tilde{P}_{i,j,t}\right)^{-\nu_2}\left(\tilde{P}_{j,t}\right)^{\nu_2-\nu_1} \tag{13}$$

where $\tilde{P}_{i,j,t} \equiv \frac{P_{i,j,t}}{P_{Y,t}}$ and $\tilde{P}_{j,t} \equiv \frac{P_{j,t}}{P_{Y,t}}$.

The (real) source of funds constraint is

$$D_{i,j,t} = \tilde{P}_{i,j,t}X_{i,j,t} - W_{j,t}L_{i,j,t} - r_t^k K_{i,j,t} - r_t^z Z_{i,j,t}$$

Taking the input prices and the pricing kernel as given, intermediate firm (i,j)'s problem is to maximize shareholder's wealth subject to the firm demand emanating from the rest of the economy:

$$\begin{aligned}
V_{i,j,t} = & \max_{\{L_{i,j,t},K_{i,j,t},Z_{i,j,t},\tilde{P}_{i,j,t}\}_{t\geqslant 0}} E_0\left[\sum_{s=0}^{\infty} M_{t,t+s}(1-\delta_n)^s D_{i,j,s}\right] \\
\text{s.t.}\;\; X_{i,j,t} = & \frac{\mathcal{Y}_t}{N_{j,t}}\left(\tilde{P}_{i,j,t}\right)^{-\nu_2}\left(\tilde{P}_{j,t}\right)^{\nu_2-\nu_1}
\end{aligned}$$

where $M_{t,t+s}$ is the marginal rate of substitution between time t and time $t+s$. Note that each sector is atomistic and take the final goods price as given. However, the measure of each firm within a sector is not zero and individual firms will take into account the impact of their price setting on the sectorial price. Further, note that there is no intertemporal decisions. The objective of the firm thus simplifies to a profit maximixation problem with constraint.

The Lagrangian of the problem is

$$\begin{aligned}
\mathcal{V}_{i,j,t} &= \tilde{P}_{i,j,t}K_{i,j,t}^{\alpha}\left(A_t Z_{i,j,t}^{\eta}\mathcal{Z}_t^{1-\eta}L_{i,j,t}\right)^{1-\alpha} - W_{j,t}L_{i,j,t} - r_{j,t}^{k}K_{i,j,t} - r_{j,t}^{z}Z_{i,j,t} \\
&\quad +\Lambda_{j,t}^{d}\left(K_{i,j,t}^{\alpha}\left(A_t Z_{i,j,t}^{\eta}\mathcal{Z}_t^{1-\eta}L_{i,j,t}\right)^{1-\alpha} - \frac{\mathcal{Y}_t}{N_{j,t}}\left(\tilde{P}_{i,j,t}\right)^{-\nu_2}\left(\tilde{P}_{j,t}\right)^{\nu_2-\nu_1}\right)
\end{aligned}$$

The corresponding first order necessary conditions are

$$\begin{aligned}
r_{j,t}^{k} &= \alpha\frac{X_{i,j,t}}{K_{i,t}}(\tilde{P}_{i,j,t}+\Lambda_t^d) \\
r_{j,t}^{z} &= \eta(1-\alpha)\frac{X_{i,j,t}}{Z_{i,j,t}}(\tilde{P}_{i,j,t}+\Lambda_t^d) \\
W_{j,t} &= (1-\alpha)\frac{X_{i,j,t}}{L_{i,j,t}}(\tilde{P}_{i,j,t}+\Lambda_t^d) \\
X_{i,j,t} &= \Lambda_{j,t}^{d}\frac{\mathcal{Y}_t}{N_{j,t}}\left[-\nu_2\tilde{P}_{i,j,t}^{-\nu_2-1}\tilde{P}_{j,t}^{\nu_2-\nu_1} + (\nu_2-\nu_1)\tilde{P}_{i,j,t}^{-\nu_2}\tilde{P}_{j,t}^{\nu_2-\nu_1-1}\frac{\partial\tilde{P}_{j,t}}{\partial P_{i,j,t}}\right]
\end{aligned}$$

where $\Lambda_{j,t}^{d}$ is the Lagrange multiplier on the inverse demand function.

In the standard Dixit-Stiglitz aggregator, $\frac{\partial\tilde{P}_{j,t}}{\partial P_{i,j,t}}=0$. This happens because each individual firm is atomistic and has no influence on the aggregate price. In our setup, it will be non-zero because the the measure of firm within an industry is strictly positive. Using the definition of the price index,

$$\frac{\partial\tilde{P}_{j,t}}{\partial P_{i,j,t}} = \frac{1}{N_{j,t}}\left(\frac{P_{i,j,t}}{P_{j,t}}\right)^{-\nu_2}$$

Imposing the symmetry condition, i.e. $\tilde{P}_{j,t} = \tilde{P}_{i,j,t} = 1$, and $\mathcal{Y}_t = N_{j,t}X_{j,t}$, our set of equilibrium conditions simplifies to:

$$
\begin{aligned}
r^k_{j,t} &= \alpha \frac{X_{j,t}}{K_{j,t}}(1 + \Lambda^d_{j,t}) \\
r^z_{j,t} &= \eta(1-\alpha)\frac{X_{j,t}}{Z_{j,t}}(1 + \Lambda^d_{j,t}) \\
W_{j,t} &= (1-\alpha)\frac{X_{j,t}}{L_{j,t}}(1 + \Lambda^d_{j,t}) \\
\Lambda^d_{j,t} &= \left[-\nu_2 + (\nu_2 - \nu_1)\frac{1}{N_{j,t}}\right]^{-1}
\end{aligned}
$$

The price markup is defined as the ratio of the optimal price set by the firm over the marginal cost of production. The marginal cost of production is obtained by solving the following cost minimization problem:

$$
\begin{aligned}
\min_{K_{i,j,t}, Z_{i,j,t}, L_{i,j,t}} \quad & r^k_{j,t}K_{i,j,t} + r^z_{j,t}Z_{i,j,t} + W_{j,t}L_{i,j,t} \\
\text{s.t.} \quad & K^{\alpha}_{i,j,t}(A_t Z^{\eta}_{i,j,t}\mathcal{Z}^{1-\eta}_t L_{i,j,t})^{1-\alpha} = X^{\star}
\end{aligned}
$$

In Lagrangian form,

$$
\mathcal{V}_{i,j,t} = r^k_{j,t}K_{i,j,t} + r^z_t Z_{i,j,t} + W_t L_{i,j,t} + \lambda_{i,j,t}\left(X^{\star} - K^{\alpha}_{i,j,t}(A_t Z^{\eta}_{i,j,t}\mathcal{Z}^{1-\eta}_t L_{i,j,t})^{1-\alpha}\right)
$$

where $\lambda_{i,j,t}$ is the Lagrange multiplier on the production objective. It is also the marginal cost of production of intermediate firms. Taking the first order conditions,

$$
\begin{aligned}
r^k_{j,t} &= \alpha\lambda_{i,j,t}\frac{X_{i,j,t}}{K_{i,j,t}} \\
r^z_{j,t} &= \eta(1-\alpha)\lambda_{i,j,t}\frac{X_{i,j,t}}{Z_{i,j,t}} \\
W_{j,t} &= (1-\alpha)\lambda_{i,j,t}\frac{X_{i,j,t}}{L_{i,j,t}}
\end{aligned}
$$

From the individual firm problem (FOC w.r.t. $L_{i,j,t}$), we know that

$$
W_{j,t} = (1-\alpha)\frac{X_{i,j,t}}{L_{i,j,t}}(\tilde{P}_{i,j,t} + \Lambda^d_{i,j,t})
$$

Putting the two FOCs w.r.t. to labour together and defining the price markup $\o_{i,j,t}$ as $\tilde{P}_{i,j,t}/\lambda_{i,j,t}$,

$$\o_{i,j,t} \quad = \quad \left(1 + \frac{\Lambda^d_{i,j,t}}{\tilde{P}_{i,j,t}}\right)^{-1}$$

Imposing the symmetry condition $\tilde{P}_{j,t} = 1$ and using the expression for $\Lambda^d_{j,t}$, the price markup is

$$\o_{i,j,t} \quad = \quad \frac{-\nu_2\, N_{j,t} + (\nu_2 - \nu_1)}{-(\nu_2 - 1)\, N_{j,t} + (\nu_2 - \nu_1)}$$

8.2 Capital producer problem

The period profit of capital producers is $r^k_{j,t}\mathcal{K}^c_{j,t} - \mathcal{I}_{j,t}$. The optimization problem faced by the representative physical capital producer is to choose $\mathcal{K}^c_{j,t+1}$ and $\mathcal{I}_{j,t}$ in order to maximize the present value of revenues, given the capital accumulation constraint:

$$\begin{aligned} V^k_{j,t} = & \max_{\{\mathcal{I}_{j,t},\mathcal{K}^c_{j,t+1}\}_{t\geqslant 0}} E_0\left[\sum_{s=0}^{\infty} M_{t,t+s}(r^k_{j,s}\mathcal{K}^c_{j,s} - \mathcal{I}_{j,s})\right] \\ \text{s.t. } & \mathcal{K}^c_{j,t+1} = (1-\delta_k)\mathcal{K}^c_{j,t} + \Phi_{k,j,t}\mathcal{K}^c_{j,t} \end{aligned}$$

The Lagrangian in recursive form is,

$$\mathcal{V}_{j,t} = r^k_{j,t}\mathcal{K}^c_{j,t} - \mathcal{I}_{j,t} + E_t\left[M_{t,t+1}\mathcal{V}_{j,t+1}\right] + Q^k_{j,t}\left((1-\delta_k)\mathcal{K}^c_{j,t} + \Phi_{k,j,t}\mathcal{K}^c_{j,t} - \mathcal{K}^c_{j,t+1}\right)$$

The first order conditions are:

$$\begin{aligned} Q^k_{j,t} &= \Phi'_k\left(\frac{\mathcal{I}_{j,t}}{\mathcal{K}_{j,t}}\right)^{-1} \\ Q^k_{j,t} &= E_t\left[M_{t,t+1}\frac{\partial \mathcal{V}_{j,t+1}}{\partial \mathcal{K}^c_{j,t+1}}\right] \end{aligned}$$

Using the enveloppe theorem,

$$\frac{\partial \mathcal{V}_{j,t}}{\partial \mathcal{K}^c_{j,t}} = \left(r^k_{j,t} + Q^k_{j,t}\left(1 - \delta_k - \left(\frac{\mathcal{I}_{j,t}}{\mathcal{K}^c_{j,t}}\right)\Phi'_{k,j,t} + \Phi_{k,j,t}\right)\right)$$

The set of equilibrium conditions for the representative capital producer is

$$\begin{aligned}
Q^k_{j,t} &= \Phi'^{-1}_{k,j,t} \\
Q^k_{j,t} &= E_t\left[M_{t,t+1}\left(r^k_{j,t+1} + Q^k_{j,t+1}\left(1-\delta_k - \left(\frac{\mathcal{I}_{j,t+1}}{\mathcal{K}^c_{j,t+1}}\right)\Phi'_{k,j,t+1} + \Phi_{k,j,t+1}\right)\right)\right] \\
\mathcal{K}^c_{j,t+1} &= (1-\delta_k)\mathcal{K}^c_{j,t} + \Phi_{k,j,t}\mathcal{K}^c_{j,t}
\end{aligned}$$

The equilibrium conditions for the technology sector are derived is the same way,

$$\begin{aligned}
Q^z_{j,t} &= \Phi'^{-1}_{z,j,t} \\
Q^z_{j,t} &= E_t\left[M_{t,t+1}\left(r^z_{j,t+1} + Q^z_{j,t+1}\left(1-\delta_z - \left(\frac{\mathcal{S}_{j,t+1}}{\mathcal{Z}^c_{j,t+1}}\right)\Phi'_{z,j,t+1} + \Phi_{z,j,t+1}\right)\right)\right] \\
\mathcal{Z}^c_{j,t+1} &= (1-\delta_z)\mathcal{Z}^c_{j,t} + \Phi_{z,j,t}\mathcal{Z}^c_{j,t}
\end{aligned}$$

where $\mathcal{S}_{j,t}$ is the aggregate investment in R&D in sector j.

Table 1: Quarterly Calibration

Parameter	Description	Model
A. Preferences		
β	Subjective discount factor	0.995
ψ	Elasticity of intertemporal substitution	1.8
γ	Risk aversion	10
χ	Labor elasticity	3
B. Production		
α	Capital share	0.33
η	Degree of technological appropriability	0.065
δ_k	Depreciation rate of capital stock	2.0%
δ_k	Depreciation rate of R&D stock	3.75%
δ_n	Firm obsolescence rate	1.0%
ζ_k	Capital adjustment cost parameter	0.738
ζ_z	R&D capital adjustment cost parameter	0.738
ν_1	Price elasticity accross industries	1.05
ν_2	Price elasticity within industries	75
C. Productivity		
ρ	Persistence of a_t	0.985
σ	Conditional volatility of a_t	1.24%

This table reports the parameter values used in the benchmark quarterly calibration of the model. The table is divided into three categories: Preferences, Production, and Productivity parameters.

Table 2: Industry moments

	Data	Model
A. Means		
$E[\log(ø)]$ (%)	13.39	15.92
E[Profit Share] (%)	7.04	10.98
B. Standard deviations		
$\sigma[\log(ø)]$ (%)	2.30	2.69
$\sigma[\Delta z_p]$ (%)	1.74	2.55
$\sigma[\Delta z]$ (%)	1.05	0.87
σ[Profit Share] (%)	2.18	2.37
$\sigma[NE]$	0.06	0.05
C. Autocorrelations		
$AC1[\log(ø)]$	0.900	0.998
$AC1[\Delta z_p]$	0.159	0.107
$AC1[\Delta z]$	0.958	0.985
$AC1$[Profit Share]	0.955	0.998
$AC1[NE]$	0.701	0.696
D. Correlations		
$\text{corr}(\log(ø), N)$	-0.139	-0.213
$\text{corr}(\log(ø), NE)$	-0.101	-0.023

This table presents the means, standard deviations, autocorrelations, for key macroeconomic variables from the data and the model. The model is calibrated at a quarterly frequency using the benchmark calibration. The growth rate of technology has been annualized (Δz_p). To obtain a stationary, unit-free measure of entry, $\log(NE)$ is filtered using a Hodrick-Prescott filter with a smoothing parameter of 1,600.

Table 3: Forecasts with growth of new incorporations

	Data			Model		
	Horizon (in quarters)					
	1	4	8	1	4	8
A. Output						
β	0.235	0.429	0.108	1.224	4.784	9.585
S.E.	0.034	0.107	0.165	0.725	2.603	5.464
R^2	0.242	0.118	0.004	0.010	0.029	0.044
B. Consumption						
β	0.071	0.206	0.157	3.310	12.041	21.516
S.E.	0.013	0.049	0.064	0.293	1.782	4.476
R^2	0.012	0.125	0.036	0.247	0.265	0.237
C. Investment						
β	1.277	1.980	0.225	1.625	5.819	10.761
S.E.	0.213	0.549	0.785	1.084	3.606	7.136
R^2	0.268	0.119	0.001	0.009	0.025	0.036

This table presents output growth, consumption growth, and investment growth forecasts for horizons of one, four, and eight quarters using the growth in net business formation from the data and the model. The n-quarter regressions, $\frac{1}{n}(x_{t,t+1} + \cdots + x_{t+n-1,t+n}) = \alpha + \beta\Delta n_t + \epsilon_{t+1}$, are estimated using overlapping quarterly data and Newey-West standard errors are used to correct for heteroscedasticity.

Table 4: Business cycle moments

	Data	A.	B.
First Moment			
$E(\Delta c)$	2.00	2.00	2.00
Second Moment			
$\sigma_{\Delta c}/\sigma_{\Delta y}$	0.64	0.49	1.11
$\sigma_{\Delta i}/\sigma_{\Delta c}$	4.38	3.00	0.99
$\sigma_{\Delta s}/\sigma_{\Delta c}$	3.44	2.77	0.92
$\sigma(\Delta c)$	1.10	1.10	1.10
$\sigma(l)$	1.52	2.24	0.98

This table reports simulated moments for two specifications of the model. Column A reports model moments for the benchmark model. Column B reports model moments for the model without entry and exit. To keep the comparison fair, we recalibrate $a^\star$ and σ to match the first and second moments of realized consumption growth. The risk premiums are levered following Boldrin, Christiano, and Fisher (2001). Growth rate moments are annualized percentage. Moments for log-hours (l) are reported in percentage of total time endowment.

Table 5: Industry cycles

	Data	Model
A. Markups		
corr($\o, Y$)	-0.174	-0.137
corr($\o, C$)	-0.283	-0.213
corr($\o, I$)	-0.164	-0.134
B. Number of firms		
corr(N, Y)	0.708	0.656
corr(N, C)	0.638	0.944
corr(N, I)	0.701	0.634
C. Entry		
corr(NE, Y)	0.449	0.838
corr(NE, C)	0.397	0.255
corr(NE, I)	0.487	0.851

This table reports correlations for key macro variables with aggregate markups ($\o$), the number of firms (NBF: Index of net business formation, and entry (INC: total number of new incorporations) for the data and the model. The model is calibrated at a quarterly frequency and all reported statistics are computed after applying an Hodrick-Prescott filter with a smoothing parameter of 1,600 to the log of all non-stationary variables.

Table 6: Summary statistics sorted on markups

	Data		Model	
	low $\o_t$	high $\o_t$	low $\o_t$	high $\o_t$
A. Output				
mean	0.436	-0.019	0.199	-0.303
std	1.030	1.970	1.336	1.433
min	-1.275	-3.798	-5.197	-5.919
max	2.319	3.536	5.076	5.399
B. Consumption				
mean	0.450	-0.158	0.202	-0.301
std	0.748	0.805	0.600	0.831
min	-0.543	-1.406	-2.023	-3.413
max	1.820	1.083	2.258	2.696
C. Investment				
mean	1.335	-0.753	0.288	-0.448
std	4.434	9.411	1.881	2.455
min	-9.264	-21.177	-7.219	-10.329
max	8.562	11.827	7.026	8.815

This table presents summary statistics for output, consumption, and investment by sorting the data on the level of markup. All non-stationary data are detrended using a Hodrick-Prescott filter with a smoothing parameter of 1,600. All units are percentage deviation from trend.

Table 7: Asset pricing moments

	Data	A.	B.
First Moment			
$E(r_f)$	1.62	1.34	2.89
$E(r_d - r_f)$	5.84	5.16	0.55
$E[pd]$	3.43	3.77	4.43
Second Moment			
$\sigma(r_f)$	0.67	0.60	0.06
$\sigma(r_d - r_f)$	17.87	6.57	2.62
$\sigma[pd]$	0.37	0.29	0.02

This table reports simulated moments for two specifications of the model. Column A reports model moments for the benchmark model. Column B reports model moments for the model without entry and exit. To keep the comparison fair, we recalibrate $a^\star$ and σ to match the first and second moments of realized consumption growth. The risk premiums are levered following Boldrin, Christiano, and Fisher (2001). Returns are in annualized percentage units.

Table 8: Stock Return Predictability

	Data					Model				
	Horizon (in years)									
	1	2	3	4	5	1	2	3	4	5
A. Log Price-Dividend Ratio										
$\beta^{(n)}$	-0.132	-0.231	-0.292	-0.340	-0.430	-0.062	-0.120	-0.172	-0.221	-0.265
S.E.	0.041	0.078	0.099	0.112	0.135	0.022	0.039	0.054	0.066	0.076
R^2	0.090	0.157	0.193	0.214	0.254	0.051	0.097	0.140	0.179	0.215
B. Net Business Formation										
$\beta^{(n)}$	-0.770	-1.006	-1.059	-1.255	-1.790	-0.054	-0.103	-0.148	-0.189	-0.227
S.E.	0.248	0.385	0.375	0.411	0.590	0.017	0.031	0.042	0.050	0.058
R^2	0.121	0.122	0.108	0.121	0.166	0.062	0.117	0.167	0.212	0.252
C. Growth in New Incorporations										
$\beta^{(n)}$	-0.396	-0.866	-1.049	-1.219	-1.323	-0.666	-1.271	-1.828	-2.333	-2.798
S.E.	0.248	0.449	0.634	0.656	0.717	0.216	0.386	0.520	0.632	0.728
R^2	0.008	0.024	0.028	0.031	0.024	0.060	0.115	0.164	0.208	0.248
D. Markup										
$\beta^{(n)}$	1.516	2.571	2.747	3.529	4.185	0.303	0.580	0.834	1.068	1.284
S.E.	0.651	1.052	1.301	1.577	2.016	0.112	0.199	0.269	0.328	0.379
R^2	0.043	0.075	0.071	0.102	0.116	0.048	0.091	0.131	0.167	0.201
E. Profit Share										
$\beta^{(n)}$	0.298	0.733	0.943	1.678	2.135	0.340	0.651	0.937	1.199	1.442
S.E.	0.620	1.056	1.554	2.375	3.060	0.126	0.224	0.302	0.369	0.426
R^2	0.001	0.005	0.007	0.018	0.022	0.048	0.091	0.130	0.167	0.201

This table reports excess stock return forecasts for horizons of one to five years, i.e. $r^{ex}_{t,t+n} - y^{(n)}_t = \alpha_n + \beta\, x_t + \epsilon_{t+1}$, where x_t is the predicting variables. The different panels present forecasting regressions using different predicting variables: the log price-dividend ratio (panel A), the linearly detrended index of net business formation (panel B), the growth in new incorporations (panel C), price markups (panel D), and the profit share (panel E). The forecasting regressions use overlapping quarterly data. Newey-West standard errors are used to correct for heteroscedasticity. The estimates from the model regression are averaged across 100 simulations that are equivalent in length to the data sample. The sample is 1948-2013 for Panel A and E, 1948-1993 for panel B and C, and 1964-2013 for panel D. The risk premiums are levered following Boldrin, Christiano, and Fisher (2001).

Table 9: Stock Return Predictability in the Long Sample

	Horizon (in years)				
	1	2	3	4	5
A. Benchmark					
$\beta^{(n)}$	-0.039	-0.075	-0.108	-0.139	-0.168
R^2	0.032	0.062	0.089	0.114	0.138
B. No Entry/Exits					
$\beta^{(n)}$	-0.018	-0.029	-0.043	-0.051	-0.051
R^2	0.000	0.000	0.000	0.000	0.000

This table reports excess stock return forecasts in the long sample for horizons of one to five years using the log-price-dividend ratio: $r^{ex}_{t,t+n} - y^{(n)}_t = \alpha_n + \beta \ \log(P_t/D_t) + \epsilon_{t+1}$. Panel A presents the forecasting regressions for the benchmark model with time-varying markup, panel B presents the regression results for the model without entry and exit and constant price markup. The forecasting regressions use overlapping quarterly data. The risk premiums are levered following Boldrin, Christiano, and Fisher (2001).

Table 10: Asset pricing moments: exogenous markups

	A.	B.	C.	D.
First Moment				
$E(r_f)$	2.89	2.55	2.22	2.15
$E(r_d - r_f)$	0.55	0.98	1.51	1.53
$E(pd)$	4.43	4.40	4.30	4.28
Second Moment				
$\sigma(r_f)$	0.06	0.17	0.19	0.33
$\sigma(r_d - r_f)$	2.62	2.92	3.40	3.45
$\sigma(pd)$	0.02	0.17	0.16	0.22

This table reports asset pricing moments for four specifications of the model with exogenous markups. Column A reports model moments for the model with constant markups ($\rho_\o = 0$, $\sigma_\o = 0$, $\varrho = 0$, and $\kappa_\o = 0$). Column B reports model moments for the time-varying markup model ($\rho_\o = 0.997$, $\sigma_\o = 0.17\%$, $\varrho = 0$, and $\kappa_\o = 0$). Column C reports model moments for the model with countercyclical markups ($\rho_\o = 0.997$, $\sigma_\o = 0.17\%$, $\varrho = -0.5$, and $\kappa_\o = 0$). Column D reports moment for the model with countercyclical markups and business cycle asymmetry ($\rho_\o = 0.997$, $\sigma_\o = 0.17\%$, $\varrho = -0.5$, and $\kappa_\o = 15$). The risk premiums are levered following Boldrin, Christiano, and Fisher (2001).

Table 11: Stock return predictability: exogenous markups

	Horizon (in years)				
	1	2	3	4	5
A. Constant markup					
$\beta^{(n)}$	-0.018	-0.029	-0.043	-0.051	-0.051
R^2	0.000	0.000	0.000	0.000	0.000
B. Time-varying, uncorrelated $ø_t$					
$\beta^{(n)}$	0.001	0.002	0.003	0.004	0.005
R^2	0.000	0.000	0.000	0.000	0.000
C. Countercyclical $ø_t$					
$\beta^{(n)}$	0.002	0.004	0.005	0.007	0.009
R^2	0.000	0.000	0.000	0.000	0.000
D. Countercyclical and heteroskedastic $ø_t$					
$\beta^{(n)}$	-0.022	-0.044	-0.066	-0.087	-0.109
R^2	0.015	0.029	0.043	0.057	0.070

This table reports long sample excess stock return forecasts in the model with exogenous price markup for horizons of one to five years using the log-price-dividend ratio: $r^{ex}_{t,t+n} - y^{(n)}_t = \alpha_n + \beta \, \log(P_t/D_t) + \epsilon_{t+1}$. Panel A reports the forecasting regressions for the model with constant markups ($\rho_ø = 0$, $\sigma_ø = 0$, $\varrho = 0$, and $\kappa_ø = 0$). Panel B reports the forecasting regressions for the time-varying markup model ($\rho_ø = 0.997$, $\sigma_ø = 0.17\%$, $\varrho = 0$, and $\kappa_ø = 0$). Panel C reports the forecasting regressions for the model with countercyclical markups ($\rho_ø = 0.997$, $\sigma_ø = 0.17\%$, $\varrho = -0.5$, and $\kappa_ø = 0$). Panel D reports the forecasting regressions for the model with countercyclical markups and business cycle asymmetry ($\rho_ø = 0.997$, $\sigma_ø = 0.17\%$, $\varrho = -0.5$, and $\kappa_ø = 15$). The risk premiums are levered following Boldrin, Christiano, and Fisher (2001).

Table 12: Asset pricing moments: wage markup

	A.	B.	C.
First Moment			
$E(r_f)$	1.34	0.62	0.00
$E(r_d - r_f)$	5.16	5.63	6.94
$E(pd)$	3.77	3.59	3.32
Second Moment			
$\sigma(r_f)$	0.60	0.72	0.90
$\sigma(r_d - r_f)$	6.57	7.02	7.90
$\sigma(pd)$	0.29	0.33	0.37

This table reports asset pricing moments for four specifications of the model with wage markups as well as the benchmark model. Column A reports moments for the benchmark model. Column B reports model moments for the benchmark model with time-varying, uncorrelated wage markup ($\sigma_{ø}^{w} = 2.88\%$, $\rho_{ø}^{w} = 0.96$, and $\varrho^{w} = 0$). Column C reports moments for the benchmark model with countercyclical wage markup ($\sigma_{ø}^{w} = 2.88\%$, $\rho_{ø}^{w} = 0.96$, and $\varrho^{w} = -0.45$). Column D reports model moments for the model with constant price markup and countercyclical wage markup ($\sigma_{ø}^{w} = 2.88\%$, $\rho_{ø}^{w} = 0.96$, and $\varrho^{w} = -0.45$). The risk premiums are levered following Boldrin, Christiano, and Fisher (2001).

Table 13: Stock return predictability: wage markup

	Horizon (in years)				
	1	2	3	4	5
A. Benchmark					
$\beta^{(n)}$	-0.039	-0.075	-0.108	-0.139	-0.168
R^2	0.032	0.062	0.089	0.114	0.138
B. Time-varying, uncorrelated $ø_t^w$					
$\beta^{(n)}$	-0.054	-0.105	-0.152	-0.196	-0.238
R^2	0.043	0.082	0.119	0.153	0.184
C. Countercyclical $ø_t^w$					
$\beta^{(n)}$	-0.173	-0.333	-0.480	-0.615	-0.740
R^2	0.119	0.215	0.294	0.357	0.408

This table reports long sample excess stock return forecasts in the model with exogenous wage markup for horizons of one to five years using the log-price-dividend ratio: $r^{ex}_{t,t+n} - y^{(n)}_t = \alpha_n + \beta \ \log(P_t/D_t) + \epsilon_{t+1}$. Panel A reports the forecasting regressions for the benchmark model. Panel B reports the forecasting regressions for the benchmark model with time-varying, uncorrelated wage markup ($\sigma_{ø}^{w} = 2.88\%$, $\rho_{ø}^{w} = 0.96$, and $\varrho^{w} = 0$). Panel C reports the forecasting regressions for the benchmark model with countercyclical wage markup ($\sigma_{ø}^{w} = 2.88\%$, $\rho_{ø}^{w} = 0.96$, and $\varrho^{w} = -0.45$). Panel D reports the forecasting regressions for the model with constant price markup and countercyclical wage markup ($\sigma_{ø}^{w} = 2.88\%$, $\rho_{ø}^{w} = 0.96$, and $\varrho^{w} = -0.45$). The risk premiums are levered following Boldrin, Christiano, and Fisher (2001).

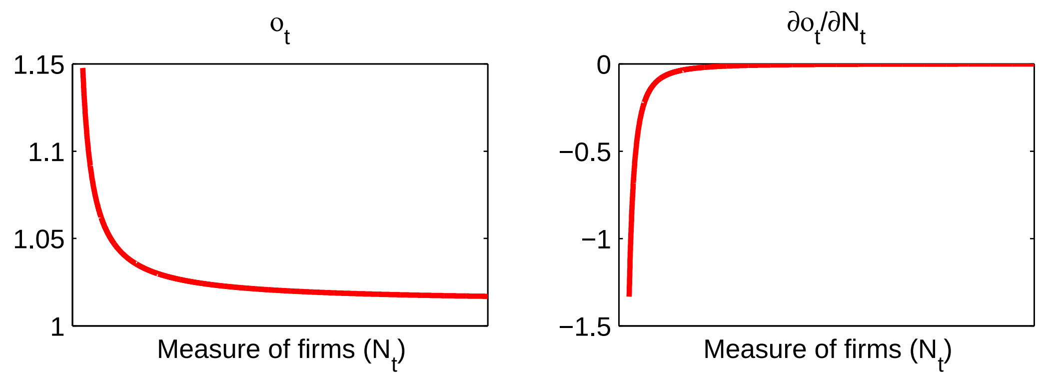

Figure 1: This figure plots the markup (left) and the first derivative of the markup with respect to $\mathcal{N}_t$ (left) as a function of the number of firms ($\mathcal{N}_t$) for the benchmark calibration of the model.

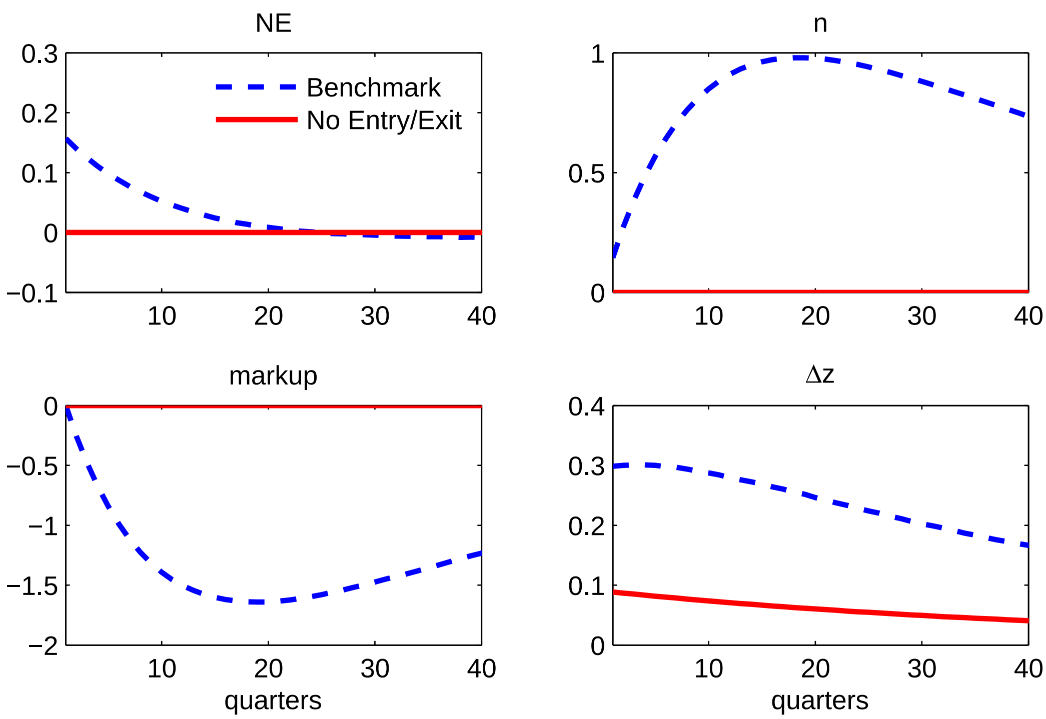

Figure 2: This figure plots the impulse response functions for entry (NE), the number of firms (n), the price markup, and the growth of technology (Δz) to a positive one standard deviation productivity shock for the benchmark model (dashed line), and the model without entry and exit (solid line). The parameters used to solve the no entry/exit model are the same as the benchmark model except for $a^{\star}$ that is modified to ensure an average growth rate of 2%, and σ that is modified to get a consumption growth volatility of 1.10%. All values on the y-axis are in annualized percentage log-deviation from the steady state.

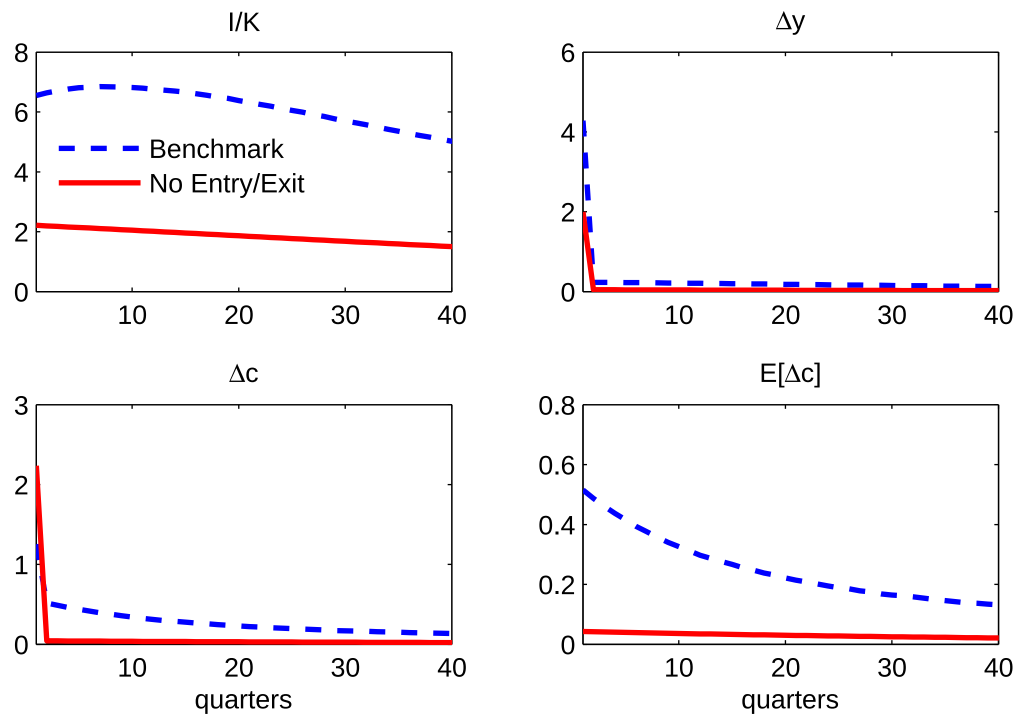

Figure 3: This figure plots the impulse response functions for the investment-to-capital ratio (I/K), output growth (Δy), consumption growth (Δc), and expected consumption growth ($E[\Delta c]$) to a positive one standard deviation productivity shock for the benchmark model (dashed line), and the model without entry and exit (solid line). The parameters used to solve the no entry/exit model are the same as the benchmark model except for $a^\star$ that is modified to ensure an average growth rate of 2%, and σ that is modified to get a consumption growth volatility of 1.10%. All values on the y-axis are in annualized percentage log-deviation from the steady state.

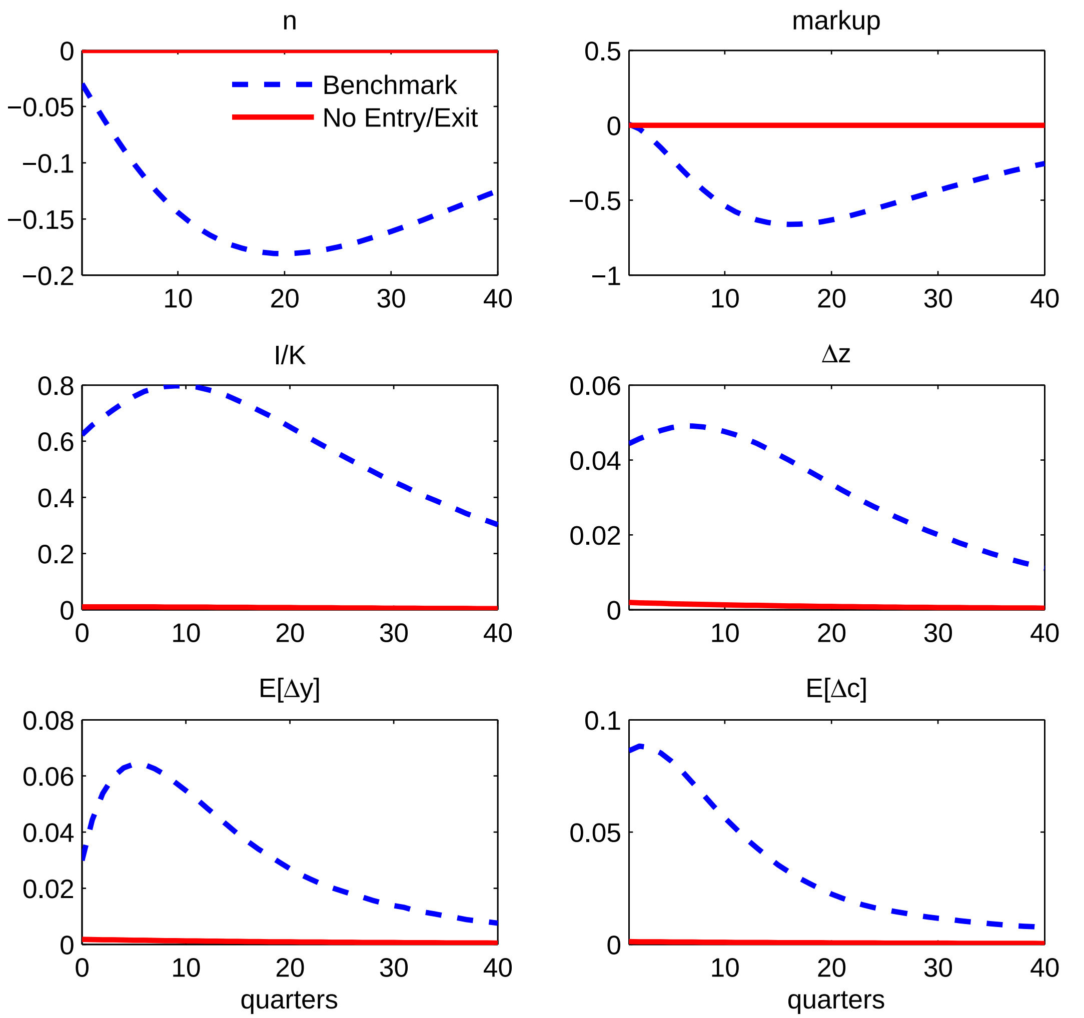

Figure 4: This figure plots the asymmetry in impulse response functions for the number of firms (n_t), the price markup, the investment-to-capital ratio (I/K), the growth in technology (Δz), and the expected growth rate of output ($E[\Delta y]$) and consumption ($E[\Delta c]$) in the benchmark model (dashed line), and the model without entry and exit (solid line). The graphs are obtained by taking the difference between minus the response to a two standard deviation negative productivity shock and the response to a positive two standard devitation shock. The parameters used to solve the no entry/exit model are the same as the benchmark model except for $a^\star$ that is modified to ensure an average growth rate of 2%, and σ that is modified to get a consumption growth volatility of 1.10%. All values on the y-axis are in annualized percentage log-deviation from the steady state.

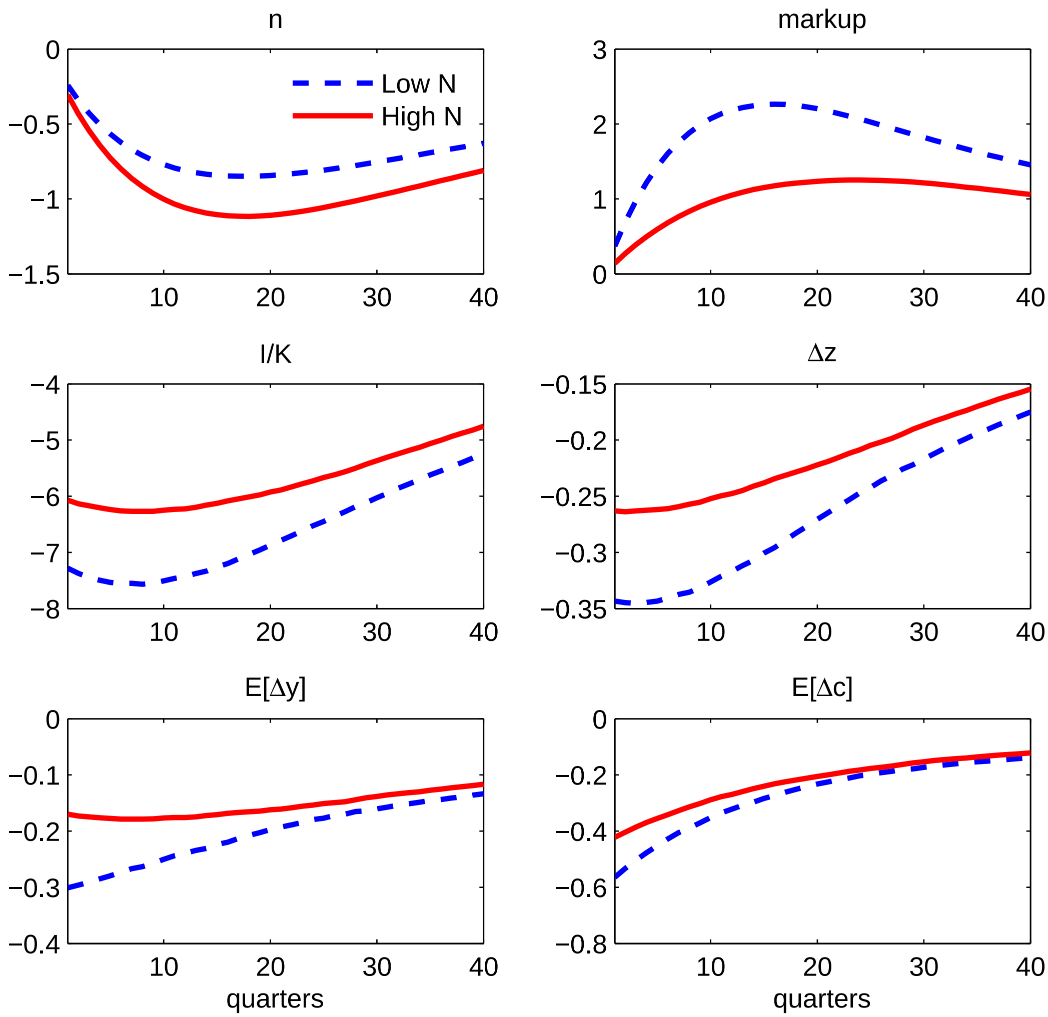

Figure 5: This figure plots the impulse response functions for the number of firms (n_t), the price markup, the investment-to-capital ratio (I/K), the growth in technology (Δz), and the expected growth rate of output ($E[\Delta y]$) and consumption ($E[\Delta c]$) in the benchmark model to a negative one standard deviation technology shock as a function of the number of firms in the economy, $\mathcal{N}_t$. The high $\mathcal{N}$ (low $\mathcal{N}$) case corresponds to the average responses accross 250 draws in the highest (lowest) quintile sorted on $\mathcal{N}_t$. The data for the sorting is obtained by simulating the economy for 50 periods prior to the realization of the negative technology shock. All values on the y-axis are in annualized percentage log-deviation from the steady state.

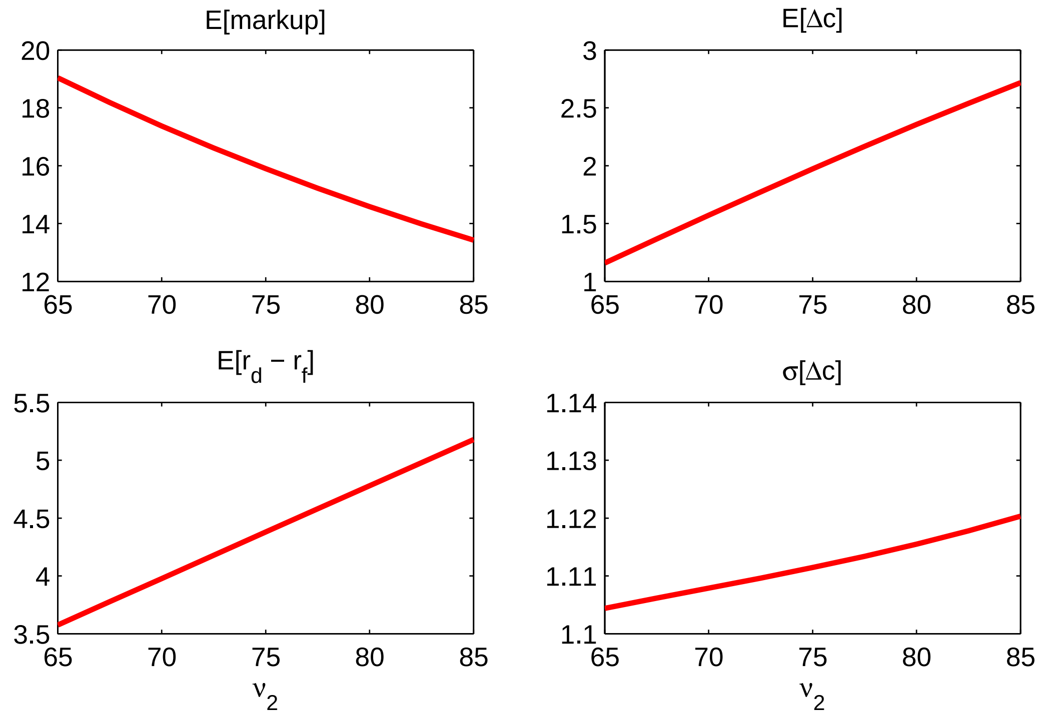

Figure 6: This figure plots the impact of varying the degree of competition within industry ν_2 on the average markup, the average output growth, the average equity premium, and the volatility of output growth. Values on y-axis are in annualized percentage units for expected consumption growth and the equity premium and in percentage units for the price markup.

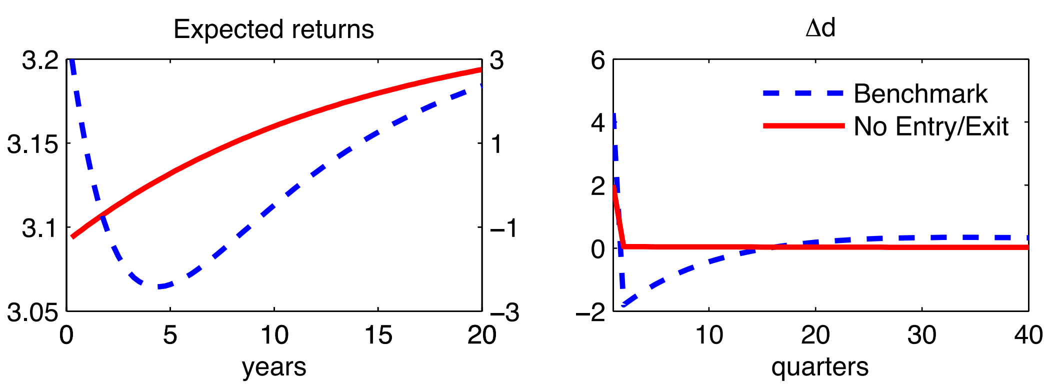

Figure 7: This figure plots the term structure of equity returns (left) and the response of dividend growth to a positive technology shock (right) in the benchmark model and in the model without entry and exit (constant markups). The parameters used to solve the no entry/exit model are the same as the benchmark model except for $a^{\star}$ that is modified to ensure an average growth rate of 2%, and σ that is modified to get a consumption growth volatility of 1.10%. All values on the y-axis are in annualized percentage.

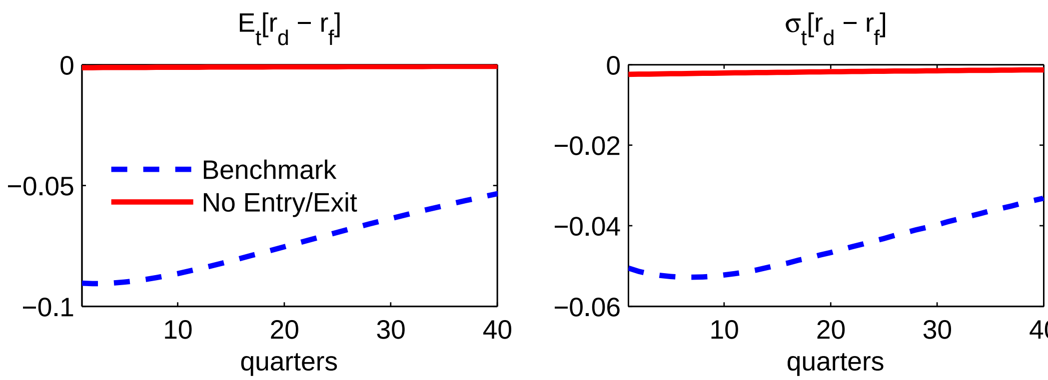

Figure 8: This figure plots the impulse response functions for the conditional risk premium ($E_t[r_d - r_f]$), and the conditional variance of the risk premium ($\sigma^2[r_d - r_f]$) to a positive one standard deviation productivity shock for the benchmark model (dashed line), and the model without entry and exit (solid line). The parameters used to solve the no entry/exit model are the same as the benchmark model except for $a^\star$ that is modified to ensure an average growth rate of 2%, and σ that is modified to get a consumption growth volatility of 1.10%. All values on the y-axis are in annualized percentage log-deviation from the steady state.

Nominal Rigidities and Asset Pricing

Michael Weber*

March 27 2015

Abstract

This paper examines the asset pricing implications of nominal rigidities. Firms that adjust their product prices infrequently earn a return premium of 4% per year. Merging unique product-price data at the firm level with stock returns, I document that the premium for sticky-price firms is a robust feature of the data and varies substantially over the business cycle. The premium is not driven by other firm and industry characteristics. Differential exposure to systematic risk fully explains the premium for sticky-price firms.

JEL classification: E12, E44, E52, G12

Keywords: Sticky Prices; Stock Returns; Monetary Policy

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I Introduction

The cover price of the Wall Street Journal was constant during the Roaring Twenties, the Great Depression, and the Second World War despite large swings in economic conditions.[1] Although the example of the Wall Street Journal is certainly extreme, rigid product prices are pervasive in micro data.[2] Nominal rigidities play a central role in macroeconomics in explaining business-cycle dynamics of aggregate real quantities, and are key ingredients of dynamic models at policy institutions.[3] Most importantly, price rigidities are the cornerstone of many economic models that rationalize the effects of purely *nominal* shocks on the *real* side of the economy.[4]

In this paper, I study whether infrequent product-price changes at the firm level are a source of macroeconomic risk that is priced in the cross section of stock returns. I find that sticky-price firms are risky and command a return premium compared to firms with flexible prices. The premium is 4% per year and in the order of magnitude of the size and value premia, which are the two most studied return premia in finance. Differential exposure to systematic risk fully explains the premium for sticky-price firms. The premium varies substantially over the business cycle and is high in recessions and stock market downturns.

Sticky prices have a long history in such different fields as macroeconomics, industrial organization, and marketing, and are central to explaining the business-cycle dynamics of real gross domestic output, consumption, and investment. I document that price rigidities are also a strong predictor of the cross section of stock returns.

I measure price stickiness as the average frequency of product-price adjustment at the firm level. I construct this metric using the confidential microdata underlying the Producer Price Index (PPI) at the Bureau of Labor Statistics (BLS), and merge it with financial data from the Center for Research in Security Prices (CRSP) and Compustat. I show that portfolios of firms sorted on the frequency of price adjustment generate a return differential of 4.2% per year between sticky- and flexible-price firms. Returns monotonically decrease in the degree of price flexibility.

[1] See Knotek II (2008).

[2] Prices at the good level for the whole U.S. economy remain unchanged for roughly six months on average. See Bils and Klenow (2004) and Nakamura and Steinsson (2008).

[3] See Christiano, Eichenbaum, and Evans (2005), Smets and Wouters (2007), and Galí (2009).

[4] See Kehoe and Midrigan (2014).

Market power, industry concentration, or durability of output can lead to infrequent product price adjustment and might be correlated with expected returns in the cross section. I first show that those and other standard cross-sectional return predictors at the firm and industry level cannot explain the premium in firm-level panel regressions. In a non-parametric analysis using conditional double sorts, I then show that the premium is also not driven by non-linear relationships between firm characteristics and returns, and is similar in magnitude to the value premium. Last, exploiting only variation in the frequency of price adjustment within industry, I find that unobserved industry-level heterogeneity also does not drive the premium for sticky-price firms.

I then investigate the properties of the return premium. First, I test whether differential exposure to systematic risk can explain the difference in returns between sticky- and flexible-price firms. The Capital Asset Pricing Model (CAPM) cannot explain the level of portfolio returns sorted on the frequency of price adjustment, but it can fully explain the cross-sectional dispersion: sticky-price firms have, on average, a sensitivity to the market excess return (β) of 1.29. βs decrease monotonically in price flexibility, resulting in a difference in exposure to market risk of 0.36 between the sticky- and flexible-price firms. Sticky-price firms are more exposed to market risk and therefore earn a return premium.

Second, I investigate why the CAPM is successful despite being typically rejected in the data. Variation in the aggregate stock market can occur either due to news about future discount rates or news about future cash flows. Differential exposure to the two sources of fundamental risk across portfolios can explain why the overall β might not be a sufficient statistic in case of different market prices of risk. I find that sticky-price firms have higher exposure to both sources of fundamental risk and are unambiguously riskier than firms with flexible prices.

Third, I study the sensitivity of portfolio returns to monetary policy shocks. Monetary policy shocks are important for aggregate risk premia. 60%-80% of the realized equity premium is earned around scheduled macroeconomics news announcements. I find that sticky-price firms are twice as responsive to monetary policy shocks compared to flexible-price firms. The differential reaction across portfolios is broadly in line with the CAPM. The CAPM has high explanatory power for the cross section of stocks sorted on the frequency of price adjustment, both unconditionally and conditionally on the realization of monetary policy shocks. These results underline the role of the frequency of price adjustment as a determinant of the cross section of stock returns and the power of monetary policy to affect the real side of the economy.

Last, I examine the time-series characteristics of the premium for sticky-price firms. The premium varies systematically over the business cycle and is high in recessions and times of low stock market returns. The Lettau and Ludvigson (2001) proxy for the consumption-wealth ratio (cay) can explain up to 60% of the business-cycle variation in long-horizon regressions. The higher cost of capital for sticky-prices firms in times of recessions and low aggregate stock returns has potentially interesting implications for firms' investment decisions, and could contribute to the importance of price ridigities for aggregate fluctuations.

Market power and industry concentration can result in rigid output prices, but they can not explain the cross-sectional return premium for firms with low frequency of price adjustment. Frictions preventing firms from adjusting prices optimally might be an alternative explanation for my empirical findings. I develop a multi-sector New Keynesian production-based asset-pricing model to asses whether such a framework can rationalize the premium for sticky-price firms. Households derive utility from a composite consumption good and leisure. The production side is organized in different sectors. Firms are monopolistically competitive and set prices as a markup over a weighted average of future marginal costs. The only heterogeneity across sectors is a different degree of price stickiness. The basic structure of my model is similar to Carvalho (2006). Mine differs in several ways. I add external habit formation in consumption and wage stickiness to get a reasonable equity premium. I also allow for different elasticities of substitution in consumption varieties within and across sectors, because they play a distinct role for cross-sectional return premia.

I calibrate the model using standard parameters to the empirical distribution of price stickiness from Nakamura and Steinsson (2008). The model is successful in replicating the novel stylized facts, a large premium for sticky-price firms that varies over the business cycle, and an equity premium and Sharpe ratio in line with historical estimates.

The central mechanism generating a cross-sectional return premium for sticky-price firms in the model is a higher cyclicality of cash flows for sticky price firms after shocks to marginal utility. Gorodnichenko and Weber (2013) show that sticky-price firms have more volatile operating income after monetary policy shocks (see their table 10). I show in appendix table A.17 that sticky-price firms have higher realized stock return volatility. Both pieces of evidence, together with the differential response to monetary policy shocks discussed above (see also Table 9), directly support the channel in the model.

A New Keynesian production-based asset-pricing model calibrated to the empirical distribution of price stickiness is consistent with a cross-sectional return premium for firms with low frequencies of price adjustment. The return premium for sticky-price firms suggests that identifying the cause of sticky prices and the determinants of differences in the frequency of price adjustment across firms within industry are vital questions for future research.

The paper makes three main contributions. First, I contribute to the macroeconomics literature by documenting that differences in the frequency of price adjustment are associated with differences in exposure to aggregate risk and expected returns. Second, I contribute to the industrial organization literature by aggregating goods-based measures of price stickiness to the establishment and firm level. The different levels of aggregation allow the test of models of price setting at the firm level using micro data from official statistics. Third, I contribute to the finance literature by documenting that the frequency of price adjustment is a predictor of the cross section of stock returns. A firm's exposure to systematic risk is a function of several parameters and factors. The frequency of product-price adjustment is a simple variable at the firm level that can account for a considerable part of the variation in firms' exposure to systematic risk.

A. Related Literature

The paper is related to a large literature in macroeconomics documenting stylized facts about the pricing behavior of firms, and to the asset-pricing literature on production-based asset pricing, the equity premium, and the relationship between firm characteristics and cross-sectional return-premia.

A.1 Macroeconomics

Zbaracki et al. (2004) document in detail for a large U.S. manufacturer the costs associated with changing prices, such as data collection, managerial costs, physical costs, or negotiation costs. The total cost of changing nominal prices is 1.22% of total revenue and 20.03% of the company's net profit margin. Bils and Klenow (2004) and Nakamura and Steinsson (2008) use the microdata underlying the Consumer Price Index (CPI) at the BLS to show that prices are fixed for roughly six months and that substantial heterogeneity is present in price stickiness across industries. Goldberg and Hellerstein (2011) confirm these findings for producer prices.[5] Gorodnichenko and Weber (2013) use the micro data underlying the PPI to test alternative theories of price stickiness in micro data. Performing high-frequency event studies around the press releases of the Federal Open Market Committee, they provide evidence consistent with a New Keynesian interpretation of price stickiness. Gilchrist, Schoenle, Sim, and Zakrajsek (2013) investigate the price-setting behavior of firms during the Great Recession as a function of balance sheet conditions.

A.2 Finance

A recent literature in finance focuses on the potential of wage and price rigidities to explain aggregate stock market patterns in production economies. Uhlig (2007) shows that external habits and real-wage stickiness generate an equity premium. Favilukis and Lin (2013) develop a production-based asset-pricing model with sticky wages and employment-adjustment costs, whereas Li and Palomino (2014) introduce sticky prices and wages. Both papers have Epstein and Zin (1989) and Weil (1989) recursive preferences and are able to generate empirically reasonable levels of the equity risk premium in calibrations.[6] I contribute to this literature by theoretically showing the impact of heterogeneity in price stickiness on cross-sectional return premia. To the best of my knowledge, this paper is the first to test for the effects of nominal rigidities on stock returns at the firm level.

In addition, I contribute to the literature linking firm characteristics to stock returns in the cross section. Fama and French (1992) offer a concise treatment of many cross-sectional relationships in a unified setting. Bustamante and Donangelo (2014), and Donangelo (2014) relate industry concentration, product market competition, and labor mobility across industries to expected returns in the cross section. Van Binsbergen (2014) studies the impact of good-specific habit formation and finds that cross-sectional variation in the demand for goods leads to differences in expected returns across industries.

I add to this literature by documenting that different pricing technologies in product

[5]Other recent contributions to this literature are Eichenbaum, Jaimovich, and Rebelo (2011); Anderson, Jaimovich, and Simester (2014); and Kehoe and Midrigan (2014). Klenow and Malin (2010) provide a review of the recent literature on price rigidity using micro price data.

[6]Kuehn, Petrosky-Nadeau, and Zhang (2012) incorporate search and matching frictions in a production-based asset-pricing model and show that this friction endogenously generates consumption disasters.

markets lead to different exposure to systematic risk. A difference in average conditional βs of almost 0.40 explains the return spread between sticky- and flexible-price firms.

II Data

This section describes my measure of the frequency of product-price adjustment at the firm level, and the financial data I use.

A. Measuring Price Stickiness

A key ingredient of my analysis is a measure of price stickiness at the firm level. I use the confidential microdata underlying the PPI at the BLS to calculate the frequency of price adjustment at the firm level. The PPI measures changes in selling prices from the perspective of producers, and tracks prices of all goods-producing industries such as mining, manufacturing, and gas and electricity, as well as the service sector.[7]

The BLS applies a three-stage procedure to determine the individual sample goods. In the first stage, the BLS compiles a list of all firms filing with the Unemployment Insurance system to construct the universe of all establishments in the United States. In the second and third stages, the BLS probabilistically selects sample establishments and goods based on either the total value of shipments or on the number of employees. The BLS collects prices from about 25,000 establishments for approximately 100,000 individual items on a monthly basis. The BLS defines PPI prices as "net revenue accruing to a specified producing establishment from a specified kind of buyer for a specified product shipped under specified transaction terms on a specified day of the month." Prices are collected via a survey that is emailed or faxed to participating establishments. Individual establishments remain in the sample for an average of seven years until a new sample is selected to account for changes in the industry structure.

I calculate the frequency of price adjustment at the good level, SA, as the ratio of price changes to the number of sample months. For example, if an observed price path is \$4 for two months and then \$5 for another three months, one price change occurs during

[7]The BLS started sampling prices for the service sector in 2005. The PPI covers about 75% of the service sector output. My sample of micro price data ranges from 1982 to 2011. The data until 1998 are equivalent to the data used in Nakamura and Steinsson (2008).

five months and the frequency is 1/5.[8] I calculate both equally weighted frequencies, U, and frequencies weighted by values of shipments associated with items/establishments, W.

I first aggregate goods-based frequencies to the establishment level via internal identifiers of the BLS. To perform the firm-level aggregation, I check whether establishments with the same or similar names are part of the same company. In addition, I use publicly available data to search for names of subsidiaries and name changes due to, for example, mergers, acquisitions, or restructuring occurring during the sample period for all firms in the data set. Appendix *C.* discusses in more detail how the aggregations are performed.

Table 1 reports mean frequencies, standard deviations, and the number of firms for the frequency of price adjustment, both for the total sample and at the industry level.[9] I focus on the unweighted frequency of price adjustment, SAU, because results are similar across the two measures.[10] The overall mean monthly frequency of price adjustment is 14.23%, which implies an average duration, $-1/ln(1-SAU)$, of 6.51 months. Substantial heterogeneity is present in the frequency across sectors, ranging from as low as 9.66% for the service sector (duration of 9.84 months) to 20.89% for trade (duration of 4.27 months). Finally, the high standard deviations highlight large heterogeneity in measured price stickiness across firms even within industries.

Different degrees of price stickiness of similar firms operating in the same industry can arise due to differences in the costs of negotiating with customers and suppliers, in the physical costs of changing prices, or in the managerial costs such as information gathering, decision making, and communication.[11]

[8] When calculating the frequency of price adjustment, I exclude price changes due to sales, using the filter of Nakamura and Steinsson (2008). Including sales does not affect my results because sales are rare in producer prices (see Nakamura and Steinsson (2008)). My baseline measure treats missing price values as interrupting price spells. The appendix contains results for alternative measures of the frequency of price adjustment; results are quantitatively and statistically similar.

[9] The coarse definition of industry is due to confidentiality reasons and partially explains the substantial variation of the measures of price stickiness within industry. A finer industry definition together with my focus on S&P500 firms (see below) would allow identification of individual firms.

[10] I report results for the weighted frequencies of price adjustment in appendix Table A.1.

[11] These differences might arise because of differences in customer and supplier structure, heterogeneous organizational structure, or varying operational efficiencies and management philosophies (see Zbaracki et al. (2004)).

B. Financial Data

I focus on firms that have been part of the S&P500 between 1982 and 2011 because of the availability of the PPI data. The S&P500 contains large U.S. firms and captures approximately 80% of the available stock market capitalization in the U.S, therefore maintaining the representativeness for the whole economy in economic terms. The BLS samples establishments based on value of shipments and I have a larger probability of finding a link between BLS pricing data and financial data when I focus on large firms. The focus on S&P 500 constituents biases against finding a return premium for sticky price firms as those firms tend to be smaller and small firms historically had higher returns (see Bhattarai and Schoenle (2014) and Fama and French (1992)). I have 1,563 unique firms in my sample due to changes in the index composition during my sample period, out of which I was able to merge 792 with the BLS pricing data. The merged and overall sample of firms look virtually identical with respect to the studied firm characteristics (compare Table 2 to Table A.2 in the appendix).

The previous literature has identified a series of financial variables that have predictive power for the cross section of stock returns. I construct measures of market capitalization (Size), sensitivity to the aggregate stock market (β (Beta)), share turnover (Turnover), and the bid-ask spread (Spread) using the CRSP database. I obtain balance-sheet data from Standard and Poor's Compustat database to construct measures of the ratio of book equity to market equity (BM), leverage (Lev), cash flow (CF), price-to-cost margin (PCM), and the Herfindahl-Hirschman index of sales at the Fama & French 48 industry level at an annual frequency (HHI).[12] Appendix *D.* contains detailed variable definitions.

Table 2 summarizes time-series averages of annual means and standard deviations of the return predictors in Panel A as well as contemporaneous correlations in Panel B. I have on average more than 500 firms per year. My sample consists of large major U.S. companies with a mean size of more than \$3 billion and a β of slightly above 1. In Panel B, we see that firms with more flexible prices have higher book-to-market ratios and leverage, but also lower βs and price-to-cost margins. The positive correlation with leverage might indicate that price flexibility in product markets increases the debt capacity

[12] I winsorize all variables at the 2.5% level to minimize the effect of extreme observations and outliers. Results are similar if I perform my analysis on unwinsorized data (see appendix Table A.14).

of firms via reduced default costs. The higher β for sticky-price firms suggests higher riskiness. The positive correlation with the price-to-cost margin highlights the importance of disentangling the frequency of price adjustment from other covariates. Firms with low frequencies of price adjustment might have market power and therefore be unresponsive to changes in costs or demand instead of facing costs of changing nominal prices.[13]

III Empirical Results

A. Portfolio Level

I sort stocks into five portfolios based on the frequency of price adjustment, SAU, to test if differences in price stickiness are associated with differences in returns. The frequency of price adjustment is by construction monotonically increasing from as low as 0.01 for portfolio 1 to 0.35 for the flexible price portfolio (see Table A.4 in the appendix for firm characteristics at the portfolio level). I measure annual returns from July of year t to June of year t+1.[14]

Panel A of Table 3 reports average equally-weighted annual returns for various sample periods. The sorting generates a spread in returns between the sticky- and flexible-price firms of 3.4%–4.2% per year. This premium is statistically significant and economically large. Mean returns decrease monotonically in the degree of price flexibility. The return premium is larger with a non-binding zero lower bound on nominal interest rates and before the start of the Great Recession. In the rest of the paper, I focus on a period from July 1982 to June 2007. I limit the analysis to 2007 in order to circumvent the concerns associated with a binding zero lower bound on nominal interest rates and the effects of the Great Recession. Results for the full sample are similar (see appendix table A.19).[15]

Panel B reports average value-weighted annual returns. Value-weighted returns are slightly smaller than equally-weighted returns across portfolios. Returns still monotonically decrease in the frequency of price adjustment. The value-weighted premium for sticky price firms ranges between 3.1%–3.8% per year and is statistically

[13] Appendix Table A.3 and Table A.4 report further descriptive statistics for the frequency of price adjustment and its' association with firm characteristics.

[14] The frequency of price adjustment at the firm level shows little variation over time. I do not rebalance portfolios but only sort once at the beginning of the sample period to minimize concerns about measurement error in the frequency of price adjustment.

[15] The return premium for sticky-price firms is also not driven by attrition or survivorship bias (see Table A.16 in the appendix).

and economically significant.

In Panel C, I report returns adjusted for firm characteristics associated with stock returns in the cross section to disentangle a premium for sticky-price firms from well-known cross sectional return predictors. A stock's market capitalization (size), its book value of equity to market value of equity (book-to-market ratio), and its past one-year return (momentum) are strong predictors of future returns in the cross section. Following Daniel, Grinblatt, Titman, and Wermers (1997), I sequentially sort all common stocks of the CRSP universe into one of 125 benchmark portfolios based on size, industry-adjusted book-to-market, and momentum. I then assign each stock in my sample to a benchmark portfolio based on its size, book-to-market ratio, and previous 12-month return. I calculate benchmark-adjusted returns by subtracting the assigned portfolio returns from the individual stock returns. An adjusted return of zero implies the stock's characteristics explain the total stock return.

Standard stock characteristics cannot explain the return premium for sticky-price firms. We see in Panel C that differences in the frequency of price adjustment still lead to a difference in returns between sticky- and flexible-price firms of 2.5%–3.2% even after controlling for these characteristics. The premium for sticky-price firms is only weakly correlated with return premia for size, book-to-market, or momentum.

For comparison, Panel D reports the average annual returns for the CRSP value-weighted and equally-weighted indexes and the size (SMB) and value premia (HML) of Fama and French (1993). The average annual return for the CRSP indexes is 15% and 16.8%, respectively, during my benchmark sample period. The size premium is less than 1% and statistically insignificant, whereas the value premium is 5.6%. The premium for sticky-price firms is therefore economically large and in the order of magnitude of two of the most studied cross-sectional-return premia in finance.

B. Panel Regressions

A limitation of the portfolio analysis is that returns may differ across portfolios for reasons other than price stickiness, such as heterogeneity in market power or cyclicality of demand. I exploit the rich cross-sectional variation in returns, measured price rigidities, and other firm characteristics to differentiate between these alternative explanations. Specifically, I run panel regressions of annual returns at the firm level, $R_{i,t}$, on the firm-specific measure of price stickiness, SAU_i, firm- and industry-level controls, $X_{i,n,t}$, and year fixed effects, μ_t:

$$R_{i,t} = \alpha + \beta_{SAU_i} \times SAU_i + \sum_n \beta_n \times X_{i,n,t} + \mu_t + \epsilon_{i,t}. \tag{1}$$

Table 4 reports results for annual, non-overlapping percentage returns. Standard errors are clustered at the firm level and reported in parentheses.[16] The coefficient on SAU in column (1) is negative and highly statistically significant.[17] Moving from a firm that never changes product prices to a firm with the most flexible prices leads to a return differential of 6% per year.[18] Adding year fixed effects in column (2) increases the coefficient on SAU in absolute value. In columns (3)–(5), we see that larger firms have lower returns (*size* effect), firms with high book value of equity compared to market value command a positive return premium (*value* effect), and firms with higher βs earn on average higher returns ($CAPM$). Controlling for these factors has little impact on the coefficient on SAU. The coefficient varies between -7.87 and -12.97, which implies a return differential between sticky- and flexible-price firms of 4.7%–7.8% per year. Controlling for additional covariates in columns (6)–(11) has no material effect on the economic or statistical significance of the coefficient of interest. In the last column, I add all explanatory variables jointly. The coefficient on the frequency of price adjustment remains negative and statistically significant, contrary to the coefficients on some of the return predictors. The specification with all controls implies an annual return premium of 3.9%. The coefficient on SAU in the panel regressions implies a similar return premium for sticky-price firms as the portfolio analysis in Table 3: the difference in the frequency of price adjustment between the two extreme portfolios of 0.34 (see Table A.4 in the appendix) implies a return differential of 2.2%–4.4%, depending on the controls employed.

Table 5 repeats the baseline analysis at the industry level to control for possibly unobserved industry heterogeneity. This exercise exploits only variation in the frequency of price adjustment within industry. I typically have fewer observations, and thus my estimates have higher sampling uncertainty. For all industries, I find a negative coefficient on SAU, which is statistically significant for three out of the six industries. These results

[16]Double-clustering standard errors at the firm-year level has little impact; see Table A.12 in the appendix.

[17]The R^2s of firm-level panel regressions are generally small; see also Table A.5 in the appendix for the other covariates.

[18]I calculate this premium by multiplying the regression coefficient on SAU by the difference in the frequency of price adjustment: 10.18 × 0.6 (see Table 1). The interquartile range in the frequency of price adjustment implies an annual return difference of 1.8%. A one-standard-deviation change in SAU is associated with a differential return of 1.3% per year.

indicate that unobserved industry characteristics do not drive the baseline effects. Instead of running regressions at the industry level and relying on small sample sizes, I add industry dummies in the last column of Table 5. The coefficient on the frequency of price adjustment is statistically significant, economically large, and consistent with previous estimates. Therefore, differences in mean return across industries for reasons orthogonal to the frequency of price adjustment can not explain the return premium for sticky-price firms.

C. Double Sorts

In Table 6, I perform conditional double sorts to allow for non-linear associations between firm characteristics and returns. Specifically, I first sort all stocks into three bins based on a cross-sectional-return predictor. Within each bin, I further sort stocks into three bins based on the frequency of price adjustment resulting in nine bins in total. For each category of price stickiness, I then take the average across sorts of the firm characteristics and report them in Table 6. In column (1), for example, I compare firms differing in their frequencies of price adjustment but with similar composition of market capitalization. Conditional double sorts allow me to study the premium for sticky-price firms controlling non-parametrically for cross-sectional return predictors.

In column (0), I report the results of an unconditional sort into tertiles based on the frequency of price adjustment. This sorting generates a statistically-significant return premium for sticky-price firms of 3%. Looking at the sorting conditional on size in column (1), we see that returns decrease monotonically in price flexibility. The premium for sticky-price firms after taking out variation in size is 2.4% per year and statistically significant. Focusing on the premium across conditioning variables in columns (2)–(9), we see that price stickiness always commands a statistically significant premium between 2.7% and 3.2% per year. These premia are similar in size to the unconditional premium in column (0).

To get a feeling for the magnitude of the return differential, I perform two more conditional double sorts in the last two columns. First, I sort all stocks into three brackets based on size. Second, within each size category, I sort stocks based on β and book-to-market. These sorts generate an annual return differential between high- and low-β stocks and value and growth sorts of 3.0% and 1.6%, respectively, after controlling for size. The conditional premium for high-β stocks is barely statistically significant, and the conditional value premium is economically small and statistically insignificant.

The premium for sticky-price firms is not driven by linear or non-linear relations with standard cross-sectional-return predictors, and is economically significant.

D. Exposure to Systematic Risk

D.1 Capital Asset Pricing Model

I perform time-series tests of the CAPM regressing portfolio excess returns, $R^e_{p,t}$, on a constant and the excess returns of the CRSP value-weighted index, $R^e_{m,t}$, to test whether differential exposure to market risk can explain the premium for sticky-price firms:

$$R^e_{p,t} = \alpha_p + \beta_p \times R^e_{m,t} + \epsilon_{p,t}.$$

The CAPM predicts that exposure to market risk fully explains the expected excess return, namely, that the α is zero.

Table 7 reports αs in percent per month and βs for the conditional CAPM.[19] I report Fama and MacBeth (1973) standard errors in parentheses and Newey and West (1987)-corrected standard errors in brackets.

The conditional CAPM cannot explain the portfolio returns. Monthly αs are positive, economically large, and statistically significant but similar across portfolios. βs monotonically decrease from 1.29 for portfolio 1 to 0.92 for portfolio 5. The conditional CAPM drives the α of the return difference between sticky- and flexible-price firms (column (6), S1-S5) all the way to 0. The difference in annual returns between stocks with high and low frequencies of price adjustment of more than 4% is fully explained by their differential exposure to market risk.

Figure 1 plots the return difference between sticky- and flexible-price firms and the market excess return. The two series track each other closely. Times of low market returns typically coincide with times of low returns for sticky-price firms compared to the returns of flexible-price firms. The unconditional correlation between the two times series is more than 50%.

Sticky-price firms are riskier and therefore earn higher returns than firms with flexible

[19] I estimate the conditional CAPM monthly on a rolling basis over the previous year, following Lewellen and Nagel (2006). Appendix Table A.6 reports results for an unconditional CAPM.

prices.[20] These findings imply the frequency of price adjustment is a significant predictor of systematic risk.

D.2 Discount-Rate and Cash-Flow News

Differences in the frequency of price adjustment lead to a spread in returns that differential exposure to systematic risk fully explains. The empirical success of the CAPM is surprising because the data generally reject this model.[21] Campbell and Vuolteenaho (2004) argue that variations in the aggregate stock market can occur either due to news about future cash flows or due to news about future discount rates. They derive a decomposition of CAPM β into a cash-flow β, β_{CF}, and a discount-rate β, β_{DR}, and they suggest that the price of risk for the covariation with discount-rate news is lower than the price of risk for the covariation with cash-flow news based on the insights of the intertemporal CAPM. Differential exposure to these two sources of fundamental risk can explain why the overall β might not be a sufficient statistic to explain expected returns. High-β stocks can earn lower returns than predicted by the CAPM if most of their overall β is due to the covariation with discount-rate news.

In Table 8, I perform the Campbell and Vuolteenaho (2004) decomposition to investigate why the CAPM performs well in my setting.

I define cash-flow and discount-rate βs as:

$$\beta_{p,CF} \equiv \frac{Cov(r^e_{p,t}, N_{CF,t})}{Var(r^e_{m,t} - \mathbb{E}_{t-1}\, r^e_{m,t})}$$

$$\beta_{p,DR} \equiv \frac{Cov(r^e_{p,t}, -N_{DR,t})}{Var(r^e_{m,t} - \mathbb{E}_{t-1}\, r^e_{m,t})},$$

where $r^e_{p,t}$ is the log excess return of portfolio p, $r^e_{m,t}$ is the log excess return of the market, $N_{CF,t}$ denotes news about future dividends, $N_{DR,t}$ denotes news about future expected returns, and $\mathbb{E}_t$ is the expectation operator conditional on the time t information set. I estimate a VAR with the market excess returns as one of the state variables. The

[20] Differences in βs fully explain differences in returns in the portfolio analysis, whereas individual firms' βs and the frequency of price adjustment are both individually significant in the panel regressions. Noting that firm-level βs are measured with noise can reconcile this apparent contradiction. The empirical asset-pricing literature has therefore moved away from explaining individual stock returns to explaining returns at the portfolio level sorted on some characteristic of interest (see Fama (1976)).

[21] See, e.g., Black, Jensen, and Scholes (1972) and Frazzini and Pedersen (2014). Lettau, Maggiori, and Weber (2014) show that a simple extension of CAPM, which allows for a separate compensation for downside risk, has high explanatory power across many important asset classes. Unconditional and downstate sensitivities to market risk for my portfolios sorted on the frequency of price adjustment are almost identical and their model boils down to standard CAPM.

news terms are simple functions of VAR innovations.[22] I calculate GMM (Hansen (1982)) standard errors conditional on the realized news series from the VAR.

We see in column (1) that cash-flow and discount-rate news contribute almost equally to the overall β of the sticky-price portfolio of 1.22: $\beta_{S1,CF}$ is 0.58 and $\beta_{S1,DR}$ is 0.63. Both βs decrease monotonically in the portfolio number to values of 0.43 and 0.47, respectively. The difference in βs between sticky- and flexible-price firms is 0.15 for $\beta_{S1-S5,CF}$, 0.16 for $\beta_{S1-S5,DR}$, and 0.31 for the overall β_{S1-S5}. The difference in discount-rate and cash-flow βs is almost constant across portfolios and varies between 0.03 and 0.04. Sticky price firms have higher exposure to both sources of fundamental risk and are unambiguously riskier than firms with flexible prices. The overall β is therefore sufficient to determine the overall riskiness of a portfolio independent of potentially different prices of risk.

D.3 Monetary Policy Shocks and Portfolio Returns

The previous section shows the mechanism of why the CAPM works: the overall β is a sufficient statistic to describe the cross section of stock returns sorted on the frequency of price adjustment. The economic reason for the good empirical performance lies in the importance of monetary policy for aggregate risk premia in equity markets during my sample period. 60%-80% of the realized equity premium is earned around macroeconomic news announcements such as the press releases of the Federal Open Market Committee (FOMC).[23] Monetary policy surprises are purely nominal shocks and are of particular interest in the context of nominal rigidities. A further advantage of monetary policy shocks is that they are easy to construct, are well identified, and are the subject of a substantial literature in macroeconomics and finance. In addition, these shocks are the main driver of risk premia in my model (see Section IV).

Table 9 reports the results from regressing monthly excess returns, $R^e_{p,t}$, of portfolios sorted on the frequency of price adjustment and the CRSP value-weighted index on the surprise component of the one-month change in the Federal Funds rate, Δi^u_t:

$$R^e_{p,t} = \alpha_p + \beta_{p,FFR} \times \Delta i^u_t + \epsilon_{p,t}.$$

The sample is restricted to a period from June 1989 to June 2007 due to the

[22]See Appendix *E.* for a detailed discussion and derivation of the key equations.

[23]Bernanke and Kuttner (2005) show that a 1% surprise increase in the Federal Funds rate leads to a drop in the CRSP value-weighted index of more than 11% in monthly time-series regressions. Savor and Wilson (2014) show that 60% of the equity premium is earned around scheduled macroeconomic news announcements, whereas Lucca and Moench (2015) find that 80% of the equity premium since 1994 is earned in the twenty-four hours before the FOMC press releases.

availability of the Federal Funds futures. The aggregate market falls by more than 9% after a 1% surprise increase in the Federal Funds rate (column (1)). The reaction varies substantially across firms. Sticky-price firms are the most responsive (fall by 11%, column (2)), whereas flexible-price firms fall by only 5% (column (6)).

This differential reaction is broadly in line with the prediction of CAPM. The sticky-price portfolio is predicted to earn -11% following a Federal Funds rate surprise. The predicted sensitivities decrease monotonically in the degree of price flexibility to a predicted drop of 7% for the flexible-price portfolio. Therefore, the CAPM has high explanatory power for the cross section of stocks sorted on the frequency of price adjustment, both unconditionally and conditional on the realization of monetary policy shocks. These results underline the role of the frequency of price adjustment as a strong determinant of the cross section of stock returns and could explain why the CAPM works well around FOMC press releases (Savor and Wilson (2014)).

E. Business-Cycle Variation in Return Premium

A large literature in finance documents variation in expected excess returns over time, which is predictable by scaled stock-price ratios. Lustig and Verdelhan (2012) show that excess returns in the United States and other OECD countries are substantially higher during recessions than during expansions. Variation in risk premia leads to variation in the cost of capital of firms to evaluate investment projects and has important implications for asset allocation and market-timing investment strategies.

I perform long-horizon forecasting regressions to test whether the premium for sticky-price firms varies systematically with business-cycle conditions. Specifically, I run m-month forecasting regressions of the cumulative log premium for sticky-price firms, r^e_{lh}, on the proxy for the consumption-wealth ratio of Lettau and Ludvigson (2001), cay:[24]

$$\sum_{s=1}^{m} r^e_{lh,t+s} = a_{lh} + b^{(m)}_{lh} dp_t + \epsilon_{t+m}.$$

Table 10 reports regression coefficients for horizons ranging from one month to five years. For each regression, the table reports OLS standard errors in parentheses, Newey and West (1987) standard errors in brackets, and Hodrick (1992) standard errors in curly brackets.

[24]Lettau and Ludvigson (2001) use quarterly data from the National Income and Product Accounts to construct cay. To get a monthly series, I linearly interpolate the quarterly observations available under http://faculty.haas.berkeley.edu/lettau/data_cay.html.

cay has strong predictive power for the premium for sticky-price firms at all horizons and explains 60% of the time-series variation at a three-year horizon. In times of a high consumption-wealth ratio, when consumption is high relative to asset wealth, sticky price firms have high expected returns.

Figure 2 plots cay at the end of June along with the subsequently realized five-years return premium for sticky-price firms. The two times series track each other fairly closely. Times of low asset returns and hence high values of cay, typically recessions and stock market downturns, predict a high premium for sticky-price firms. The raw correlation between the two time series is 73.51%.

The results from the long-horizon predictive regressions establish that firms with sticky prices have higher expected returns than firms with flexible prices in recessions and in times of low aggregate stock market returns. The higher cost of capital for these firms in bad times should, ceteris paribus, lead to lower investment at the firm level and might explain why price rigidities are important for business-cycle variation.[25]

The findings in this section document that the cross-sectional-return premium for firms with sticky product prices is a compensation for risk. The portfolio of stocks with low frequencies of price adjustment has a higher co-movement with the aggregate stock market than the flexible-price portfolio, and is more sensitive to monetary policy shocks. The return premium varies systematically with business-cycle conditions and is highly predictable in the time series.

IV Model

In this section, I develop a dynamic New Keynesian production-based asset-pricing model to test whether the premium for sticky-price firms can be rationalized within such a framework. Households have external habit formation in consumption and derive utility from a composite consumption good and leisure. They provide different labor services and have market power in setting wages. The production side of the economy is organized in different sectors producing output according to a technology that is linear in labor. Individual firms in each sector are monopolistically-competitive suppliers of differentiated

[25] The appendix contains additional results and robustness checks, such as panel regression for monthly returns, full sample results, regressions on unwinsorized data, and results for realized volatilities and for different measures of the frequency of price adjustment. All additional results are similar to those reported in the main body of the paper and discussed in detail in section *F.* of the appendix.

goods and competitive demanders in the market of homogeneous labor input. I consider a cashless economy with nominal bonds in zero net supply. The monetary authority sets short-term interest rates according to a Taylor rule. In the interest of space, I will discuss the model verbally and focus on key equations. Appendix *A.* contains detailed derivations of the model and Appendix *B.* summarizes the equilibrium conditions.

A. Firms

There is a continuum of monopolistically-competitive firms divided into different sectors. Firms are indexed by their sector, $k \in [0, 1]$, and by $j \in [0, 1]$. The distribution of firms across sectors is given by the density f on [0,1]. Firms have market power and follow time-dependent pricing rules. The time for price adjustment arrives stochastically. Each period, a fraction $1 - \theta_k$ of firms in sector k adjusts prices. The probability of price adjustment, or Calvo (1983)–rate, is equal across firms in a given sector and is independent of the time the price has been in effect.[26] Firms are demand-constrained and satisfy all demand at posted prices. They rent homogeneous labor services, H_t, taking the wage rate, W_t, as given to produce output, $Y_{kj,t}$, according to a linear technology in labor, $H_{kj,t}$. The log of aggregate technology follows an AR(1) process.

The pricing problem of a firm that adjusts in period t is then to set the reset price $X_{kj,t}$ to maximize the expected present value of discounted profits over all future histories in which it will not have a chance to adjust the price:

$$\mathbb{E}_t \sum_{s=0}^{\infty} (\beta\theta_k)^s \frac{\Lambda_{t+s}}{\Lambda_t} \left(X_{kj,t} Y_{kj,t+s} - W_{t+s} H_{kj,t+s} \right),$$

subject to its demand function and production technology. Λ_t equals the Lagrange multiplier on the household budget constraint, and β is the time discount factor. Firms charge a constant markup over a weighted average of current and future real marginal costs. Adjusting firms take into account that they might not have a chance to reset prices in future periods. The Calvo probabilities distort the discount factor: the probability that a price set today will still be in effect in period t+s is θ_k^s. Adjusting firms set prices optimally, taking the prices of other firms and aggregate prices as given. All price adjusters in a given sector choose identical prices by the symmetry of the problem.

The value of the firm with current price $P_{kj,t}$ can be written as a simple function of

[26] The Calvo model is the workhorse New Keynesian model because it is tractable and easily allows aggregation. Modeling price adjustment in a state-dependent framework instead of a time-dependent fashion has similar implications for macroeconomic aggregates in times of low and stable inflation (see Dotsey, King, and Wolman (1999)).

sector k variables:

$$V(P_{kj,t}) = \mathbb{E}_t \left\{ \frac{1}{\lambda_t} P_t \left[RS_{k,t} \left(\frac{P_{kj,t}}{P_t} \right)^{1-\varepsilon_{ck}} - CS_{k,t} \left(\frac{P_{kj,t}}{P_t} \right)^{-\varepsilon_{ck}} + RF_{k,t} - CF_{k,t} \right] \right\}, \quad (2)$$

where $RS_{k,t}$, $CS_{k,t}$, $RF_{k,t}$, and $CF_{k,t}$ are the revenues (R) and costs (C) coming from expected price stickiness (S) and flexibility (F), respectively, and ε_{ck} is the elasticity of substitution of within-sector consumption varieties.

B. Households

There is a large number of identical, infinitely lived households. Households have a love for variety and derive utility from many different consumption goods. Each household supplies all types of differentiated labor services, $h_{i,t}, i \in [0, 1]$.

The representative household has additively separable utility in consumption and leisure and maximizes:

$$\mathbb{E}_t \sum_{s=0}^{\infty} \beta^s \left[\frac{(C_{t+s} - bC_{t+s-1})^{1-\gamma}}{1-\gamma} - \psi_L \int_0^1 \frac{h_{i,t+s}^{1+\sigma}}{1+\sigma} \mathrm{d}i \right],$$

subject to a flow budget constrained. C_t is the composite consumption good, $b \geq 0$ is a habit-persistence parameter in consumption, $h_{i,t}$ denotes hours worked of type i, and $\psi_L \geq 0$ is a parameter. Profits are redistributed via lump-sum transfer at the end of each period. The parameters γ and σ denote the coefficient of relative risk aversion and the inverse of the Frisch elasticity of labor supply, respectively. The per-period budget constraint equalizes total consumption expenditure and total disposable income, which consists of labor income from the different labor types, and gross payoffs from previous-period bond holdings net of new bond purchases plus aggregate dividends. The composite consumption good is a double Dixit-Stiglitz aggregate of many individual goods produced in different sectors.

C. Wage Rate

The structure of the labor market follows Erceg, Henderson, and Levin (2000). The representative household sells labor services to a representative, competitive labor aggregator. The aggregator transforms the different labor types into aggregate labor input, H_t. Homogeneous labor is a Dixit-Stiglitz aggregate of the different labor types. For each labor type i, a monopoly union represents all workers of this type. Individual unions set wages optimally, subject to a Calvo–style wage friction.

The optimization problem of adjusting unions is given by:

$$\mathbb{E}_t \sum_{s=0}^{\infty} (\beta\theta_w)^s \left\{ -\psi_L \frac{h_{i,t+s}^{1+\sigma}}{1+\sigma} + \frac{\Lambda_{t+s}}{\Lambda_t} U_{i,t} h_{i,t+s} \right\},$$

subject to the demand curve for labor type i. 1–θ_w equals the Calvo-wage rate and $U_{i,t}$ is the optimal reset wage.

Unions set wages to equalize the expected discounted marginal disutility of providing one additional unit of labor to its expected discounted utility. Again, the optimal reset wage is identical for all unions resetting wages in period t.

Wage stickiness increases the level of the equity premium in the model. Dividends equal output minus wages. In an economy with frictionless labor markets, wages equal the marginal product of labor and are therefore perfectly correlated with output. A drop in demand leads to a drop in output, but at the same time, it also decreases the wage bill. Hence, dividends exhibit too little variation in any reasonable calibration. The Calvo–style wage-setting friction de-couples the average wage paid by a firm from the marginal product of labor. In times of low output and high marginal utility, the wage rate of some labor types cannot be adjusted downward. Firms therefore have to incur higher wages in bad times. This mechanism makes claims on dividends risky and boosts the level of the equity premium.[27]

D. Monetary Policy

The monetary authority sets the short-term nominal interest rate according to:

$$i_t = \phi_\pi \pi_t + \phi_x x_t + \log\left(\frac{1}{\beta}\right) + u_{m,t},$$

where i_t is $\log R_t$, $\pi_t = \log P_t - \log P_{t-1}$ is aggregate inflation, $x_t = \log Y_t - \log Y_{t-1}$ is growth in output, ϕ_π and ϕ_x are parameters, and $u_{m,t}$ is a monetary policy shock. The policy shock follows an AR(1) process.

E. Equilibrium

General equilibrium is defined by the optimality conditions for the household utility-maximization problem; by every firm kj's profit optimization; by market clearing in the product, labor, and financial markets; and by rational expectations.

[27] Wage stickiness is equal across sectors and therefore primarily affects the level of the equity premium. A constant degree of wage stickiness across industries seems justified given the findings Barattieri, Basu, and Gottschalk (2014) of little heterogeneity in the frequency of wage adjustment across industries.

F. Inefficiency

Knowledge of aggregate labor input, H_t, is not sufficient to determine aggregate output. Cross-sectional dispersion of wage rates across different labor types and product prices within and across sectors increases the required amount of labor input for the production of a given level of the aggregate output index. Different labor types are imperfect substitutes in production, whereas different consumption varieties are imperfect substitutes in the consumption index. As each labor type enters the labor aggregator and the household's utility function symmetrically, optimality requires equal hours across types. Equivalently, as different consumption varieties enter the consumption index symmetrically and firms face identical production technologies, an optimal allocation requires equal production across firms. After a shock, some firms and unions are unable to adjust their product prices and wages, respectively, which leads to dispersion in prices and wages. Wage dispersion across different labor types increases the required amount of labor types for a given level of homogeneous labor. Price dispersion increases the required amount of homogeneous labor for a given level of the output index. Price and wage dispersion and hence *aggregate inefficiency* increase in the curvature of the respective aggregators, that is, the elasticity of substitution across different labor types and the elasticities of substitution of consumption within and across sectoral varieties. *Inefficiencies across sectors* are driven by the elasticity of substitution of consumption varieties within sector as wage dispersion is identical across sectors. The more elastic the demand is for varieties of a given sector and the lower the frequency of price adjustment, the larger the price dispersion (see Woodford (2003)).

G. Calibration

I calibrate a five-sector version of the model at the quarterly frequency to compare the implications of the model to my empirical findings. I use standard parameter values in the literature.[28] Specifically, the time discount factor β is 0.99, implying an annual risk-free rate of 4% in the non-stochastic steady state. I employ the estimate for the habit-persistence parameter $b = 0.76$ from Altig, Christiano, Eichenbaum, and Linde (2011). I set the parameters of the utility function $\gamma = 5$ and $\psi = 1$ following Jermann (1998) and Altig et al. (2011), and I calibrate the inverse of the Frisch elasticity of labor supply, σ, to a value of 2.5. I set the elasticity of substitution of within-sector consumption varieties

[28]See Table A.8 in the appendix.

and across sectoral subcomposites, ε_{ck} and ε_c, to values of 12 and 8, respectively, following Carvalho (2006). The sectoral elasticity implies a steady-state markup of roughly 9%, in line with empirical evidence by Burnside (1996) and Basu and Fernald (1997). I follow Erceg et al. (2000) and set θ_w to a value of 0.825. This value implies an average duration of wage contracts of five quarters. ε_w is calibrated to a value of 8, which corresponds to a wage markup of 14% in the range of estimates used in the literature.[29] I set the parameter values of the monetary policy reaction function, ϕ_π and ϕ_y, to standard values of 1.24 and 0.33/4, respectively, in line with results reported in Rudebusch (2002). I use the empirical distribution of the frequencies of price adjustment of Nakamura and Steinsson (2008) to calibrate $\langle 1-\theta_k\rangle_{k=1}^{5}$. In particular, I sort industries by their frequency of price adjustment and construct five synthetic sectors. The sectors correspond to the quintiles of the distribution of the frequency of price adjustment observed in the data. Each sector covers one fifth of consumer spending. The Calvo rates of price adjustment range from 0.105 to 0.985 per quarter. I calibrate the autoregressive parameters of the two shock processes to $\rho_a = 0.95$ for the technology shock and $\rho_m = 0.90$ for the technology shock – well within the range of empirical estimates (e.g., Smets and Wouters (2007) and Coibion and Gorodnichenko (2012)). I set the standard deviations of the shocks, σ_a and σ_{mp}, to 0.0085 to match the historical standard deviation of log quarterly real gross domestic product (GDP) for my sample period.[30]

In the benchmark case, I solve the model numerically using a second-order approximation as implemented in *dynare*, and simulate the model for 400 firms in each sectors and 500 periods, discarding the first 250 periods as burn-in.[31] For each firm and time period, I then calculate the firm value, $V(P_{kj,t})$, dividends, $D(P_{kj,t})$, and returns as $R_{kj,t} = \frac{V(P_{kj,t})}{V(P_{kj,t-1})-D(P_{kj,t-1})}$.

[29] Altig et al. (2011) set the wage markup to 5%, whereas Erceg et al. (2000) calibrate ε_w to 4, implying a markup of 33%. As displayed in Table 11, results are not very sensitive to changes in this parameter.

[30] I download seasonally adjusted real GDP in billions of chained 2009 dollars from the FRED database. Consistent with findings of Gorodnichenko and Ng (2010), I apply the Hodrick-Prescott filter with a smoothing parameter of 1600 to both historical and model-generated data to calibrate the shock standard deviations.

[31] I employ the pruning package of Andreasen, Fernández-Villaverde, and Rubio-Ramírez (2014) to ensure the simulated sample paths do not explode. Pruning leaves out terms of higher order than the approximation order.

G.1 Simulation Results

Table 11 reports annualized mean excess returns over the risk-free rate at the sector level, the spread in mean returns between the portfolios containing firms with low and high frequencies of price adjustment, and the annualized equity risk premium and Sharpe ratio, as well as the regression coefficient of annualized returns at the firm level on the monthly frequency of price adjustment.

The baseline calibration in line (1) results in annualized excess returns of almost 8% for the sticky-price sector. Excess returns decrease monotonically in the degree of price flexibility to as low as 5.5% for the flexible-price sector. The return premium for sticky price firms is almost 2.4% per annum, in line with my empirical findings in Table 4. The model displays an equity premium of 6.6% and an annual Sharpe ratio of 0.39. The coefficient of annual firm-level returns on the frequency of price adjustment is negative and highly statistically significant. The coefficient implies that moving from a firm with totally sticky prices to a firm with totally flexible prices is associated with a decrease in annual returns of 2.5% per annum.

The baseline calibration documents that heterogeneity in the frequency of price adjustment leads to a cross-sectional difference in returns. The following lines of Table 11 evaluate the robustness of this finding and carve out the key driving forces behind this result. Lines (2)–(5) investigate the effect of variations in the within- and across-sector elasticities on the equity premium and the return differential. In lines (2) and (3), we see that changes in ϵ_{ck} have an immediate effect on the premium for sticky-price firms while hardly affecting the overall level of the equity premium. In particular, increasing ϵ_{ck} from a baseline value of 12 to 13 increases the cross-sectional difference in returns by almost 50%. On the other hand, varying the across-sector elasticity of substitution (lines (4) and (5)) has only small effects on the level of the risk premium or the cross-sectional-return difference. In lines (6) and (7), we see that lowering the elasticity of substitution between different labor types has only negligible effects, whereas calibrating the Frisch elasticity of labor supply to a value of 1 increases both the cross-sectional spread in returns and the overall equity premium.

In the next exercise, I evaluate the effects of higher aggregate risk. Specifically, I increase the standard deviations for both the monetary policy and the technology shocks. Higher aggregate risk increases the returns for all sectors, but disproportionately for sectors with lower frequencies of price adjustment. The premium for sticky-price firms doubles and the equity premium increases by almost 1% per year.

Lines (9) and (10) check how changes in the responsiveness of monetary policy affect the findings. A more aggressive stance on inflation dampens the equity premium by 1% and reduces the dispersion in returns across sectors by a factor of 4. Changes in the reaction to output growth, however, have little impact on stock returns. Lines (11) and (12) disentangle the contributions of the two shocks: the cross-sectional and the level effects are almost exclusively driven by monetary policy shocks. Increasing the persistence of technology shocks in line (13) increases the cross-sectional premium for price stickiness and the overall level of the equity premium.

G.2 Two-Sector Model

To gain a better understanding of the different margins behind the cross-sectional-return premium, I work with a two-sector version of the model in the following. The advantage of the two-sector model is that I can directly relate movements in aggregate variables to movements in the sticky- and flexible-price sectors.

Instead of simulating dividends and valuations at the firm level, I report returns for a claim on aggregate dividends at the sector level. I show in the appendix that sector dividends are given by sector output times the sector profit margin, which can be expressed as the sector markup, $\mu_{k,t}$, minus 1 over the markup. I can decompose the markup further into a relative price and a price dispersion component:

$$D_{k,t} = Y_{k,t}\left[1 - \left(\frac{W_t}{P_t}\right)\left(\frac{1}{A_t}\right)\left(\frac{P_{k,t}}{P_t}\right)^{-1} DS_{p,k,t}\right].$$

Expressing this relation in percentage deviations from steady state:

$$\check{D}_{k,t} = \check{Y}_{k,t} - \frac{Y_k - D_k}{D_k}\left[\left(\frac{\check{W}_t}{P_t}\right) - \check{A}_t - \left(\frac{\check{P}_{k,t}}{P_t}\right) + \check{DS}_{p,k,t}\right]. \tag{3}$$

Differences in sector dividends, $\check{D}_{1,t} - \check{D}_{2,t}$, are therefore determined by three margins: (i) a quantity margin, $(\check{Y}_{1,t} - \check{Y}_{2,t})$; (ii) a relative price margin, $(\check{P}_{1,t} - \check{P}_{2,t})$; and (iii) an inefficiency or price-dispersion margin, $-(\check{DS}_{p,1,t} - \check{DS}_{p,2,t})$. The quantity margin captures the sensitivity of sectoral output to price differentials across sectors, which is the price margin, whereas the inefficiency margin reflects lost output due to dispersion in prices.

Figure 3 graphically analyzes the cross-sectional-return premium for sticky-price firms. I plot the average difference in dividends between the sectors with low and high frequencies of price adjustment, $(Div_{sticky} - Div_{flexible})$, and marginal utility,

$(C_t - bC_{t-1})^{-\gamma}$, as a function of aggregate output. I simulate the model 500 times, sort the difference in sector dividends and marginal utility based on the realization of aggregate output, and take the average across simulations. In times of low aggregate output and high marginal utility, the sector with low frequency of price adjustment has lower dividends than the flexible price sector. Negative relative payoffs in times of high marginal utility are key for a positive return premium for sticky-price firms.

Figure 4 plots the impulse response functions of several aggregate and sector-level variables to a one-standard-deviation monetary policy shock. Contractionary monetary policy shocks lead to a drop in real output, Y; inflation, π, and the aggregate real-wage rate, w, decrease, whereas marginal utility, λ, goes up. The drop in real wages is less than the drop in output, and the increase in marginal utility is an order of magnitude larger in absolute value due to the stickiness of wages and habit formation.

In terms of dividends, firms in the sticky-price sector are on average stuck at their current price. The relative price of sector 1, $P1$, increases compared to sector 2, in line with the real reset price of sector 1, $X1$. The last line of Figure 4 shows an increase in price dispersion, DS. The dispersion in prices is substantially larger for the sticky-price sector.

We see in line 1 of Figure 5 that the drop in aggregate output, Y, leads to a decrease in output at the sector level, $Y1$ and $Y2$. The decline in output for the sticky-price sector is larger compared to sector 2 due to the higher relative price. We see in the following lines of the figure that contractionary monetary policy leads to a drop in sector dividends, $D1$ and $D2$; stock prices, $S1$ and $S2$; and returns, $Ret1$ and $Ret2$. Negative payoffs in times of high marginal utility is the key condition for a positive equity premium.

Firms in the stick-price sector gain along the price margin compared to firms in the flexible-price sector but lose along the quantity and inefficiency margins. All three margins combined result in lower sector dividends, D, stock prices, S, and returns, Ret, for firms in sector 1 compared to flexible-price firms. Low relative payoffs in times of high marginal utility are central for a cross-sectional return premium for sticky-price firms.

Figure 4 and Figure 5 also plot impulse response functions for different values of the elasticity of substitution of within-sector consumption composites to gain intuition for the effects of ε_{ck} on the premium for sticky-price firms documented in Table 11.[32] The

[32] ε_{ck} low, medium, and high correspond to values of 8, 12, and 16, respectively. The premium for sticky-price firms increases from 0.92% to 6.73% per year.

disadvantage for sticky-price firms in the quantity margin and the advantage in the price margin decrease in the elasticity of substitution of within-sector consumption varieties. The negative effect of price dispersion on dividends increases in ε_{ck}. Taken together, the effects on the price and price-dispersion margins are quantitatively more important. The difference in sector dividends decreases and the premium for sticky-price firms increases in ε_{ck}.

I show in the appendix that the elasticity of substitution of consumption varieties across sectors, ε_c, only affects the quantity margin $(\check{Y}_{1,t} - \check{Y}_{2,t})$. Increasing ε_c translates into larger negative differences in dividends between the sticky- and flexible-price sector and therefore increases the premium for sticky-price firms. This channel, however, is quantitatively small and of second order compared to the effects of ε_{ck}.[33]

A dynamic New Keynesian asset-pricing model, therefore, is consistent with the novel empirical findings, a large premium for sticky-price firms that varies over the business cycle, and an equity premium in line with historical estimates.

V Conclusions

Sticky prices have a long history in such different fields as macroeconomics, industrial organization, and marketing, and are key to explaining the business-cycle dynamics of real gross domestic output, consumption, and investment. I document that price rigidities are also a strong predictor of the cross section of stock returns. CAPM βs are a function of many parameters and factors, and we have little knowledge about the fundamental drivers. The frequency of product-price adjustment is a simple statistic at the firm level that can account for a considerable part of the variation of firms' exposure to systematic risk. Therefore, price rigidities are important for both business-cycle dynamics in aggregate quantities and cross-sectional variation in stock returns, and further bridge macroeconomics and finance.

I document that a dynamic New Keynesian asset-pricing model in which firms differ in their frequency of price adjustment is consistent with my novel stylized facts. A sufficiently high elasticity of substitution between consumption varieties within sectors, ε_{ck}, is the central condition for large premium for sticky price firms. Three margins determine the

[33] In the appendix, I also study why technology shocks only lead to a small premium, and document substantial business-cycle variation in the premium for sticky-price firms in simulated data.

cross-sectional-return difference: a quantity margin, a price margin, and an inefficiency margin associated with price dispersion. Whereas the first margin, ceteris paribus, lowers the return premium, the other two margins increase the difference in returns between sticky- and flexible-price firms with increasing ε_{ck}.

There are several potential extensions for future research. Labor is the only production factor in my current setup. Allowing for capital and investigating how investment at the firm level interacts with price stickiness would be interesting.[34] New Keynesian models have strong predictions on how production is distributed across firms and sectors after aggregate shocks, with interesting implications for firm-level investment. Furthermore, the current setup completely abstracts from capital-structure considerations. The positive correlation between leverage and the frequency of price adjustment indicates that a departure from this assumption could be a fruitful avenue for future research. In addition, my current analysis neglects potential heterogeneity in wage stickiness across firms and industries. The importance of wage stickiness for the aggregate level of equity risk premia and the interaction with price stickiness underlines the importance of this question for future research. Ultimately, the cause of sticky prices and the determinants of differences in the frequency of price adjustment across firms within industry are the vital questions.

Using information contained in asset pricing more generally is a fruitful avenue for future research in macroeconomics. Starting with Lucas (1987), researchers have used the information content of stock prices to calculate the welfare cost of business-cycle fluctuations. Gorodnichenko and Weber (2013) employ information from stock returns to distinguish between alternative macro models for the observed level of price stickiness in micro data, whereas information in credit spreads can potentially be useful for identifying the cost of inflation uncertainty.

[34] To get interesting macro and asset-pricing implications, one has to depart from the convenient modeling tool of economy-wide rental markets for capital (see, e.g., Altig et al. (2011) and Lettau and Uhlig (2000)) and allow for firm-specific capital.

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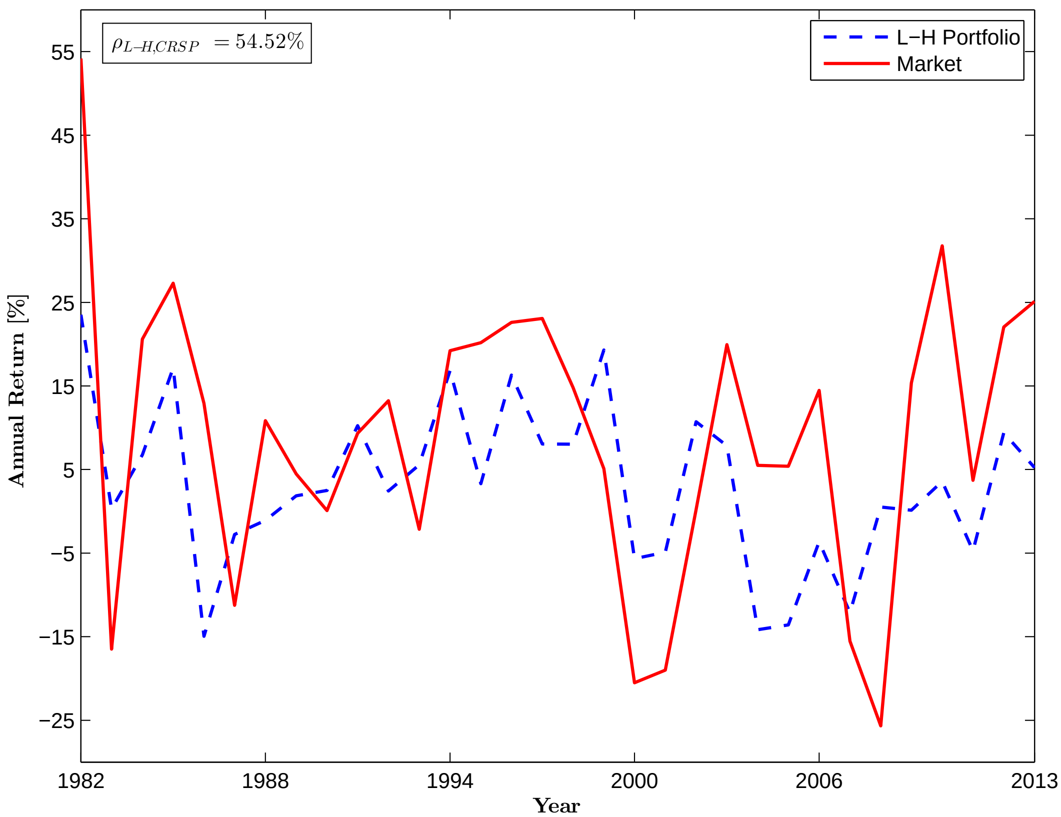
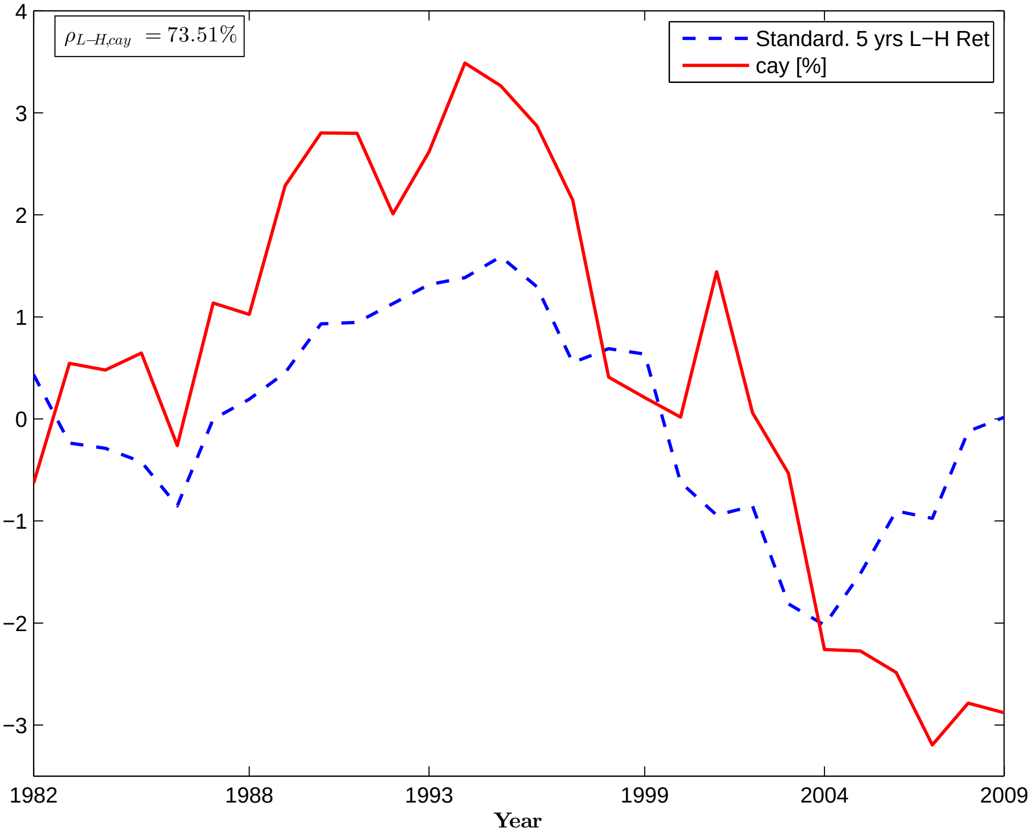
Figure 1: **Market Excess Return and Sticky minus Flexible Price Portfolio**



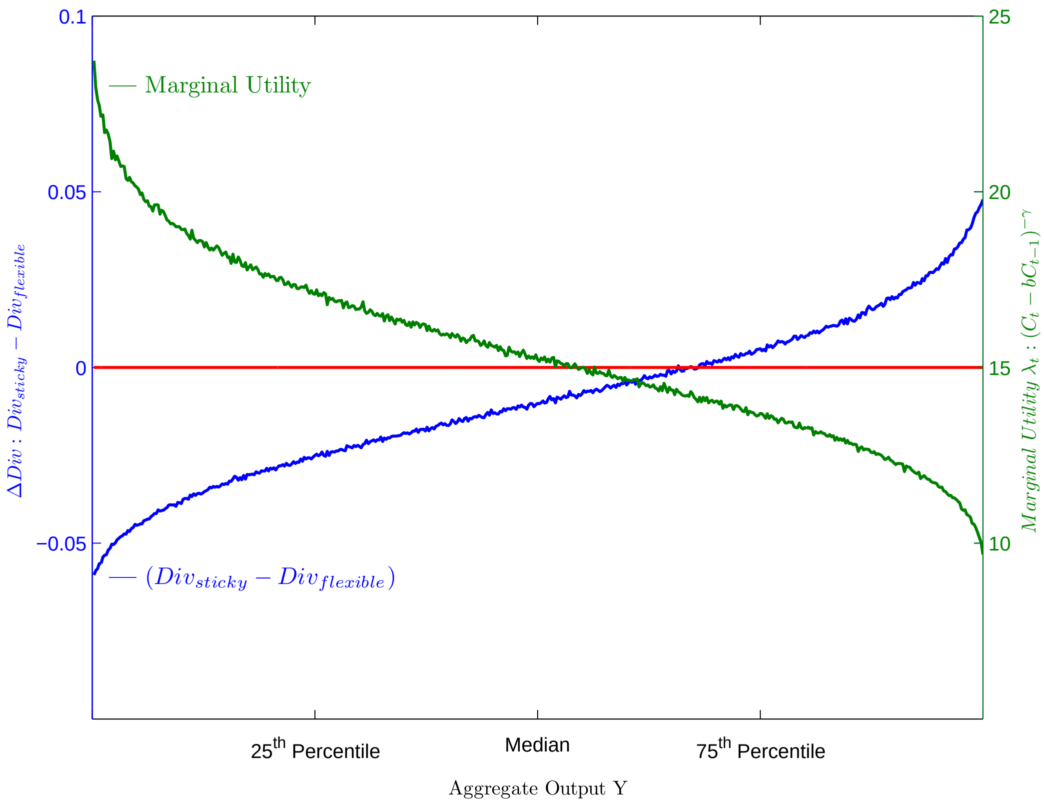
This figure plots the annual excess return of the CRSP value-weighted index (market) and the annual return of the zero-cost portfolio of going long the portfolio of stocks with low frequencies of price adjustment and shorting the portfolio of stocks with high frequencies of price adjustment, L-H. The sampling frequency is annual. The sample period is July 1982 to June 2014.

Figure 2: **Consumption Wealth Ratio (cay) and Following 5 Years Returns**



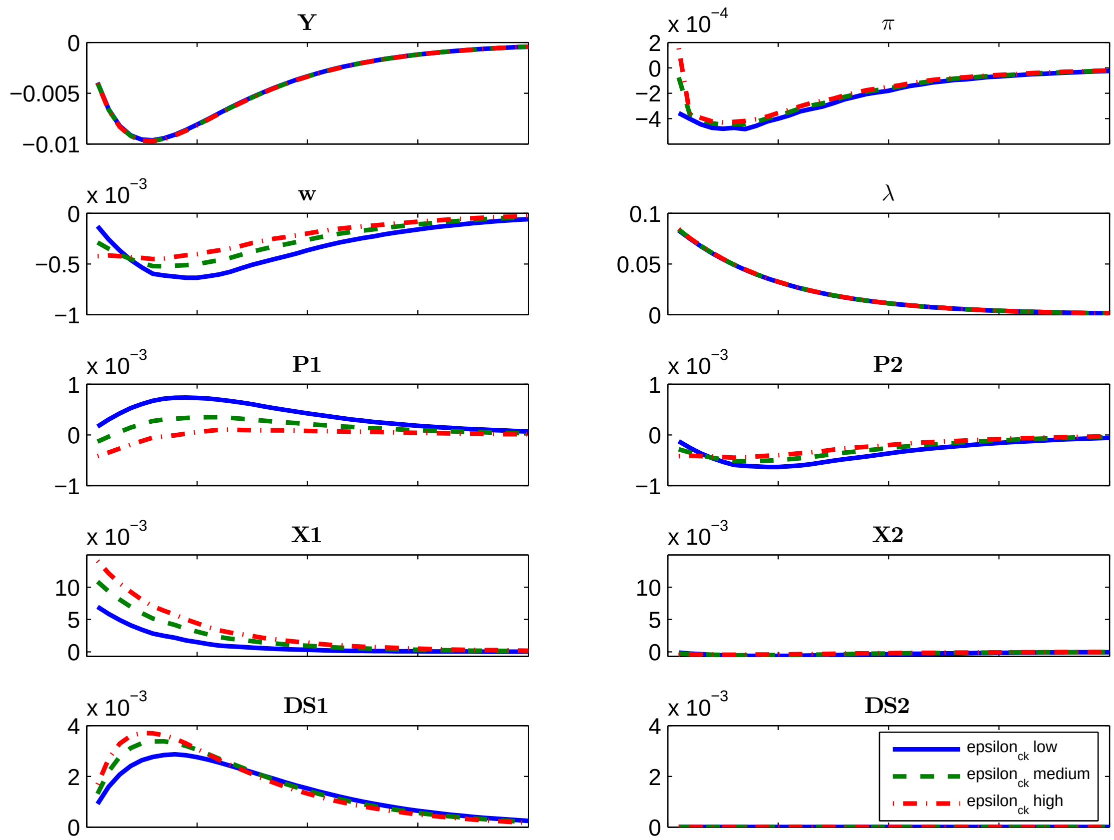
This figure plots the Lettau and Ludvigson (2001) proxy for the consumption wealth ratio, cay, and the subsequently realized five years return of the zero-cost portfolio of going long the portfolio of stocks with low frequencies of price adjustment, and shorting the portfolio of stocks with high frequencies of price adjustment, L-H. The sampling frequency is annual with cay observed at end of June of year t and returns measured from July of year t to June of year t+5. The sample period for cay is June 1982 to June 2009.

Figure 3: **Difference in Sector Dividends and Marginal Utility**



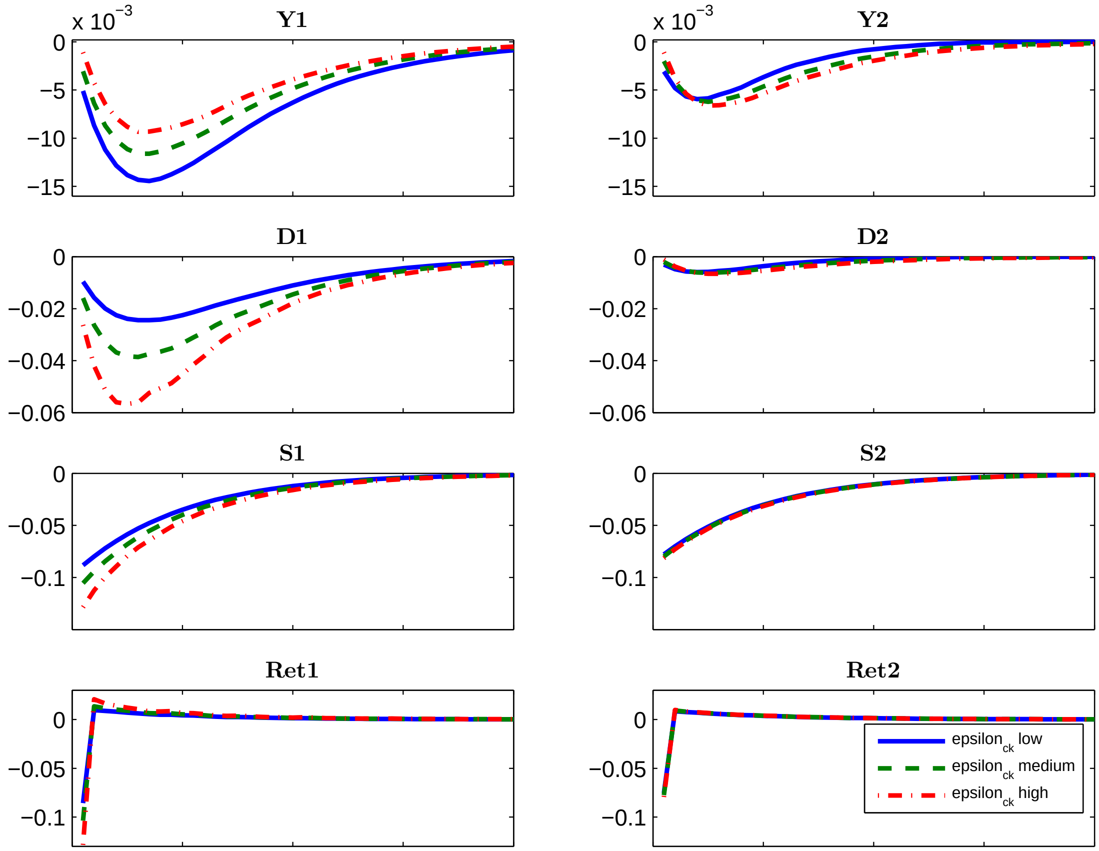
This figure plots the average difference in dividends of the sectors with low and high frequencies of price adjustment, $(Div_{sticky} - Div_{flexible})$*, and marginal utility,* $(C_t - bC_{t-1})^{-\gamma}$*, as a function of aggregate output,* Y*. I simulate a two sector version of the model of Section IV 500 times, sort the difference in sector dividends and marginal utility based on the realization of aggregate output, and take the average across simulations. The difference in dividends is measured on the left y-axis, whereas marginal utility is measured on the right y-axis.*

Figure 4: **Impulse Response Functions to Monetary Policy Shock (varying ε_{ck})**



This figure plots the impulse response functions of several macroeconomic variables of the model of Section IV to a one-standard-deviation contractionary monetary policy shock for different values of the elasticity of substitution of within-sector consumption varieties, ε_{ck}. ε_{ck} low, medium, and high correspond to values of 8, 12, and 16, respectively. Y is output; π, inflation; w, aggregate real wage; λ, the marginal utility of consumption; P1 and P2, the relative prices of sectors one and two; X1 and X2, the optimal real reset prices; and DS1 and DS2, the price dispersions in the two sectors.

Figure 5: **Impulse Response Functions to Monetary Policy Shock (varying ε_{ck})**



This figure plots the impulse response functions of several macroeconomic variables of the model of Section IV to a one-standard-deviation contractionary monetary policy shock for different values of the elasticity of substitution of within-sector consumption varieties, ε_{ck}. ε_{ck} low, medium, and high correspond to values of 8, 12, and 16, respectively. Y1 and Y2 are the output of the sectors, D1 and D2 are sector-level dividends, S1 and S2 are the prices of claims to aggregate sector dividends, and Ret1 and Ret2 are the returns of these claims.

Table 1: **Frequency of Price Adjustment by Industry**

This table reports equally-weighted average monthly frequencies of price adjustment, SAU, at the industry and aggregate levels with standard deviations in parentheses. Frequencies of price adjustments are calculated at the firm level using the micro data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. The sample period is July 1982 to June 2007.

	Agriculture	Manufacturing	Utilities	Trade	Finance	Service	Total
Mean	19.07%	11.78%	19.74%	20.89%	13.07%	9.66%	14.23%
Std	(16.77%)	(11.35%)	(13.54%)	(15.54%)	(11.47%)	(10.08%)	(13.09%)
Max	54.24%	59.48%	53.89%	60.00%	45.65%	43.02%	60.00%
Min	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
N	90	354	107	47	122	72	792

Table 2: **Summary Statistics and Correlations for Characteristics and Return Predictors (Benchmark Sample)**

This table reports time-series averages of annual cross-sectional means and standard deviations for firm characteristics and return predictors used in the subsequent analysis in Panel A and contemporaneous correlations of these variables in Panel B. SAU measures the frequency of price adjustment. Equally-weighted probabilities of price adjustments are calculated at the firm level using the micro data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. Size is the natural logarithm of the market capitalization in thousands, BM is the book-to-market ratio, Beta is the regression coefficient on the market excess return in rolling times-series regressions, Lev is financial leverage, CF measures cash flows, Turnover is the fraction of shares traded to shares outstanding, spread is the mean bid - ask spread, PCM is the price-to-cost margin, and HHI is the Herfindahl - Hirschman index of sales at the Fama & French 48 industry level. Stock-level data are from CRSP and financial statement data are from Compustat. The sample period is July 1982 to June 2007.

	SAU	Size	BM	Beta	Lev	CF	Turnover	Spread	PCM	HHI
	Panel A. Means and Standard Deviations									
Mean	0.14	14.74	0.63	1.05	0.40	0.09	0.10	0.01	0.37	0.07
Std	0.13	1.26	0.37	0.42	0.23	0.06	0.08	0.01	0.18	0.06
N	562	562	553	545	560	560	562	562	560	556
	Panel B. Contemporaneous Correlations									
Size	0.07									
BM	0.25	−0.15								
Beta	−0.16	−0.19	−0.17							
Lev	0.17	0.00	0.26	−0.13						
CF	−0.04	0.19	−0.44	−0.07	−0.50					
Turnover	−0.03	−0.18	−0.10	0.44	−0.17	0.05				
Spread	0.02	−0.30	0.13	0.15	0.07	−0.14	−0.01			
PCM	−0.15	0.11	−0.34	0.07	−0.08	0.28	0.10	−0.13		
HHI	−0.12	0.01	−0.18	0.10	−0.09	0.16	0.01	0.04	0.06	

Table 3: **Mean Portfolio Returns (SAU)**

This table reports time-series averages of annual equally-weighted portfolio raw returns in Panel A, value-weighted raw returns in Panel B, and characteristic-adjusted (DGTW) returns following Daniel et al. (1997) in Panel C for various sample periods with OLS standard errors in parentheses. Stocks are assigned to one of five baskets based on the frequency of price adjustment, SAU. Equally-weighted probabilities of price adjustments are calculated at the firm level using the micro data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. Panel D reports time-series averages of annual returns for the CRSP value-weighted index (CRSP VW), the CRSP equally-weighted index (CRSP EW), the size (SMB), and value (HML) factors of Fama and French (1993).

	Sticky	S2	S3	S4	Flexible	S1-S5
	Panel A. Annual Mean Returns (equally weighted)					
07/1982 - 06/2014	21.49***	20.41***	20.11***	18.64***	18.14***	3.35 **
	(3.96)	(3.42)	(3.72)	(3.29)	(3.09)	(1.70)
07/1982 - 06/2007	24.12***	22.20***	22.09***	21.02***	19.90***	4.22 **
	(4.29)	(3.53)	(3.89)	(3.31)	(3.35)	(2.13)
	Panel B. Annual Mean Returns (value weighted)					
07/1982 - 06/2014	19.35***	18.30***	18.13***	16.81***	16.32***	3.10 **
	(3.59)	(3.05)	(3.34)	(2.96)	(2.76)	(1.57)
07/1982 - 06/2007	21.72***	19.89***	19.90***	18.94***	17.96***	3.80 **
	(3.90)	(3.12)	(3.49)	(2.97)	(2.99)	(1.93)
	Panel C. Annual DGTW-adjusted Returns					
07/1982 - 06/2014	5.85***	5.20***	4.24***	3.55***	3.38***	2.47 **
	(1.26)	(0.70)	(1.03)	(0.99)	(1.16)	(1.21)
07/1982 - 06/2007	6.89***	5.55***	4.71***	4.56***	3.64***	3.24 **
	(1.50)	(0.78)	(1.15)	(1.14)	(1.41)	(1.38)

	CRSP VW	CRSP EW	SMB	HML
	Panel D. Annual Factor Returns			
07/1982 - 06/2014	13.46***	14.96***	1.16	4.16
	(3.19)	(3.96)	(1.52)	(2.66)
07/1982 - 06/2007	14.99***	16.75***	0.80	5.61*
	(3.46)	(4.54)	(1.83)	(3.22)

Standard errors in parentheses

$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 4: **Panel Regressions of Annual Stock Returns on Price Stickiness and Firm Characteristics (Benchmark Sample)**

This table reports the results of regressing annual percentage returns on the frequency of price adjustment, SAU, firm characteristics, return predictors, and year fixed effects, where indicated. Standard errors are clustered at the firm level and reported in parentheses. Equally-weighted probabilities of price adjustments are calculated at the firm level using the micro data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. Size is the natural logarithm of the market capitalization in thousands, BM is the book-to-market ratio, Beta is the regression coefficient on the market excess return in rolling times-series regressions, Lev is financial leverage, CF measures cash flows, Turnover is the fraction of shares traded to shares outstanding, Spread is the mean bid - ask spread, PCM is the price-to-cost margin, and HHI is the Herfindahl - Hirschman index of sales at the Fama & French 48 industry level. Stock-level data are from CRSP and financial statement data are from Compustat. The sample period is July 1982 to June 2007.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SAU	−10.18***	−11.07***	−7.98***	−12.97***	−7.87***	−11.01***	−10.98***	−9.87***	−10.31***	−9.53***	−10.74***	−6.46**
	(1.06)	(2.25)	(2.42)	(2.47)	(2.30)	(2.29)	(2.28)	(2.24)	(2.32)	(2.22)	(2.27)	(2.69)
Size			−4.34***									−4.87***
			(0.28)									(0.31)
BM				3.31***								3.88***
				(0.83)								(1.07)
Beta					5.30***							1.23
					(0.72)							(0.91)
Lev						1.02						4.80***
						(1.35)						(1.78)
CF							−10.56*					5.67
							(5.49)					(7.51)
Turnover								52.49***				35.06***
								(3.82)				(4.80)
Spread									−5.55***			−7.60***
									(0.54)			(0.57)
PCM										5.87***		8.00***
										(1.63)		(1.96)
HHI											2.95	11.28**
											(4.70)	(5.54)
Year Fixed Effects	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	14,026	14,026	14,026	13,791	13,594	13,965	13,976	14,026	14,026	13,974	13,866	13,253
R^2	0.11%	19.83%	21.85%	19.94%	20.36%	19.72%	19.74%	21.35%	20.91%	19.80%	19.41%	24.82%

Standard errors in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 5: **Panel Regressions of Annual Stock Returns on Price Stickiness (Benchmark Sample, within Industry)**

This table reports the results of regressing annual percentage returns on the frequency of price adjustment, SAU, year fixed effects, and industry fixed effects, where indicated. Standard errors are clustered at the firm level and reported in parentheses. Equally-weighted probabilities of price adjustments are calculated at the firm level using the micro data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. The sample period is July 1982 to June 2007.

	Baseline	Agriculture	Manufacturing	Utilities	Trade	Finance	Services	Dummies
SAU	−11.07***	−15.40 **	−7.38*	−9.73 **	−9.13	−2.50	−12.16	−7.93***
	(2.25)	(6.85)	(4.08)	(4.14)	(8.92)	(4.78)	(19.37)	(2.40)
Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Industry Fixed Effects	N	N	N	N	N	N	N	Y
Observations	14,026	764	6,932	2,075	1,058	2,270	927	14,026
R^2	19.83%	26.88%	20.24%	25.34%	39.26%	44.46%	21.62%	20.10%

Standard errors in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 6: **Mean of Double Sortings**

This table reports average annual returns for double-sorted portfolios. I first assign stocks into tertiles based on various firm characteristics, and then within each portfolio, I assign stocks into tertiles based on the frequency of price adjustment, SAU, resulting in nine portfolios in total. I report mean returns across characteristic sorts for the sticky-, intermediate-, and flexible-price portfolios as well as the conditional premium for sticky-price firms. OLS standard errors are reported in parentheses. Equally-weighted probabilities of price adjustments are calculated at the firm level using the micro data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. Size is the natural logarithm of the market capitalization in thousands, BM is the book-to-market ratio, Beta is the regression coefficient on the market excess return in rolling times-series regressions, Lev is financial leverage, CF measures cash flows, Turnover is the fraction of shares traded to shares outstanding, Spread is the mean bid - ask spread, PCM is the price-to-cost margin, and HHI is the Herfindahl - Hirschman index of sales at the Fama & French 48 industry level. Stock-level data are from CRSP and financial statement data are from Compustat. The last two columns report results for conditional double sorts of Beta and BM on size. The sample period is July 1982 to June 2007.

	Uncond (0)	Size (1)	BM (2)	Beta (3)	Lev (4)	Spread (5)	PCM (6)	Turnover (7)	CF (8)	HHI (9)	Beta cond Size (10)	BM cond Size (11)
Sticky	23.35	21.51	21.98	21.97	22.11	21.88	22.05	21.58	21.91	21.80	19.75	22.09
S2	21.90	20.70	20.14	20.06	20.18	20.49	20.02	20.92	20.15	20.14	20.55	19.95
Flexible	20.35	19.11	18.90	19.22	18.92	18.94	19.18	18.90	19.18	19.11	22.79	20.51
S1 - S3	3.00 * *	2.41 * *	3.07***	3.20***	2.75 * *	2.94 * *	2.87***	2.67 * *	2.73***	2.69***	−3.04*	1.58
	(1.17)	(1.22)	(0.92)	(1.14)	(1.14)	(1.18)	(0.86)	(1.16)	(0.88)	(0.95)	(1.78)	(1.53)

Standard errors in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 7: **CAPM Regressions (Benchmark Sample)**

This table reports results for the conditional CAPM. Stocks are assigned to one of five baskets based on the frequency of price adjustment; SAU and returns are equally weighted at the portfolio level. Equally-weighted probabilities of price adjustments are calculated at the firm level using the micro data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. α is the intercept and β the slope of times series regressions of monthly portfolio excess returns on a constant and the excess return of the CRSP value weighted index. Fama and MacBeth (1973) standard errors are reported in parentheses and Newey and West (1987) standard errors in brackets. The conditional CAPM is monthly estimated on a rolling basis over the last twelve months following the methodology of Lewellen and Nagel (2006). The sample period is July 1982 to June 2007.

	Sticky (1)	S2 (2)	S3 (3)	S4 (4)	Flexible (5)	S1-S5 (6)
α_p	0.40	0.36	0.37	0.38	0.40	0.00
SE_{FMB}	(0.05)***	(0.04)***	(0.04)***	(0.04)***	(0.04)***	(0.04)
SE_{NW}	[0.15]***	[0.11]***	[0.12]***	[0.11]***	[0.12]***	[0.12]
β_p	1.29	1.22	1.16	1.07	0.92	0.36
SE_{FMB}	(0.02)***	(0.01)***	(0.01)***	(0.01)***	(0.02)***	(0.02)***
SE_{NW}	[0.04]***	[0.03]***	[0.04]***	[0.03]***	[0.05]***	[0.04]***

Standard errors in parentheses

$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 8: **Cash-Flow and Discount-Rate Betas (Benchmark Sample)**

This table reports results for a beta decomposition into cash-flow β, β_{CF}, and discount-rate β, β_{DR}, following Campbell and Vuolteenaho (2004) as well as their sum. GMM (Hansen (1982)) standard errors conditional on the estimated news series are reported in parentheses. Stocks are assigned to one of five baskets based on the frequency of price adjustment, SAU, and returns are equally weighted at the portfolio level. Equally-weighted probabilities of price adjustments are calculated at the firm level using the micro data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. The sample period is from July 1982 to June 2007.

	Sticky	S2	S3	S4	Flexible	S1-S5
	(1)	(2)	(3)	(4)	(5)	(6)
$\beta_{p,CF}$	0.58 * **	0.57 * **	0.55 * **	0.50 * **	0.43 * **	0.15 * **
	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.03)
$\beta_{p,DR}$	0.63 * **	0.61 * **	0.57 * **	0.53 * **	0.47 * **	0.16 * **
	(0.07)	(0.06)	(0.06)	(0.06)	(0.07)	(0.03)
β_p	1.22	1.18	1.12	1.02	0.90	0.31

Standard errors in parentheses

$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 9: **Return Sensitivities to Federal Funds Rate Surprises**

This table reports results from regressing monthly percentage excess returns on a constant and the surprise component of the one-month change in the Federal Funds rate and the CAPM predicted response for five portfolios sorted on the frequency of price adjustment and the CRSP value-weighted index (market). Stocks are assigned to one of five baskets based on the frequency of price adjustment, SAU, and returns are equally weighted at the portfolio level. Equally-weighted probabilities of price adjustments are calculated at the firm level using the micro data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. OLS standard errors are reported in parentheses and Newey and West (1987) standard errors are in brackets. The sample period is June 1989 to June 2007.

	Market (1)	Sticky (2)	S2 (3)	S3 (4)	S4 (5)	Flexible (6)	S1-S5 (7)
$\beta^{actual}_{p,FFR}$	−9.35	−11.45	−10.28	−9.39	−8.81	−5.07	−6.38
	(2.51)***	(3.02)***	(2.85)***	(2.82)***	(2.63)***	(2.56)***	(1.54)***
	[2.66]***	[4.10]***	[3.55]***	[3.38]***	[3.36]***	[2.93]***	[2.19]***
$\beta^{pred}_{p,FFR}$		−10.46	−9.87	−9.45	−8.74	−7.35	−3.10

Standard errors in parentheses

$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 10: **Long-Horizon Predictability (Benchmark Sample)**

This table reports results for m-month forecasting regressions of the log premium for sticky-price firms on the proxy for the consumption-wealth ratio of Lettau and Ludvigson (2001), cay. Stocks are assigned to one of five baskets based on the frequency of price adjustment, SAU, and returns are equally weighted at the portfolio level. Equally-weighted probabilities of price adjustments are calculated at the firm level using the micro data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. For each regression, the table reports OLS standard errors in parentheses, Newey and West (1987) standard errors in brackets, and Hodrick (1992) standard errors in curly brackets. The sample period is July 1982 to June 2007.

Horizon m (Months)	1	6	12	24	36	48	60
$b_{lh}^{(m)}$	0.22	1.50	3.09	5.92	8.53	10.14	12.18
SE_{OLS}	(0.08)***	(0.18)***	(0.23)***	(0.35)***	(0.45)***	(0.63)***	(0.68)***
SE_{NW}	[0.07]***	[0.26]***	[0.47]***	[0.97]***	[1.48]***	[1.76]***	[1.30]***
SE_H	{0.07}***	{0.41}***	{0.84}***	{1.58}***	{2.49}***	{3.72}***	{3.88}***
R^2	2.85%	19.68%	38.32%	51.05%	58.27%	51.25%	57.67%

Standard errors in parentheses

$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 11: **Model-Implied Stock Returns**

This table reports annualized mean excess returns for simulated data of the model of Section IV, the model-implied equity risk premium (ERP), the Sharpe ratio (SR) as well as the sensitivity (β_{SAU}) of annualized returns on the monthly frequency of price adjustment: $R_{jk,t} = \alpha + \beta_{SAU} \times (1 - \theta_k)$. A five-sector version of the model is calibrated using standard parameter values reported in Table A.8 and the empirical distribution of the frequency of price adjustment of Nakamura and Steinsson (2008). The model is solved using a second-order approximation as implemented in dynare, employing the pruning package of Andreasen et al. (2014), calibrated at a quarterly frequency and simulated for 400 firms in each sector for 500 periods discarding the first 250 periods as burn in.

		Sticky	S2	S3	S4	Flexible	S1-S5	ERP	SR	β_{SAU}
(1)	Baseline	7.91	6.84	6.56	5.96	5.51	2.39	6.56	0.39	-2.48^{***}
(2)	$\epsilon_{ck} = 13$	8.70	6.81	6.41	5.68	5.15	3.55	6.55	0.36	-3.41^{***}
(3)	$\epsilon_{ck} = 11$	7.40	6.89	6.70	6.21	5.85	1.55	6.61	0.41	-1.76^{***}
(4)	$\epsilon_c = 10$	8.15	6.86	6.55	5.94	5.50	2.66	6.60	0.39	-2.66^{***}
(5)	$\epsilon_c = 6$	7.71	6.82	6.57	5.98	5.53	2.18	6.52	0.39	-2.33^{***}
(6)	$\epsilon_w = 6$	7.98	7.03	6.72	6.17	5.76	2.22	6.73	0.42	-2.31^{***}
(7)	$\sigma = 1$	8.51	7.07	6.70	6.20	5.82	2.69	6.86	0.43	-2.55^{***}
(8)	Shock std = 0.009	10.21	7.66	7.19	6.40	5.82	4.39	7.46	0.38	-4.05^{***}
(9)	$\phi_{pi} = 1.3$	5.98	5.88	5.76	5.41	5.16	0.82	5.64	0.38	-1.08^{***}
(10)	$\phi_x = 0.5/4$;	7.90	6.84	6.56	5.96	5.51	2.39	6.55	0.39	-2.47^{***}
(11)	MP shocks only	6.81	5.87	5.64	5.03	4.59	2.23	5.59	0.34	-2.37^{***}
(12)	Technol shocks only	1.08	0.97	0.89	0.83	0.81	0.27	0.92	0.47	-0.27^{***}
(13)	$\phi_x = 0.975$	9.19	7.85	7.46	6.80	6.32	2.87	7.52	0.43	-2.90^{***}

$*p < 0.10, **p < 0.05, ***p < 0.01$

Online Appendix: Nominal Rigidities and Asset Pricing

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Not for Publication

A. Model Derivations

A.1 Households

The representative household has additively separable utility in consumption and leisure and maximizes

$$\mathbb{E}_t \sum_{s=0}^{\infty} \left[\beta^s \frac{(C_{t+s} - bC_{t+s-1})^{1-\gamma}}{1-\gamma} - \psi_L \int_0^1 \frac{h_{i,t+s}^{1+\sigma}}{1+\sigma} di \right]$$

$$\text{s.t.} \qquad P_t C_t = \int_0^1 W_{i,t} h_{i,t} di + R_{t-1} B_{t-1} - B_t + D_t,$$

where $\mathbb{E}_t$ is the expectation operator conditional on the time t information set of the representative household, β is the discount factor, C is the composite consumption good, b ≥ 0 is a habit persistence parameter in consumption, $h_{i,t}$ denotes hours worked of type i, $\psi_L \geq 0$ is a parameter, P is the composite price index defined below, $W_{i,t}$ time t nominal wage for labor type i, R_t is the gross nominal interest rate, B_t denotes nominal bond holdings, and D_t are aggregate dividends by the firm sector. Profits are redistributed via lump-sum transfer at the end of each period. The parameters γ and σ denote, respectively, the coefficient of relative risk aversion and the inverse of the Frisch elasticity of labor supply.

The first order conditions for the representative household for consumption and bond holdings are given by:

$$(C_t - bC_{t-1})^{-\gamma} = \Lambda_t P_t = \lambda_t$$

$$\mathbb{E}_t(\beta \Lambda_{t+1} R_t) = \Lambda_t.$$

Hence,

$$\frac{1}{P_t}(C_t - bC_{t-1})^{-\gamma} = \beta R_t \, \mathbb{E}_t \left[\frac{1}{P_{t+1}} (C_{t+1} - bC_t)^{-\gamma} \right]$$

$$1 = \beta R_t \, \mathbb{E}_t \left[\frac{1}{\pi_{t+1}} \left(\frac{C_{t+1} - bC_t}{C_t - bC_{t-1}} \right)^{-\gamma} \right].$$

A.2 Optimal Consumption Allocation

The composite consumption good is given by:

$$C_t \equiv \left[\int_0^1 f(k)^{\frac{1}{\varepsilon_c}} C_{k,t}^{\frac{\varepsilon_c-1}{\varepsilon_c}} dk\right]^{\frac{\varepsilon_c}{\varepsilon_c-1}}, \tag{A.1}$$

$$C_{k,t} \equiv f(k)\left[\int_0^1 C_{kj,t}^{\frac{\varepsilon_{ck}-1}{\varepsilon_{ck}}} dj\right]^{\frac{\varepsilon_{ck}}{\varepsilon_{ck}-1}}. \tag{A.2}$$

Let $P_{kj,t}$ denote the price charged by firm j in sector k for the consumption good C_{kj} in period t. The consumption price index is then given by:

$$P_t = \left[\int_0^1 f(k) P_{k,t}^{1-\varepsilon_c} dk\right]^{\frac{1}{1-\varepsilon_c}} \tag{A.3}$$

$$P_{k,t} = \left[\int_0^1 P_{kj,t}^{1-\varepsilon_{ck}} dj\right]^{\frac{1}{1-\varepsilon_{ck}}}. \tag{A.4}$$

Assume that the representative household maximizes equation (A.2) for any given expenditure level Q_t:

$$\int_0^1 P_{kj,t} C_{kj,t} dj = Q_t. \tag{A.5}$$

The Lagrangian associated with this problem is given by:

$$\mathfrak{L} = f(k)\left(\int_0^1 C_{kj,t}^{\frac{\varepsilon_{ck}-1}{\varepsilon_{ck}}} dj\right)^{\frac{\varepsilon_{ck}}{\varepsilon_{ck}-1}} - \Omega_t\left(\int_0^1 P_{kj,t} C_{kj,t} dj - Q_t\right),$$

where Ω_t is the associated Lagrange multiplier.

The first-order conditions are:

$$f(k)\frac{\varepsilon_{ck}}{\varepsilon_{ck}-1}\left(\int_0^1 C_{kj,t}^{\frac{\varepsilon_{ck}-1}{\varepsilon_{ck}}} dj\right)^{\frac{1}{\varepsilon_{ck}-1}} \frac{\varepsilon_{ck}-1}{\varepsilon_{ck}} C_{kj,t}^{-\frac{1}{\varepsilon_{ck}}} = \Omega_t P_{kj,t} \quad \forall j \in [0,1].$$

Rearranging and dividing by the expression for subcomposite $C_{ki,t}$:

$$C_{kj,t} = C_{ki,t}\left(\frac{P_{kj,t}}{P_{ki,t}}\right)^{-\varepsilon_{ck}}.$$

Substituting this expression into equation (A.5) we get:

$$\int_0^1 P_{kj,t} C_{ki,t}\left(\frac{P_{kj,t}}{P_{ki,t}}\right)^{-\varepsilon_{ck}} dj = Q_t$$

$$\Longleftrightarrow$$

$$C_{ki,t} P_{ki,t}^{\varepsilon_{ck}} \int_0^1 P_{kj,t}^{1-\varepsilon_{ck}} dj = Q_t.$$

Substituting for $\int_0^1 P_{kj,t}^{1-\varepsilon_{ck}} dj$ using equation (A.4):

$$C_{ki,t} P_{ki,t}^{\varepsilon_{ck}} P_{k,t}^{1-\varepsilon_{ck}} = Q_t \tag{A.6}$$

$$\Longleftrightarrow$$

$$C_{ki,t} = \frac{Q_t}{P_{k,t}}\left(\frac{P_{ki,t}}{P_{k,t}}\right)^{-\varepsilon_{ck}}.$$

Substituting the last expression for subcomposite kj in equation (A.2):

$$C_{k,t} = f(k) \left\{ \int_0^1 \left[\frac{Q_t}{P_{k,t}} \left(\frac{P_{kj,t}}{P_{k,t}} \right)^{-\varepsilon_{ck}} \right]^{\frac{\varepsilon_{ck}-1}{\varepsilon_{ck}}} dj \right\}^{\frac{\varepsilon_{ck}}{\varepsilon_{ck}-1}}.$$

Using the definition of the price index, equation (A.4), we get:

$$C_{k,t} = f(k) \frac{Q_t}{P_{k,t}}$$

$$\iff$$

$$\frac{Q_t}{P_{k,t}} = C_{k,t} f(k)^{-1}. \tag{A.7}$$

Combining equation (A.7) with equation (A.6) for good kj:

$$C_{k,t} f(k)^{-1} = C_{kj,t} \left(\frac{P_{kj,t}}{P_{k,t}} \right)^{\varepsilon_{ck}}.$$

Solving for $C_{kj,t}$ we arrive at the demand for subcomposite kj:

$$C_{kj,t} = f(k)^{-1} C_{k,t} \left(\frac{P_{kj,t}}{P_{k,t}} \right)^{-\varepsilon_{ck}}.$$

Following the same logic as above, we can derive the demand for the composite consumption good for a given expenditure level of Z_t:

$$\int_0^1 P_{k,t} C_{k,t} dk = Z_t. \tag{A.8}$$

The Lagrangian is given by:

$$\mathfrak{L} = \left(\int_0^1 f(k)^{\frac{1}{\varepsilon_c}} C_{k,t}^{\frac{\varepsilon_c - 1}{\varepsilon_c}} dk \right)^{\frac{\varepsilon_c}{\varepsilon_c - 1}} - \Theta_t \left(\int_0^1 P_{k,t} C_{k,t} dk - Z_t \right),$$

where Θ_t is the associated Lagrange multiplier. The first-order conditions are:

$$\frac{\varepsilon_c}{\varepsilon_c - 1} \left(\int_0^1 f(k)^{\frac{1}{\varepsilon_c}} C_{k,t}^{\frac{\varepsilon_c - 1}{\varepsilon_c}} dk \right)^{\frac{1}{\varepsilon_c - 1}} \frac{\varepsilon_c - 1}{\varepsilon_c} C_{k,t}^{-\frac{1}{\varepsilon_c}} f(k)^{\frac{1}{\varepsilon_c}} = \Theta_t P_{k,t} \quad \forall k \in [0, 1].$$

Rearranging and dividing by the expression for the consumption composite of sector l, $C_{kl,t}$:

$$C_{k,t} = C_{l,t} \frac{f(k)}{f(l)} \left(\frac{P_{k,t}}{P_{l,t}} \right)^{-\varepsilon_c}.$$

Substituting this expression into equation (A.8) we get:

$$\int_0^1 P_{k,t} \frac{f(k)}{f(l)} C_{l,t} \left(\frac{P_{k,t}}{P_{l,t}} \right)^{-\varepsilon_c} dk = Z_t$$

$$\iff$$

$$C_{l,t} P_{l,t}^{\varepsilon_c} \frac{1}{f(l)} \int_0^1 f(k) P_{k,t}^{1-\varepsilon_c} dk = Z_t.$$

Substituting for $\int_0^1 f(k) P_{k,t}^{1-\varepsilon_c} dk$ using equation (A.3)

$$C_{l,t} P_{l,t}^{\varepsilon_c} \frac{1}{f(l)} P_t^{1-\varepsilon_c} = Z_t \tag{A.9}$$

$$\Longleftrightarrow$$

$$C_{l,t} = f(l) \frac{Z_t}{P_t} \left(\frac{P_{l,t}}{P_t} \right)^{-\varepsilon_c}.$$

Substituting the last expression for the sector k consumption good in equation (A.1):

$$C_t = \left\{ \int_0^1 f(k)^{\frac{1}{\varepsilon_c}} \left[f(k) \frac{Z_t}{P_t} \left(\frac{P_{k,t}}{P_t} \right)^{-\varepsilon_c} \right]^{\frac{\varepsilon_c - 1}{\varepsilon_c}} dk \right\}^{\frac{\varepsilon_c}{\varepsilon_c - 1}}.$$

Using the definition of the price index, equation (A.3), we get:

$$C_t = \frac{Z_t}{P_t}. \tag{A.10}$$

Combining equation (A.10) with equation (A.9) for sector k:

$$\frac{Z_t}{P_t} = \frac{1}{f(k)} C_{k,t} \left(\frac{P_{k,t}}{P_t} \right)^{\varepsilon_c}.$$

Solving for $C_{k,t}$ we arrive at the demand for sector k composite consumption good:

$$C_{k,t} = f(k) C_t \left(\frac{P_{k,t}}{P_t} \right)^{-\varepsilon_c}.$$

A.3 Demand for Different Labor Types

The competitive labor contractor demands labor of different types i to maximize:

$$W_t H_t - \int_0^1 W_{i,t} h_{i,t} \mathrm{d}i$$

$$\text{s.t.} \qquad H_t = \left[\int_0^1 h_{i,t}^{\frac{\varepsilon_w - 1}{\varepsilon_w}} di \right]^{\frac{\varepsilon_w}{\varepsilon_w - 1}},$$

where W is the aggregate wage rate, H is homogeneous labor, W_i is wage rate of labor type i, and h_i and $\varepsilon_w \geq 1$ is the elasticity of substitution among different labor types. Following similar steps as in the derivation for the optimal consumption allocation, we arrive at:

$$h_{i,t} = \left(\frac{W_{i,t}}{W_t} \right)^{-\varepsilon_w} H_t.$$

The resulting demand curves are identical to a setup without competitive labor contractor where firms directly demand different labor types.

Note that the aggregate wage rate, W can be simply derived from:

$$\begin{aligned}
W_t H_t &= \int_0^1 W_{i,t} h_{i,t} \mathrm{d}i \\
&= \int_0^1 W_{i,t} \left(\frac{W_{i,t}}{W_t}\right)^{-\varepsilon_w} H_t \mathrm{d}i \\
W_t^{1-\varepsilon_w} &= \int_0^1 W_{i,t}^{1-\varepsilon_w} \mathrm{d}i.
\end{aligned}$$

A.4 Optimal Reset Wage

Let U_t be the optimal reset wage. The optimizing problem of the union representing labor of type i, $h_{i,t}$, is given by:

$$\mathbb{E}_t \sum_{s=0}^{\infty} (\beta\theta_w)^s \left\{ -\psi_L \frac{h_{i,t+s}^{1+\sigma}}{1+\sigma} + \frac{\Lambda_{t+s}}{\Lambda_t} U_{i,t} h_{i,t+s} \right\}$$

$$\text{s.t.} \qquad h_{i,t+s} = \left(\frac{U_{i,t}}{W_{t+s}}\right)^{-\varepsilon_w} H_{t+s},$$

where θ_w is the probability that the union cannot reset the wage rate of labor type i, $W_{i,t}$; σ is the inverse of the Frisch labor supply elasticity; Λ is the Lagrange multiplier on the households budget constraint; ϵ_w is the elasticity of substitution among different labor types; and ψ_L is a parameter.

The first order condition is given by:

$$\mathbb{E}_t \sum_{s=0}^{\infty} (\beta\theta_w)^s \left\{ -\psi_L h_{i,t+s}^{1+\sigma} \frac{1}{U_{i,t}} (-\varepsilon_w) + \Lambda_{t+s}(1-\varepsilon_w) h_{i,t+s} \right\} = 0$$

$$\Longleftrightarrow$$

$$\mathbb{E}_t \sum_{s=0}^{\infty} (\beta\theta_w)^s \left\{ \lambda_{t+s} \left(\frac{U_{i,t}}{P_{t+s}}\right) \left(\frac{U_{i,t}}{W_{t+s}}\right)^{-\varepsilon_w} H_{t+s} - \frac{\varepsilon_w}{\varepsilon_w - 1} \psi_L \left(\frac{U_{i,t}}{W_{t+s}}\right)^{-\varepsilon_w(1+\sigma)} H_{t+s}^{1+\sigma} \right\} = 0$$

$$\Longleftrightarrow$$

$$\mathbb{E}_t \sum_{s=0}^{\infty} (\beta\theta_w)^s \{ \lambda_{t+s} \left(\frac{U_{i,t}}{P_t}\right) \left(\frac{P_t}{P_{t+s}}\right) \left(\frac{U_{i,t}}{W_t}\right)^{-\varepsilon_w} \left(\frac{W_t}{W_{t+s}}\right)^{-\varepsilon_w} H_{t+s} - \frac{\varepsilon_w}{\varepsilon_w - 1} \psi_L \left(\frac{U_{i,t}}{W_t}\right)^{-\varepsilon_w(1+\sigma)}$$
$$\left(\frac{W_t}{W_{t+s}}\right)^{-\varepsilon_w(1+\sigma)} H_{t+s}^{1+\sigma} \} = 0$$

$$\Longleftrightarrow$$

$$\begin{aligned}
&\mathbb{E}_t \sum_{s=0}^{\infty} (\beta\theta_w)^s \left\{ \lambda_{t+s} \left(\frac{U_{i,t}}{P_t}\right) \left(\frac{P_t}{P_{t+s}}\right) \left(\frac{W_t}{W_{t+s}}\right)^{-\varepsilon_w} H_{t+s} \right\} \\
&\quad = \mathbb{E}_t \sum_{s=0}^{\infty} (\beta\theta_w)^s \left\{ \frac{\varepsilon_w}{\varepsilon_w - 1} \psi_L \left(\frac{U_{i,t}}{W_t}\right)^{-\varepsilon_w \sigma} \left(\frac{W_t}{W_{t+s}}\right)^{-\varepsilon_w(1+\sigma)} H_{t+s}^{1+\sigma} \right\}.
\end{aligned}$$

Then,

$$\frac{U_{i,t}}{P_t} = \frac{\varepsilon_w}{\varepsilon_w - 1}\psi_L \left(\frac{U_{i,t}}{W_t}\right)^{-\varepsilon_w \sigma} \frac{\mathbb{E}_t \sum_{s=0}^{\infty}(\beta\theta_w)^s \left\{ \left(\frac{W_t}{W_{t+s}}\right)^{-\varepsilon_w(1+\sigma)} H_{t+s}^{1+\sigma} \right\}}{\mathbb{E}_t \sum_{s=0}^{\infty}(\beta\theta_w)^s \left\{ \lambda_{t+s} \left(\frac{P_t}{P_{t+s}}\right) \left(\frac{W_t}{W_{t+s}}\right)^{-\varepsilon_w} H_{t+s} \right\}}.$$

Note that all unions resetting wages in period t face an identical problem and therefore choose the same reset wage, U_t. Therefore, we can write the optimal real reset wage as:

$$\left(\frac{U_t}{P_t}\right)^{1+\varepsilon_w \sigma} = \frac{\varepsilon_w}{\varepsilon_w - 1}\psi_L \left(\frac{W_t}{P_t}\right)^{\varepsilon_w \sigma} \frac{F_{w,t}}{K_{w,t}}, \tag{A.11}$$

where

$$\begin{aligned}
F_{w,t} &= \mathbb{E}_t \sum_{s=0}^{\infty}(\beta\theta_w)^s \left[\left(\frac{W_t}{W_{t+s}}\right)^{-\varepsilon_w(1+\sigma)} H_{t+s}^{1+\sigma} \right] \\
&= H_t^{1+\sigma} + \mathbb{E}_t \sum_{s=1}^{\infty}(\beta\theta_w)^s \left[\left(\frac{W_t}{W_{t+s}}\right)^{-\varepsilon_w(1+\sigma)} H_{t+s}^{1+\sigma} \right] \\
&= H_t^{1+\sigma} + \beta\theta_w \, \mathbb{E}_t \left(\frac{W_t}{W_{t+1}}\right)^{-\varepsilon_w(1+\sigma)} \sum_{s=0}^{\infty}(\beta\theta)^s \left[\left(\frac{W_{t+1}}{W_{t+1+s}}\right)^{-\varepsilon_w(1+\sigma)} H_{t+1+s}^{1+\sigma} \right] \\
&= H_t^{1+\sigma} + \beta\theta_w \, \mathbb{E}_t \left(\frac{W_t}{W_{t+1}}\right)^{-\varepsilon_w(1+\sigma)} F_{w,t+1} \\
&= H_t^{1+\sigma} + \beta\theta_w \, \mathbb{E}_t \, \pi_{w,t+1}^{\varepsilon_w(1+\sigma)} F_{w,t+1}
\end{aligned}$$

and

$$\begin{aligned}
K_{w,t} &= \mathbb{E}_t \sum_{s=0}^{\infty}(\beta\theta_w)^s \left[\lambda_{t+s} \left(\frac{P_t}{P_{t+s}}\right) \left(\frac{W_t}{W_{t+s}}\right)^{-\varepsilon_w} H_{t+s} \right] \\
&= \lambda_t H_t + \mathbb{E}_t \sum_{s=1}^{\infty}(\beta\theta_w)^s \left[\lambda_{t+s} \left(\frac{P_t}{P_{t+s}}\right) \left(\frac{W_t}{W_{t+s}}\right)^{-\varepsilon_w} H_{t+s} \right] \\
&= \lambda_t H_t + \beta\theta_w \, \mathbb{E}_t \left(\frac{P_t}{P_{t+1}}\right) \left(\frac{W_t}{W_{t+1}}\right)^{-\varepsilon_w} \sum_{s=0}^{\infty}(\beta\theta_w)^s \left[\lambda_{t+1+s} \left(\frac{P_{t+1}}{P_{t+1+s}}\right) \left(\frac{W_{t+1}}{W_{t+1+s}}\right)^{-\varepsilon_w} H_{t+1+s} \right] \\
&= \lambda_t H_t + \beta\theta_w \, \mathbb{E}_t \left(\frac{P_t}{P_{t+1}}\right) \left(\frac{W_t}{W_{t+1}}\right)^{-\varepsilon_w} \sum_{s=0}^{\infty}(\beta\theta_w)^s K_{w,t+1} \\
&= \lambda_t H_t + \beta\theta_w \, \mathbb{E}_t \frac{\pi_{w,t+1}^{\varepsilon_w}}{\pi_{t+1}} K_{w,t+1}.
\end{aligned}$$

In case of frictionless labor markets, equation (A.11) simplifies to:

$$\begin{aligned}\left(\frac{U_t}{P_t}\right) &= \frac{\varepsilon_w}{\varepsilon_w - 1}\psi_L \left(\frac{U_t}{W_t}\right)^{-\varepsilon_w \sigma} \frac{H_t^{1+\sigma}}{\lambda_t H_t} \\ &= \frac{\varepsilon_w}{\varepsilon_w - 1}\psi_L \left(\frac{U_t}{W_t}\right)^{-\varepsilon_w \sigma} \frac{h_{i,t}^{\sigma}}{\lambda_t} \left(\frac{U_t}{W_t}\right)^{-\varepsilon_w \sigma} \\ &= \frac{\varepsilon_w}{\varepsilon_w - 1}\frac{\psi_L h_{i,t}^{\sigma}}{\lambda_t},\end{aligned}$$

where the second equality exploited the demand curve for labor type i.

Exploiting the fact that all unions resetting wages in period t set the same wage and the Calvo (1983) assumption that the probability of being able to reset the wage rate is independent of time and across labor types, we can write the aggregate wage as a weighted average of the reset wage and last periods aggregate wage where the weights are given by the fraction (which equals the overall probability that a given union is able to reset the wage rate) of unions which adjust their wage in period t:

$$W_t^{1-\varepsilon_w} = (1-\theta_w) U_t^{1-\varepsilon_w} + \theta_w W_{t-1}^{1-\varepsilon_w}$$

and

$$\left(\frac{W_t}{P_t}\right)^{1-\varepsilon_w} := w_t^{1-\varepsilon_w} = (1-\theta_w)\left(\frac{U_t}{P_t}\right)^{1-\varepsilon_w} + \theta_w \left(\frac{W_{t-1}}{P_{t-1}}\right)^{1-\varepsilon_w} \left(\frac{P_t}{P_{t-1}}\right)^{\varepsilon_w - 1}.$$

Wage inflation $\pi_{w,t+1}$ can be expressed as:

$$\frac{W_{t+1}}{W_t} := \pi_{w,t+1} = \frac{W_{t+1}/P_{t+1}}{W_t/P_t}\frac{P_{t+1}}{P_t} = \frac{w_{t+1}}{w_t}\pi_{t+1},$$

and

$$\pi_{t+1} := \frac{P_{t+1}}{P_t}$$

is price inflation.

A.5 Optimal Reset Price

Recall:

$$\begin{aligned} C_{kj,t} &= f(k)^{-1} C_{k,t} \left(\frac{P_{kj,t}}{P_{k,t}}\right)^{-\varepsilon_{ck}} \\ C_{k,t} &= f(k) C_t \left(\frac{P_{k,t}}{P_t}\right)^{-\varepsilon_c}.\end{aligned}$$

Therefore, by imposing market clearing in the good markets, we can write:

$$Y_{kj,t} = \left(\frac{P_{kj,t}}{P_{k,t}}\right)^{-\varepsilon_{ck}} \left(\frac{P_{k,t}}{P_t}\right)^{-\varepsilon_c} Y_t.$$

The problem of a firm j in sector k which is able to reoptimize in period t is then to choose $X_{kj,t}$ to maximize:

$$\mathbb{E}_t \sum_{s=0}^{\infty} (\beta\theta_k)^s \frac{\Lambda_{t+s}}{\Lambda_t} \left(X_{kj,t} Y_{kj,t+s} - W_{t+s} H_{kj,t+s} \right)$$

$$\text{s.t.} \qquad Y_{kj,t+s} = \left(\frac{X_{kj,t}}{P_{k,t+s}} \right)^{-\varepsilon_{ck}} \left(\frac{P_{k,t+s}}{P_{t+s}} \right)^{-\varepsilon_c} Y_{t+s}$$

$$Y_{kj,t+s} = A_{t+s} H_{kj,t+s},$$

where $Y_{kj,t}$ is the output of firm j in sector k, Λ is the Lagrange multiplier on the household budget constraint, θ_k is the probability with which a firm in sector k is not able to reset its price, W is the aggregate wage rate of homogeneous labor H, and ϵ_c and ϵ_{ck} are the elasticities of substitution in consumption between sectoral subcomposites and within sector varieties.

Substituting the constraints into the objective function:

$$\mathbb{E}_t \sum_{s=0}^{\infty} (\beta\theta_k)^s \frac{\Lambda_{t+s}}{\Lambda_t} \left[X_{kj,t} \left(\frac{X_{kj,t}}{P_{k,t+s}} \right)^{-\varepsilon_{ck}} \left(\frac{P_{k,t+s}}{P_{t+s}} \right)^{-\varepsilon_c} Y_{t+s} \right.$$
$$\left. - W_{t+s} \left(\frac{1}{A_{t+s}} \right) \left(\frac{X_{kj,t}}{P_{k,t+s}} \right)^{-\varepsilon_{ck}} \left(\frac{P_{k,t+s}}{P_{t+s}} \right)^{-\varepsilon_c} Y_{t+s} \right]$$

$$\Longleftrightarrow$$

$$\mathbb{E}_t \sum_{s=0}^{\infty} (\beta\theta_k)^s \frac{\lambda_{t+s}}{\lambda_t} P_t \left[\left(\frac{X_{kj,t}}{P_t} \right)^{1-\varepsilon_{ck}} \left(\frac{P_t}{P_{t+s}} \right)^{1-\varepsilon_{ck}} \left(\frac{P_{k,t+s}}{P_{t+s}} \right)^{\varepsilon_{ck}} \left(\frac{P_{k,t+s}}{P_{t+s}} \right)^{-\varepsilon_c} Y_{t+s} \right.$$
$$\left. - \left(\frac{W_{t+s}}{P_{t+s}} \right) \left(\frac{1}{A_{t+s}} \right) \left(\frac{X_{kj,t}}{P_t} \right)^{-\varepsilon_{ck}} \left(\frac{P_{k,t+s}}{P_{t+s}} \right)^{\varepsilon_{ck}} \left(\frac{P_{k,t+s}}{P_{t+s}} \right)^{-\varepsilon_c} \left(\frac{P_t}{P_{t+s}} \right)^{-\varepsilon_{ck}} Y_{t+s} \right].$$

The first order condition is given by:

$$\mathbb{E}_t \sum_{s=0}^{\infty} (\beta\theta_k)^s \frac{\lambda_{t+s}}{\lambda_t} \left[(1-\varepsilon_{ck}) \left(\frac{X_{kj,t}}{P_t} \right)^{-\varepsilon_{ck}} \left(\frac{P_{k,t+s}}{P_{t+s}} \right)^{\varepsilon_{ck}} \left(\frac{P_{k,t+s}}{P_{t+s}} \right)^{-\varepsilon_c} \left(\frac{P_t}{P_{t+s}} \right)^{1-\varepsilon_{ck}} Y_{t+s} \right.$$
$$\left. + \varepsilon_{ck} \left(\frac{W_{t+s}}{P_{t+s}} \right) \left(\frac{1}{A_{t+s}} \right) \left(\frac{X_{kj,t}}{P_t} \right)^{-\varepsilon_{ck}-1} \left(\frac{P_{k,t+s}}{P_{t+s}} \right)^{\varepsilon_{ck}} \left(\frac{P_{k,t+s}}{P_{t+s}} \right)^{-\varepsilon_c} \left(\frac{P_t}{P_{t+s}} \right)^{-\varepsilon_{ck}} Y_{t+s} \right]$$

$$\Longleftrightarrow$$

$$\mathbb{E}_t \sum_{s=0}^{\infty} (\beta\theta_k)^s \frac{\lambda_{t+s}}{\lambda_t} \left[\left(\frac{X_{kj,t}}{P_t} \right) \left(\frac{P_{k,t+s}}{P_{t+s}} \right)^{\varepsilon_{ck}} \left(\frac{P_{k,t+s}}{P_{t+s}} \right)^{-\varepsilon_c} \left(\frac{P_t}{P_{t+s}} \right)^{1-\varepsilon_{ck}} Y_{t+s} \right]$$
$$= \mathbb{E}_t \sum_{s=0}^{\infty} (\beta\theta_k)^s \frac{\lambda_{t+s}}{\lambda_t} \left[\frac{\varepsilon_{ck}}{1-\varepsilon_{ck}} \left(\frac{W_{t+s}}{P_{t+s}} \right) \left(\frac{1}{A_{t+s}} \right) \left(\frac{P_{k,t+s}}{P_{t+s}} \right)^{\varepsilon_{ck}} \left(\frac{P_{k,t+s}}{P_{t+s}} \right)^{-\varepsilon_c} \left(\frac{P_t}{P_{t+s}} \right)^{-\varepsilon_{ck}} Y_{t+s} \right].$$

Rearranging, we get:

$$\frac{X_{kj,t}}{P_t} = \frac{\varepsilon_{ck}}{\varepsilon_{ck}-1}\frac{\mathbb{E}_t \sum_{s=0}^{\infty}(\beta\theta_k)^s \frac{\lambda_{t+s}}{\lambda_t}\left[\left(\frac{W_{t+s}}{P_{t+s}}\right)\left(\frac{1}{A_{t+s}}\right)\left(\frac{P_{k,t+s}}{P_{t+s}}\right)^{\varepsilon_{ck}}\left(\frac{P_{k,t+s}}{P_{t+s}}\right)^{-\varepsilon_c}\left(\frac{P_t}{P_{t+s}}\right)^{-\varepsilon_{ck}} Y_{t+s}\right]}{\mathbb{E}_t \sum_{s=0}^{\infty}(\beta\theta_k)^s \frac{\lambda_{t+s}}{\lambda_t}\left[\left(\frac{P_{k,t+s}}{P_{t+s}}\right)^{\varepsilon_{ck}}\left(\frac{P_{k,t+s}}{P_{t+s}}\right)^{-\varepsilon_c}\left(\frac{P_t}{P_{t+s}}\right)^{1-\varepsilon_{ck}} Y_{t+s}\right]}.$$

As this expression is independent of firm specific variables, all firms in sector k which are able to reset their prices in period t will choose the identical real price, $\frac{X_{k,t}}{P_t}$:

$$\frac{X_{k,t}}{P_t} := \frac{\varepsilon_{ck}}{1-\varepsilon_{ck}}\frac{F_{p,k,t}}{K_{p,k,t}},$$

where

$$F_{p,k,t} = \lambda_t \left(\frac{W_t}{P_t}\right)\left(\frac{1}{A_t}\right)\left(\frac{P_{k,t}}{P_t}\right)^{\varepsilon_{ck}}\left(\frac{P_{k,t}}{P_t}\right)^{-\varepsilon_c} Y_t + \beta\theta_k\,\mathbb{E}_t\left(\frac{P_{t+1}}{P_t}\right)^{\varepsilon_{ck}} F_{p,k,t+1}$$

$$K_{p,k,t} = \lambda_t \left(\frac{P_{k,t}}{P_t}\right)^{\varepsilon_{ck}}\left(\frac{P_{k,t}}{P_t}\right)^{-\varepsilon_c} Y_t + \beta\theta_k\,\mathbb{E}_t\left(\frac{P_{t+1}}{P_t}\right)^{\varepsilon_{ck}-1} K_{p,k,t+1}.$$

A.6 Aggregate Output

Technically, the model does not possess an aggregate production function in the sense that knowing the state of technology, A_t, and the number of people working, L_t, is not sufficient to determine aggregate output, Y_t. Frictions in the labor market and price frictions lead to distortions in the optimal allocation of resources implying that aggregate output will be generally lower than implied by a frictionless model, $Y_t \leq A_t L_t$. In the following, I derive the "aggregate production function."

Aggregate labor supply in period t is given by:

$$L_t = \int_0^1 h_{i,t}\mathrm{d}i = \int_0^1 \left(\frac{W_{i,t}}{W_t}\right)^{-\varepsilon_w} H_t \mathrm{d}i = H_t DS_{w,t},$$

where wage dispersion $DS_{w,t}$ is defined as:

$$\begin{aligned}
DS_{w,t} &= \int_0^1 \left(\frac{W_{i,t}}{W_t}\right)^{-\varepsilon_w} \mathrm{d}i \\
&= \int_{wage\ adjuster} \left(\frac{W_{i,t}}{W_t}\right)^{-\varepsilon_w} \mathrm{d}i + \int_{wage\ non-adjuster} \left(\frac{W_{i,t}}{W_t}\right)^{-\varepsilon_w} \mathrm{d}i \\
&= \left[(1-\theta_w)\left(\frac{U_t}{W_t}\right)^{-\varepsilon_w} + \int_{wage\ non-adjuster} \left(\frac{W_{i,t}}{W_t}\right)^{-\varepsilon_w} \mathrm{d}i\right] \\
&= \left[(1-\theta_w)\left(\frac{U_t}{W_t}\right)^{-\varepsilon_w} + \theta_w \left(\frac{W_{t-1}}{W_t}\right)^{-\epsilon_w} \int_0^1 \left(\frac{W_{i,t-1}}{W_{t-1}}\right)^{-\varepsilon_w} \mathrm{d}i\right] \\
&= \left[(1-\theta_w)\left(\frac{U_t}{W_t}\right)^{-\varepsilon_w} + \theta_w \left(\frac{W_{t-1}}{W_t}\right)^{-\varepsilon_w} DS_{w,t-1}\right] \\
&= \left[(1-\theta_w)\left(\frac{U_t}{P_t}\right)^{-\varepsilon_w} \left(\frac{W_t}{P_t}\right)^{\varepsilon_w} + \theta_w \pi_w^{\varepsilon_w} DS_{w,t-1}\right].
\end{aligned}$$

Aggregate labor demand in period t is given by:

$$\begin{aligned}
H_t &= \int_0^1 \int_0^1 H_{kj,t} \mathrm{d}j \mathrm{d}k \\
&= \int_0^1 \int_0^1 \frac{Y_{kj,t}}{A_t} \mathrm{d}j \mathrm{d}k \\
&= \frac{1}{A_t} Y_t \int_0^1 \int_0^1 \left(\frac{P_{kj,t}}{P_{k,t}}\right)^{-\varepsilon_{ck}} \left(\frac{P_{k,t}}{P_t}\right)^{-\varepsilon_c} \mathrm{d}j \mathrm{d}k \\
&= \frac{1}{A_t} Y_t \int_0^1 f(k) DS_{p,k,t} \left(\frac{P_{k,t}}{P_t}\right)^{-\varepsilon_c} \mathrm{d}k \\
&= \frac{1}{A_t} Y_t DS_{p,t},
\end{aligned}$$

where price dispersion in sector k $DS_{p,k,t}$ is given by:

$$\begin{aligned}
DS_{p,k,t} &= \int_0^1 \left(\frac{P_{kj,t}}{P_{k,t}}\right)^{-\epsilon_{ck}} \mathrm{d}j \qquad \text{(A.12)} \\
&= \int_{price\ adjuster} \left(\frac{P_{kj,t}}{P_{k,t}}\right)^{-\epsilon_{ck}} \mathrm{d}j + \int_{price\ non-adjuster} \left(\frac{P_{kj,t}}{P_{k,t}}\right)^{-\epsilon_{ck}} \mathrm{d}j \\
&= \left[(1-\theta_k)\left(\frac{X_{k,t}}{P_{k,t}}\right)^{-\varepsilon_{ck}} + \theta_k \left(\frac{P_{k,t-1}}{P_{k,t}}\right)^{-\varepsilon_{ck}} DS_{p,k,t-1}\right] \\
&= \left[(1-\theta_k)\left(\frac{X_{k,t}}{P_t}\right)^{-\varepsilon_{ck}} \left(\frac{P_t}{P_{k,t}}\right)^{-\varepsilon_{ck}} + \theta_k \left(\frac{P_{k,t-1}}{P_{t-1}}\right)^{-\varepsilon_{ck}} \left(\frac{P_{t-1}}{P_t}\right)^{-\varepsilon_{ck}} \left(\frac{P_t}{P_{k,t}}\right)^{-\varepsilon_{ck}} DS_{p,k,t-1}\right]
\end{aligned}$$

and aggregate price dispersion $DS_{p,t}$ by:

$$DS_{p,t} = \int_0^1 f(k) \left(\frac{P_{k,t}}{P_t}\right)^{-\varepsilon_c} DS_{p,k,t} \mathrm{d}k. \qquad \text{(A.13)}$$

Hence, aggregate output in period t is given by:

$$Y_t = \frac{A_t L_t}{DS_{p,t} DS_{w,t}}.$$

Price and wage dispersion, $DS_{p,t}$ and $DS_{w,t}$, will be larger than 1 away from the zero inflation steady state. For instance, for wage dispersion:

$$\begin{aligned} DS_{w,t} &= \int_0^1 \left(\frac{W_{i,t}}{W_t} \right)^{-\varepsilon_w} \mathrm{d}i \\ &= \int_0^1 \left[\left(\frac{W_{i,t}}{W_t} \right)^{1-\varepsilon_w} \right]^{\frac{-\varepsilon_w}{1-\varepsilon_w}} \mathrm{d}i \\ &\geq \int_0^1 \left[\left(\frac{W_{i,t}}{W_t} \right)^{1-\varepsilon_w} \mathrm{d}i \right]^{\frac{-\varepsilon_w}{1-\varepsilon_w}} \\ &= 1^{\frac{-\varepsilon_w}{1-\varepsilon_w}} \\ &= 1, \end{aligned}$$

where the inequality follows from Jensen's inequality and the penultimate equality is due to the definition of the aggregate wage rate:

$$W_t^{1-\varepsilon_w} = \left[\int_0^1 W_{i,t}^{1-\varepsilon_w} di \right].$$

Hence, as stated at the beginning of this section, output will be generally inefficiently low due to distortions in the labor and product markets.

A.7 Price of Claim on Sector Dividends

Real dividends of sector k are given by:

$$D_{k,t} = \frac{1}{P_t} \int_0^1 \left(P_{kj,t} Y_{kj,t} - H_{kj,t} W_t \right) dj.$$

Recall that demand of firm j in sector k and the production function are given by:

$$\begin{aligned} Y_{kj,t} &= \left(\frac{P_{kj,t}}{P_{k,t}} \right)^{-\epsilon_{ck}} \left(\frac{P_{k,t}}{P_t} \right)^{-\epsilon_c} Y_t \\ H_{kj,t} &= \frac{Y_{kj,t}}{A_t}. \end{aligned}$$

Therefore,

$$
\begin{aligned}
D_{k,t} &= \int_0^1 \left[\left(\frac{P_{kj,t}}{P_{k,t}} \right)^{1-\epsilon_{ck}} \left(\frac{P_{k,t}}{P_t} \right)^{1-\epsilon_c} Y_t - \left(\frac{W_t}{P_t} \right) \left(\frac{1}{A_t} \right) \left(\frac{P_{kj,t}}{P_{k,t}} \right)^{-\epsilon_{ck}} \left(\frac{P_{k,t}}{P_t} \right)^{-\epsilon_k} Y_t \right] dj \\
&= \left(\frac{P_{k,t}}{P_t} \right)^{1-\epsilon_c} Y_t \left[\int_0^1 \left(\frac{P_{kj,t}}{P_{k,t}} \right)^{1-\epsilon_{ck}} dj - \left(\frac{W_t}{P_t} \right) \left(\frac{1}{A_t} \right) \left(\frac{P_{k,t}}{P_t} \right)^{-1} \int_0^1 \left(\frac{P_{kj,t}}{P_{k,t}} \right)^{-\epsilon_{ck}} dj \right] \\
&= \left(\frac{P_{k,t}}{P_t} \right)^{1-\epsilon_c} Y_t \left[1 - \left(\frac{W_t}{P_t} \right) \left(\frac{1}{A_t} \right) \left(\frac{P_{k,t}}{P_t} \right)^{-1} DS_{p,k,t} \right] \qquad \text{(A.14)} \\
&= \left(\frac{P_{k,t}}{P_t} \right)^{1-\epsilon_c} Y_t \left[1 - \frac{1}{\mu_{k,t}} \right], \qquad \text{(A.15)}
\end{aligned}
$$

where I made use of the definition of the sectoral price index, equation (A.4), the sectoral price dispersion, and equation (A.12); $\mu_{k,t}$ is the markup in sector k. Note that the terms in brackets can be interpreted as sector k profit margin.

Hence, we can write the price of a claim to sector k dividends as follows:

$$
\begin{aligned}
P_{k,t} &= \mathbb{E}_t \sum_{s=0}^{\infty} \beta^s \frac{\lambda_{t+s}}{\lambda_t} D_{k,t+s} \\
&= D_{k,t} + \mathbb{E}_t \sum_{s=1}^{\infty} \beta^s \frac{\lambda_{t+s}}{\lambda_t} D_{k,t+s} \\
&= D_{k,t} + \mathbb{E}_t \, \beta \frac{\lambda_{t+1}}{\lambda_t} \sum_{s=0}^{\infty} \beta^s \frac{\lambda_{t+1+s}}{\lambda_{t+1}} D_{k,t+1+s} \\
&= D_{k,t} + \mathbb{E}_t \, \beta \frac{\lambda_{t+1}}{\lambda_t} P_{k,t+1}.
\end{aligned}
$$

A.8 Cross Sectional Stock Returns at the Sector Level

Starting from the Euler equation or the "central asset pricing formula" (see Cochrane (2005) chapter one) and assuming log-normality, I first derive the expected excess return of a generic asset and then the expected return and return difference across sectors of a claim to sector dividends, which pays off only one period in the future to develop intuition for the key driving forces of the observed cross sectional return premium for sticky-price firms.

$$
1 = \mathbb{E}_t [M_{t,t+1} R_{t+1}],
$$

where $M_{t,t+1}$ is the stochastic discount factor to price asset between periods t and $t+1$ and R_{t+1} is the gross return of any generic asset.

Exploiting the assumption of log-normality, I get:

$$
1 = \exp \left[\mathbb{E}_t \, m_{t,t+1} + \mathbb{E}_t \, r_{t+1} + \frac{1}{2} \operatorname{var}_t m_{t,t+1} + \frac{1}{2} \operatorname{var}_t r_{t+1} + \operatorname{cov}_t(m_{t,t+1}, r_{t+1}) \right],
$$

where lower case variables correspond to the natural logarithm of upper case variables. Taking logs and subtracting the expression for the risk-free rate, r^f_{t+1}, I can write log expected excess returns as

$$\mathbb{E}_t\, r_{t+1} - r^f_{t+1} + \frac{1}{2}\operatorname{var} r_{t+1} = -\operatorname{cov}_t(m_{t+1}, r_{t+1}).$$

Consider the return to a claim to sector k dividends in period $t+1$ with current price $P_{k,t}$, $R_{k,t+1} = D_{k,t+1}/P_{k,t}$.

I can write the expected excess return of a claim to sector one dividends over the return of a claim to sector two dividends (plus Jensen's inequality terms) as:

$$\begin{aligned}\mathbb{E}_t\, r_{1,t+1} - \mathbb{E}_t\, r_{2,t+1} + \left[\frac{1}{2}\operatorname{var} r_{1,t+1} - \frac{1}{2}\operatorname{var} r_{2,t+1}\right] &= -\operatorname{cov}_t(m_{t+1}, r_{1,t+1} - r_{2,t+1})\\ &= -\operatorname{cov}_t(m_{t+1}, d_{1,t+1} - d_{2,t+1}).\end{aligned}$$

Using equation (A.15), I can write the log difference in dividends as:

$$d_{1,t+1} - d_{2,t+1} = (1-\varepsilon_c)(p_{1,t+1} - p_{2,t+1}) + \left[\log\left(1 - \frac{1}{\mu_{1,t+1}}\right) - \log\left(1 - \frac{1}{\mu_{2,t+1}}\right)\right].$$

Taking a first-order Taylor series approximation around the steady state markup, $\mu_1 = \mu_2 = \varepsilon_{ck}/(\varepsilon_{ck} - 1)$:

$$\log\left(1 - \frac{1}{\mu_{k,t+1}}\right) \approx \log\left(1 - \frac{1}{\mu_k}\right) + \frac{1}{\mu_k - 1}\left(\log \mu_{k,t+1} - \mu_k\right).$$

Hence, I can write differences in log dividends as:

$$d_{1,t+1} - d_{2,t+1} = (1-\varepsilon_c)(p_{1,t+1} - p_{2,t+1}) + (\varepsilon_{ck} - 1)(\log \mu_{1,t+1} - \log \mu_{2,t+1}).$$

Making use of equation (A.14), I can express this relation as:

$$d_{1,t+1} - d_{2,t+1} = (1-\varepsilon_c)(p_{1,t+1} - p_{2,t+1}) + (\varepsilon_{ck} - 1)[(p_{1,t+1} - p_{2,t+1}) - (ds_{p,1,t+1} - ds_{p,2,t+1})].$$

Thus, expected excess returns are given by:

$$\begin{aligned}\mathbb{E}_t\, r_{1,t+1} - \mathbb{E}_t\, r_{2,t+1} + \left[\frac{1}{2}\operatorname{var} r_{1,t+1} - \frac{1}{2}\operatorname{var} r_{2,t+1}\right] &= -(\varepsilon_{ck} - \varepsilon_c)\operatorname{cov}_t(m_{t,t+1}, (p_{1,t+1} - p_{2,t+1}))\\ &\quad - (1 - \varepsilon_{ck})\operatorname{cov}_t(m_{t,t+1}, (ds_{p,1,t+1} - ds_{p,2,t+1})).\end{aligned}$$

B. Summary of Equilibrium Conditions

B.1 Sector Specific Conditions

Reset Price

$$\frac{X_{k,t}}{P_t} = \frac{\varepsilon_{ck}}{\varepsilon_{ck} - 1}\frac{F_{p,k,t}}{K_{p,k,t}}$$

$$F_{p,k,t} = \lambda_t\left(\frac{W_t}{P_t}\right)\left(\frac{1}{A_t}\right)\left(\frac{P_{k,t}}{P_t}\right)^{\varepsilon_{ck}}\left(\frac{P_{k,t}}{P_t}\right)^{-\varepsilon_c} Y_t + \beta\theta_k\left(\frac{P_{t+1}}{P_t}\right)^{\varepsilon_{ck}} F_{p,k,t+1}$$

$$K_{p,k,t} = \lambda_t\left(\frac{P_{k,t}}{P_t}\right)^{\varepsilon_{ck}}\left(\frac{P_{k,t}}{P_t}\right)^{-\varepsilon_c} Y_t + \beta\theta_k\left(\frac{P_{t+1}}{P_t}\right)^{\varepsilon_{ck}-1} K_{p,k,t+1}$$

Relative Price

$$P_{k,t} = \left[(1-\theta_k)X_{k,t}^{1-\varepsilon_{ck}} + \theta_k P_{k,t-1}^{1-\varepsilon_{ck}}\right]^{\frac{1}{1-\varepsilon_{ck}}}$$

Price Dispersion

$$DS_{p,k,t} = \left[(1-\theta_k)\left(\frac{X_{k,t}}{P_t}\right)^{-\varepsilon_{ck}}\left(\frac{P_t}{P_{k,t}}\right)^{-\varepsilon_{ck}} + \theta_k\left(\frac{P_{k,t-1}}{P_{t-1}}\right)^{-\varepsilon_{ck}}\left(\frac{P_{t-1}}{P_t}\right)^{-\varepsilon_{ck}}\left(\frac{P_t}{P_{k,t}}\right)^{-\varepsilon_{ck}} DS_{p,k,t-1}\right]$$

B.2 Aggregate Conditions

Law of Motion for Price Level

$$1 = \int_0^1 f(k)\left[(1-\theta_k)\left(\frac{X_{k,t}}{P_t}\right)^{(1-\varepsilon_c)} + \theta_k\left(\frac{P_{k,t-1}}{P_{t-1}}\right)^{(1-\varepsilon_c)}\left(\frac{P_{t-1}}{P_t}\right)^{(1-\varepsilon_c)}\right]\mathrm{d}k$$

Aggregate Price dispersion

$$DS_{p,t} = \int_0^1 f(k)\left(\frac{P_{k,t}}{P_t}\right)^{-\varepsilon_c} DS_{p,k,t}\mathrm{d}k.$$

Reset Wage

$$\left(\frac{U_t}{P_t}\right)^{1+\varepsilon_w\sigma} = \frac{\varepsilon_w}{\varepsilon_w-1}\psi_L\left(\frac{W_t}{P_t}\right)^{\varepsilon_w\sigma}\frac{F_{w,t}}{K_{w,t}}$$

$$F_{w,t} = H_t^{1+\sigma} + \beta\theta_w\,\mathbb{E}_t\,\pi_{w,t+1}^{\varepsilon_w(1+\sigma)}F_{w,t+1}$$

$$K_{w,t} = \lambda_t H_t + \beta\theta_w\,\mathbb{E}_t\,\frac{\pi_{w,t+1}^{\varepsilon_w}}{\pi_{t+1}}K_{w,t+1}.$$

Wage Dispersion

$$DS_{w,t} = \left[(1-\theta_w)\left(\frac{U_t}{P_t}\right)^{-\varepsilon_w}\left(\frac{W_t}{P_t}\right)^{\varepsilon_w} + \theta_w\pi_w^{\varepsilon_w}DS_{w,t-1}\right]$$

Aggregate Real Wage

$$\frac{W_t}{P_t} = \left[(1-\theta_w)\left(\frac{U_t}{P_t}\right)^{1-\varepsilon_w} + \theta_w\left(\frac{W_{t-1}}{P_{t-1}}\right)^{1-\varepsilon_w}\left(\frac{P_{t-1}}{P_t}\right)^{1-\varepsilon_w}\right]^{\frac{1}{1-\varepsilon_w}}$$

Wage Inflation

$$\frac{W_{t+1}}{W_t} = \pi_{w,t+1} = \frac{W_{t+1}/P_{t+1}}{W_t/P_t}\frac{P_{t+1}}{P_t} = \frac{w_{t+1}}{w_t}\pi_{t+1}$$

Consumption Euler Equation

$$1 = \beta R_t\,\mathbb{E}_t\left[\frac{1}{\pi_{t+1}}\left(\frac{C_{t+1}-bC_t}{C_t-bC_{t-1}}\right)^{-\gamma}\right]$$

Aggregate Output

$$Y_t = \frac{A_t L_t}{DS_{p,t}DS_{w,t}}$$

Monetary Policy

$$i_t = \phi_\pi\pi_t + \phi_x x_t + \log\left(\frac{1}{\beta}\right) + u_{m,t}$$

$$u_{m,t} = \rho_m u_{m,t-1} + \sigma_{mp}\varepsilon_{mp,t+1}$$

Technology

$$a_{t+1} = \rho_a a_t + \sigma_a \varepsilon_{a,t+1},$$

C. Aggregation of good-based Frequencies of Price Adjustment

In this section I discuss in more detail how I aggregate good-based frequencies of price adjustment to the firm level in a two stage procedure.

I first aggregate goods' based frequencies to the establishment level via internal identifiers of the BLS. To perform the firm level aggregation, I check whether establishments with the same or similar names are part of the same company. In addition, I use publicly available data to search for names of subsidiaries and name changes e.g. due to mergers, acquisitions or restructuring occurring during the sample period for all firms in the dataset.

I discuss the fictitious case of the company Milkwell Inc, to illustrate aggregation to the firm level. Assume I observe product prices of items for the establishments Milkwell Advanced Circuit, Milkwell Aerospace, Milkwell Automation and Control, Milkwell Mint and Bier Good. In the first step, I calculate the frequency of product price adjustment at the item level and aggregate this measure at the establishment level for all of the above mentioned establishments. I calculate both equally weighted frequencies, U and frequencies weighted by values of shipments associated with items/establishments, W, say for establishment Milkwell Aerospace. I then use publicly available information to check whether the individual establishments are part of the same company. Let's assume that I find that all of the above mentioned establishments with Milkwell in the establishment name but Milkwell Mint are part of Milkwell Inc. Looking at the company structure, I also find that Milkwell has several subsidiaries, Honeymoon, Pears and Bier Good. Using this information, I then aggregate the establishment level frequencies of Milkwell Advanced Circuit, Milkwell Aerospace, Milkwell Automation and Control and Bier Good to the company level, again calculating equally weighted and value of shipments weighted frequencies.

D. Definition of Financial Data

In this section I discuss in more detail the construction of financial variables.

Stock return, shares outstanding, and volume data are from the CRSP Monthly Stock file. I focus on firms that have been part of the S&P500 between 1994 and 2009 because of the availability of the PPI data and to keep the manual merging between the two datasets manageable. Size of year t is the natural logarithm of the total market capitalization at the firm level as of December t-1. β (Beta) is the regression coefficient in rolling time-series regressions of monthly excess returns on a constant and the excess returns of the CRSP value-weighted index over a sixty-month period. Turnover is the ratio of volume to shares outstanding (in percent). Spread is the monthly average of the daily bid-ask spreads from the CRSP Daily Stock file.

I obtain balance-sheet data from the Standard and Poor's Compustat database. I define book equity (BE) as total stockholders' equity plus deferred taxes and investment tax credit (if available) minus the book value of preferred stock. Based on availability, I use the redemption value, liquidation value, or par value (in that order) for the book value of preferred stock. I prefer the shareholders' equity number as reported by Compustat. If not available, I calculate shareholders' equity as the sum of common and preferred equity. If neither of the two is available, I define shareholders' equity as the difference between total assets and total liabilities. The book-to-market (BM) ratio of year t is then the book equity for the fiscal year ending in calendar year t-1 over the market equity as of December t-1. Leverage (Lev) is the ratio of total long-term debt and debt in current liabilities over the sum of the numerator and shareholders' equity. Cash flow (CF) is the sum of income before extraordinary items and depreciation and amortization over total assets. I calculate the price-to-cost margin (PCM) as net sales minus cost of goods sold over net sales and HHI as the Herfindahl-Hirschman index of sales at the Fama & French 48 industry level at an annual frequency.

E. Cash Flow and Discount Rate Betas

In this section I derive the key equations of the Campbell and Vuolteenaho (2004) decomposition of CAPM β into cash flow and discount rate β.

Following Campbell and Shiller (1988) and Campbell (1991), I use a loglinear approximation for the one period log return and iterate the resulting relationship forward to obtain an accounting identity expressing unexpected returns, $r_{t+1} - \mathbb{E}_t\, r_{t+1}$, as a function of revisions in future dividend growth, Δd_{t+1+s}, and returns

$$\begin{aligned} r_{t+1} - \mathbb{E}_t\, r_{t+1} &= (\mathbb{E}_{t+1} - \mathbb{E}_t) \sum_{s=0}^{\infty} \rho^s \Delta d_{t+1+s} - (\mathbb{E}_{t+1} - \mathbb{E}_t) \sum_{s=1}^{\infty} \rho^s r_{t+1+s} \\ &= N_{CF,t+1} - N_{DR,t+1}, \end{aligned}$$

where ρ is a discount coefficient slightly below one, $N_{CF,t+1}$ denotes news about future dividends and $N_{DR,t+1}$ news about future expected returns.[1]

To obtain the news terms, I estimate a first-order VAR

$$z_{t+1} = a + \Gamma z_t + u_{t+1}$$

where z_{t+1} is a $m \times 1$ state vector with r_{t+1} as its first element, a and Γ are a $m \times 1$ vector and a $m \times m$ matrix of coefficients and u_{t+1} is a $m \times 1$ vector of one-step ahead forecast errors.[2]

Cash flow and discount rate news are then functions of $t+1$ shocks

$$N_{CF,t+1} = (e1' + e1'\lambda)u_{t+1} \tag{A.16}$$

$$N_{DR,t+1} = e1'\lambda u_{t+1}, \tag{A.17}$$

where $e1$ is a $m \times 1$ selection vector whose first element is one and whose other elements are zero, λ is defined as $\lambda \equiv \rho\Gamma(I - \rho\Gamma)^{-1}$ and I is a $m \times m$ identity matrix.

I follow Campbell and Vuolteenaho (2004) and estimate a VAR(1) over the full sample period at a monthly frequency using four state variables: the log excess return on the CRSP value weighted index, the yield spread between the 10-year constant maturity bonds (Global Financial Data (GFD) symbol IGUSA10D) and the 1-year constant maturity notes (GFD symbol IGUSA1D), the 10-year smoothed price-earnings ratio of Shiller (2000) as well as the small stock value spread calculated as in Campbell and Vuolteenaho (2004).[3]

I define cash flow and discount rate betas as

$$\beta_{p,CF} \equiv \frac{Cov(r^e_{p,t}, N_{CF,t})}{Var(r^e_{m,t} - \mathbb{E}_{t-1}\, r^e_{m,t})}$$

$$\beta_{p,DR} \equiv \frac{Cov(r^e_{p,t}, -N_{DR,t})}{Var(r^e_{m,t} - \mathbb{E}_{t-1}\, r^e_{m,t})},$$

where $r^e_{p,t}$ is the log excess return of portfolio p and $r^e_{m,t}$ is the log excess return of the market. $\beta_{p,CF}$ and $\beta_{p,DR}$ add up to the CAPM beta, β_p. I estimate these betas using the VAR-fitted news series to construct sample variances and covariances allowing for one additional lag of the news terms. I calculate GMM standard errors conditional on the realized news series from the VAR.[4]

[1] See Campbell and Vuolteenaho (2004) for an interpretation of ρ. I follow them and set ρ to a value of 0.95 at an annual frequency.

[2] This formulation is not restrictive as any higher-order VAR can be written in its companion form as a VAR(1) by suitably augmenting the state vector.

[3] This is the VAR specification as in the original contribution of Campbell and Vuolteenaho (2004).

[4] Specifically, I write the covariances and variances as functions of sample means and apply the Delta method as advocated in chapter 11 of Cochrane (2005).

F. Additional Results

This section contains several robustness checks and results for alternative measures of the frequency of price adjustment.

As discussed in the main body of Weber (2015), I calculate the frequency of price adjustment as the mean fraction of months with price changes during the sample period of an item. Because the collected data may have missing values, I construct different measures of the frequency of price adjustment, S. In the first approach, labeled A, I treat missing values as interrupting price spells. For example, if a price was \$4 for two months, then misses for a month, and is again observed at \$5 for another three months, I treat the data as reporting two price spells with durations of two and three months where none of the spells has a price change and hence the frequency is zero. In the second approach, labeled B, missing values do not interrupt price histories. In the previous example, approach B concatenates spells of \$4 and \$5 prices and yields one price change in five months so that the frequency is 1/5. Approach C takes the union of A and B; that is, there is a price change if either A or B identify a price change. I employ approach SA in the main paper weighting item-based frequencies equally (U). Results are very similar if I make use of these alternative measures or weight individual item-based frequencies with their value of shipment (W).

Table A.1 reports mean frequencies, standard deviations, and the number of firm-months observations for these different measures of the frequency of price adjustment, both for the total sample and for different industries separately.

Table A.2 reports descriptive statistics for the firm characteristics and return predictors for the benchmark sample period from July 1982 to June 2007 for all firms independent of missing data on the frequency of price adjustment. The full and merged sample (Table 2 of Weber (2015)) is virtually identical based on observables, which is expected given the probabilistic sampling underlying the construction of the producer price index.

Table A.3 runs panel regressions with my measure of price stickiness as left-hand-side variable. Individually, we see that book-to-market, beta, leverage, and the price-to-cost margin are most strongly related with price stickiness. Firms with more flexible prices have lower CAPM beta and price-to-cost margins but higher book-to-market ratios and leverage. Jointly, these firm characteristics can explain up to 12% of the variation in SAU across firms.

Table A.4 contains times series means of portfolio average firm characteristics. Column 1 shows that the frequency of price adjustment is by construction monotonically increasing from as low as 0.01 per month for portfolio 1 to 0.35 for the flexible price portfolio. The following columns document similar facts as the correlations in Table 2: firms with flexible prices are on average larger and have a slightly higher book-to-market ratio, but lower systematic risk as measured by beta. There is no difference in cash flows, turnover, or bid-ask spreads. The last two columns document that part of the difference in the frequency of price adjustment could reflect market power, as the portfolio with flexible price firms has a lower price-to-cost margin and Herfindahl - Hirschman index than the portfolio containing sticky-price firms.

Table A.5 repeats the baseline regression of annual stock returns on firm characteristics and return predictors only. The individual coefficients generally have the expected signs, and most of them are individually statistically significant. R^2s are small in all firm-level panel regressions and typically below 1%.

I construct a zero-cost portfolio, which invests in stocks with low frequency of price adjustment, and funds this investment by selling short flexible price firms (L-H in the following). Table A.6 reports αs in percent per month and βs for the unconditional CAPM. I evaluate statistical significance using the time-series variability of the slope and intercept coefficients following Fama and MacBeth (1973) in parentheses and Newey and West (1987)-corrected standard errors in brackets. The unconditional CAPM cannot explain the portfolio returns. Monthly αs range between 0.47% and 0.56% per month and are highly statistically significant. In column (6), we also see that the L-H portfolio has a statistically insignificant α of 0.10% per month.

Table A.7 reports results for long-horizon forecasting regressions of log excess returns of the zero-cost portfolio of going long the portfolio of stocks with high book-to-market value of equity and shorting the portfolio of stocks with low book-to-market value of equity of Fama and French (1993), HML, in Panel A, and the CRSP value-weighted excess return in Panel B on the proxy for the consumption-wealth ratio of Lettau and Ludvigson (2001). cay has a marginally statistically significant forecasting power, the log excess return of the CRSP value-weighted index. The maximal R^2 is 35% at a four-year horizon. cay negatively predicts the HML factor of Fama and French (1993) with a maximum explanatory power of 22% at a five-year forecasting horizon; again barely statistically significant however.

Table A.8 report the parameter values used in the model calibration.

Habit formation in consumption implies that expected returns vary over time and are particularly high during recessions. To test this hypothesis, I define recessions and expansions as months in the bottom and top 25^{th} percentile of the GDP growth distribution, respectively, and measure the subsequently realized return spread between sticky- and flexible-price sectors in simulated data. The spread in annual returns in the two years after recessions is 4.1%, whereas it is only 1.1% after expansions, indicating substantial variation in expected returns.

To test more systematically for time variation in expected returns, I run long-horizon regressions on simulated data. I regress the cumulative log excess returns of the L-H portfolio on log consumption surplus. Table A.9 shows the classical patterns: high consumption compared to habit predicts low future excess returns. The regression coefficients increase in absolute value from -0.14 for one-quarter-ahead excess returns to -0.81 for the three-year horizon and then start to decline. The explanatory power peaks at a two-year horizon with consumption-surplus explaining 22% of the time-series variation.

Table A.10 repeats the baseline exercise for the benchmark period for overlapping annual returns at the monthly frequency. Results are quantitatively as well as statistically very similar to my benchmark analysis. None of these variations has a material impact on the coefficient on the frequency of price adjustment; the return premium for sticky price firms varies between 2.8% per annum when including the full set of controls (column (11)) and 7.5% in the specification only controlling for book-to-market (column (2)).

Table A.11 adds the durability of output from Bils et al. (2012) as additional covariate. Controlling for the variation in durability actually slightly increases the premium for sticky-price firms.

In Table A.12, I add a specification in which I cluster standard errors along the time and firm dimensions. While the statistical significance of the coefficient on the frequency of price adjustment only slightly decreases, some other standard return predictors lose their explanatory power. Table A.13 repeats my within-industry results, but adds finer defined industry dummies. In particular, I add dummies at the Fama & French 10 and 17 industry level. As expected, the more I restrict the variation in the data by adding additional fixed effects, the smaller the coefficient on the frequency of price adjustment becomes.

Table A.14 repeats the baseline panel specifications on unwinsorized variables. The coefficient on SAU tends to be larger in absolute value at continuously high statistical significance, while the explanatory power of the model somewhat decreases.

Table A.16 reports results at the portfolio level for a subset of firms which were part of the S&P500 at the end of June 1994 in Panel A, while Panel B chooses 2006 as the cutoff year. Results are very similar to my baseline finding and show that overall premium for sticky price firms is not due to attrition or selection.

Table A.15reports results at the portfolio level for alternative measures of the frequency of price adjustment, both for raw returns. Return premia for the L-H portfolio range between 2.87% (SCW, 1982-2014) and 3.78% (SAW, 1982-2007) per annum, similar in magnitude to the numbers reported in the main part of the paper (see Table 3).

The higher riskiness of firms with lower frequencies of price adjustment might potentially also be reflected in higher realized volatilities at the firm level. I construct this measure by taking the square root of the sum of daily squared returns over one year. Table A.17 documents a similar pattern for realized volatilities as we have seen for returns: across specifications – controlling for firm characteristics both individually and jointly – price flexibility is associated with lower realized volatilities, which is highly statistically significant for most estimations. Going from firms with most flexible product prices in sample to firms with stickiest prices is associated with an increase in realized volatility of 6.05% per annum in column (1) for the regression without additional controls and varies between 3.88% in column (12) when I only control for all covariates and 6.49% in column (9) when the bid-ask spread is the sole additional control. The specification controlling for β in column (5) is an exception, as β drives out the measure of price stickiness. This might indicate that β to some extent already captures the higher riskiness of sticky-price firms.[5] Once I add all controls, though, the coefficient on SAU is again highly statistically significant.

Table A.18 reports descriptive statistics for the firm characteristics and return predictors for the full sample period from July 1982 to June 2014 and Table A.19 the corresponding results of panel regressions of annual stock returns on the measure for the frequency of price adjustment, SAU, and controls according to equation (1). Results are very similar to the benchmark sample period, and the regression coefficients imply a premium in returns moving from firms with low frequencies of price adjustment to

[5]This result is somewhat expected as I look at total realized volatilities and not at idiosyncratic realized volatilities controlling for exposure to market risk.

firms with high frequencies of price adjustment between 2.7% in column (12) and 6.6% in column (4).[6]

Figures A.1 and A.2 show why there is only a small risk premium associated with technology shocks. The mean reversion in technology has it that aggregate output moves only little in reaction to the shock, translating into a small reaction in marginal utility and finally dividends, stock prices and returns.

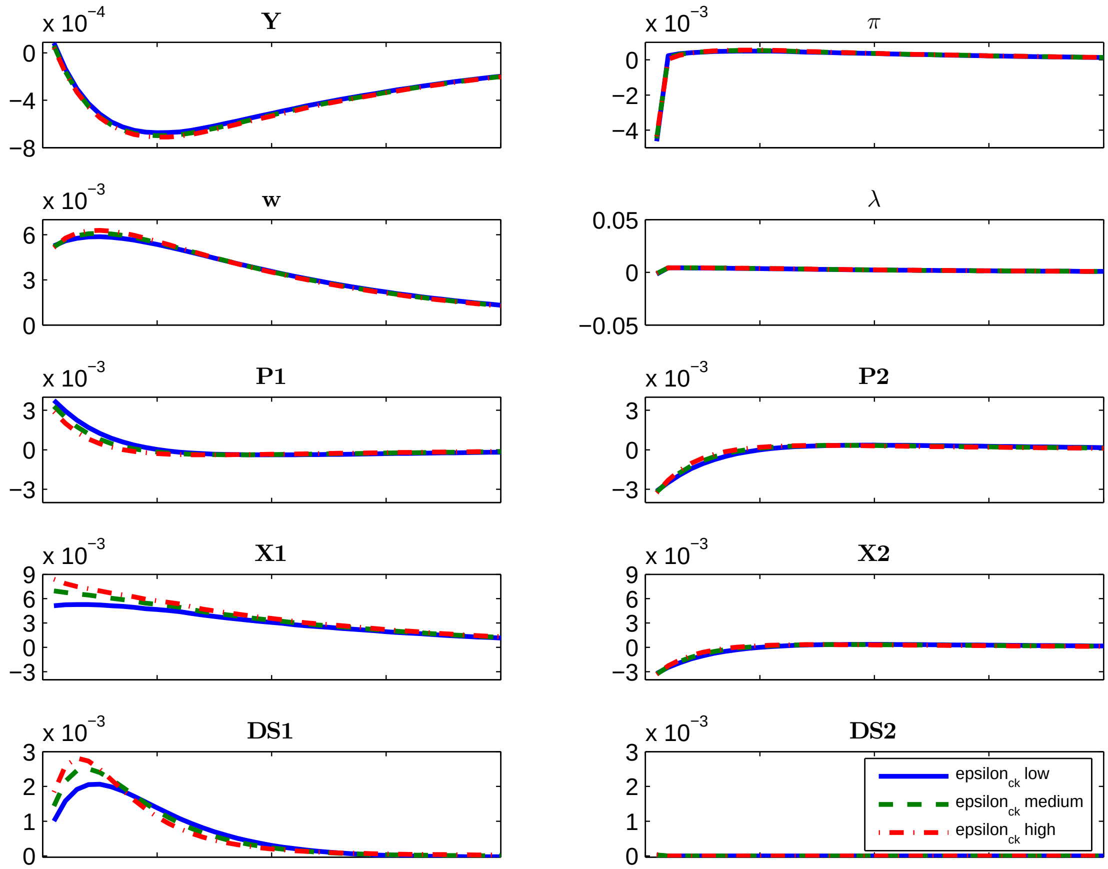
Figures A.3 and A.6 show why variations in the within-sector elasticity of substitutions are quantitatively more important than variations in the elasticity of substitution between sectoral consumption aggregates.[7] Sector price indices are independent of ε_c and therefore the variation in relative sector price indices we see in Figure A.3 is driven by the effect of ε_c on the aggregate price level when aggregating sector prices. Once we look at differences across sectors, this effect cancels out, and hence variation in ε_c has no effect on the price margin in equation (3). Equation (A.12) shows that sector price dispersion is independent of the across-sector elasticity of substitution in consumption and, therefore, the inefficiency margin is also not impacted by changes in ε_c. Hence, ε_c only affects the quantity margin $(\check{Y}_{1,t} - \check{Y}_{2,t})$. Real sector output is determined by aggregate output times the relative sector price $P_{k,t}/P_t$ to the power of $(1 - \varepsilon_c)$. Increasing the across-sector elasticity of substitution in consumption translates into more negative differences in dividends between the sticky- and flexible-price sector, and therefore increases the cross sectional return difference. This channel, however, is quantitatively small and of second order compared the effects of the within-sector elasticity of substitution.[8]

[6] These premia are calculated by multiplying the regression coefficient on the frequency of price adjustment by 0.6, the differential in the frequency of price adjustment between firms which most infrequently change their product prices and firms which are most flexible in adjusting prices (see Table A.1).

[7] ε_c low, medium, and high correspond to values of between sectoral consumption aggregates of 4, 8 and 12, respectively. The return of the zero cost portfolio of going long the portfolio of stocks with low frequencies of price adjustment and shorting the flexible price portfolio increases from 2.34% per year to 3.69%.

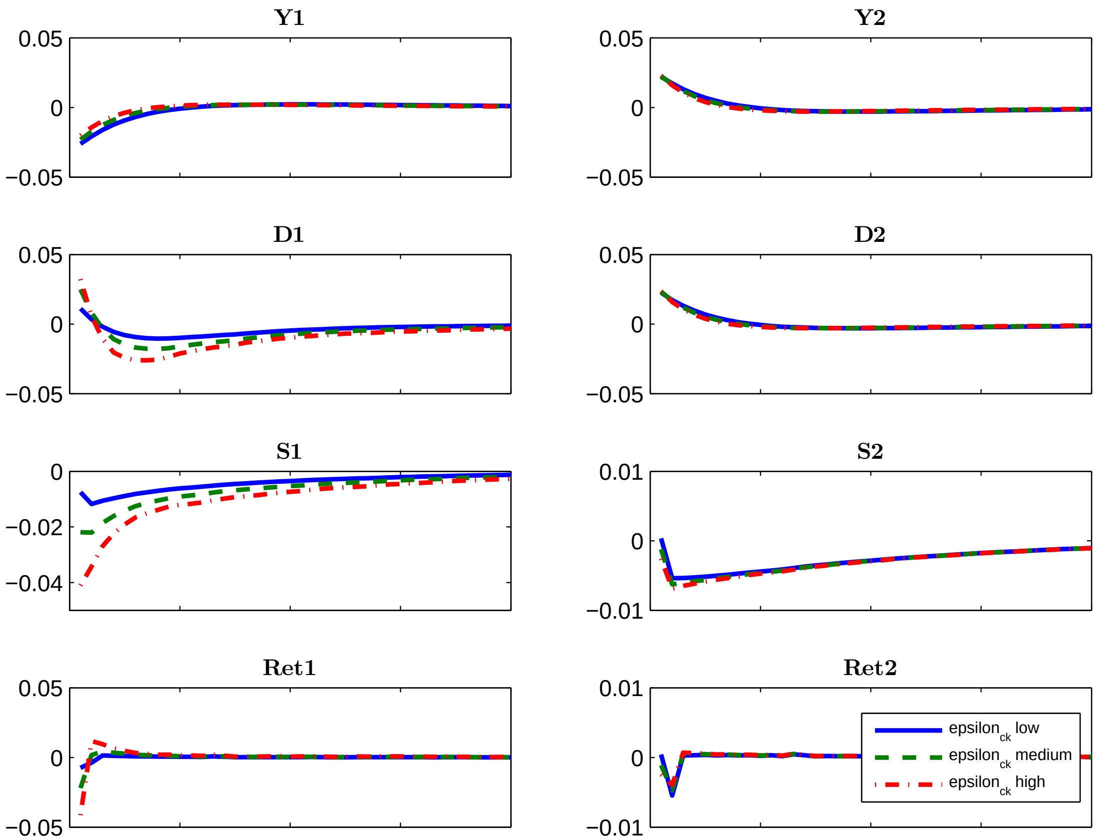
[8] As Figure A.3 shows, changes in ε_c also barely affect aggregate quantities and therefore also have no indirect effects on stock returns via a valuation channel.

Figure A.1: **Impulse Response Functions to Technology Shock (varying ε_{ck})**



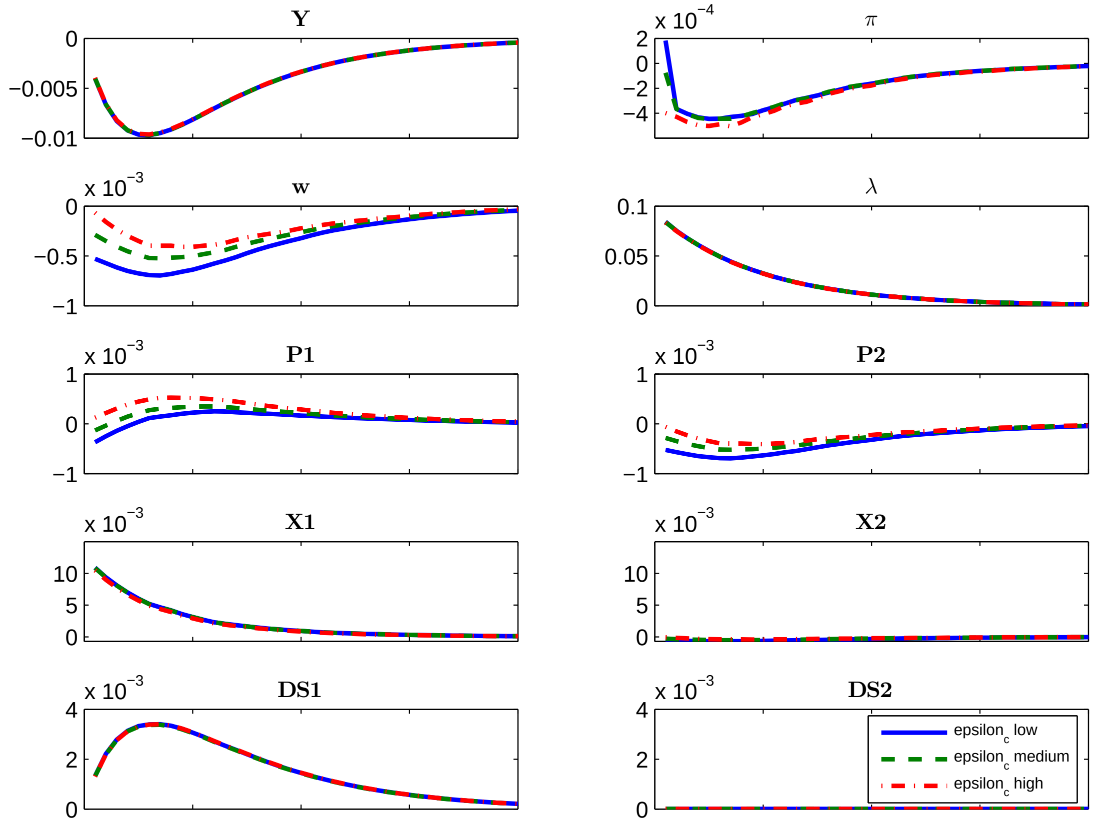
This figure plots the impulse response functions of several macroeconomic variables of a two sector version of the model of Section IV to a one standard deviation technology shock for different values of the elasticity of substitution of within sector consumption varieties, ε_{ck}. ε_{ck} low, medium and high correspond to values of 8, 12 and 16, respectively. Y is output, π inflation, w aggregate real wage, λ the marginal utility of consumption, P1 and P2 the relative prices of sectors one and two, X1 and X2 the optimal real reset prices, and DS1 and DS2 the price dispersion in the two sectors.

Figure A.2: **Impulse Response Functions to Technology Shock (varying ε_{ck})**



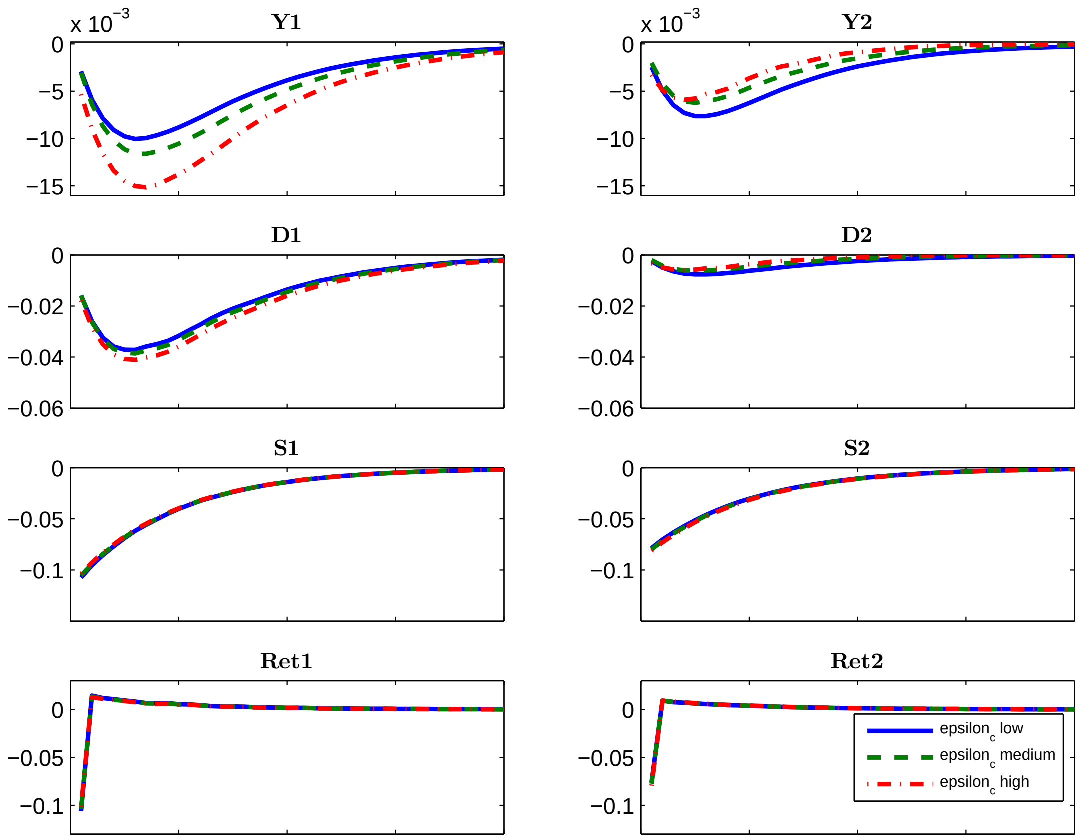
This figure plots the impulse response functions of several macroeconomic variables and asset returns of a two sector version of the model of Section IV to a one standard deviation technology shock for different values of the elasticity of substitution of within sector consumption varieties, ε_{ck}. ε_{ck} low, medium and high correspond to values of 8, 12 and 16, respectively. Y1 and Y2 are the output of sectors one and two, D1 and D2 sector level dividends, S1 and S2 the prices of claims to aggregate sector dividends and Ret1 and Ret2 the returns of these claims.

Figure A.3: **Impulse Response Functions to Monetary Policy Shock (varying ε_c)**



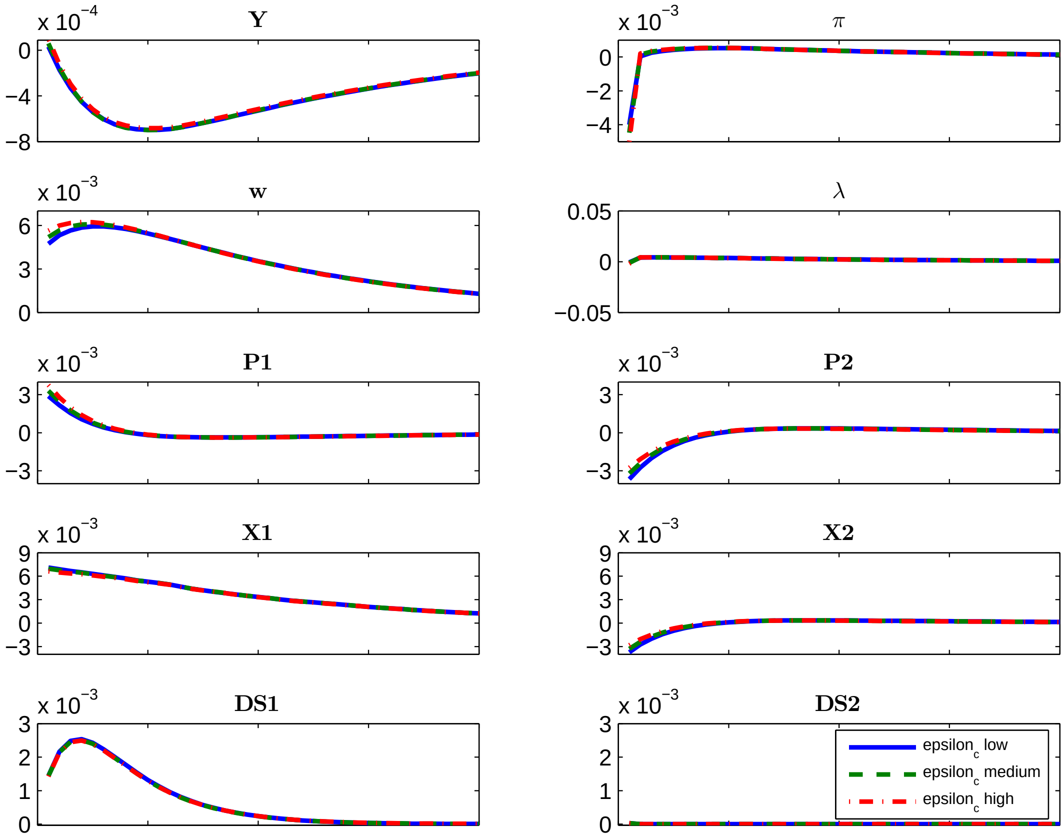
This figure plots the impulse response functions of several macroeconomic variables of the model of Section IV to a one standard deviation monetary policy shock for different values of the elasticity of substitution of across sector consumption varieties, ε_c. ε_c low, medium and high correspond to values of 4, 8 and 12, respectively. Y is output, π inflation, w aggregate real wage, λ the marginal utility of consumption, P1 and P2 the relative prices of sectors one and two, X1 and X2 the optimal real reset prices, and DS1 and DS2 the price dispersion in the two sectors.

Figure A.4: **Impulse Response Functions to Monetary Policy Shock (varying ε_c)**



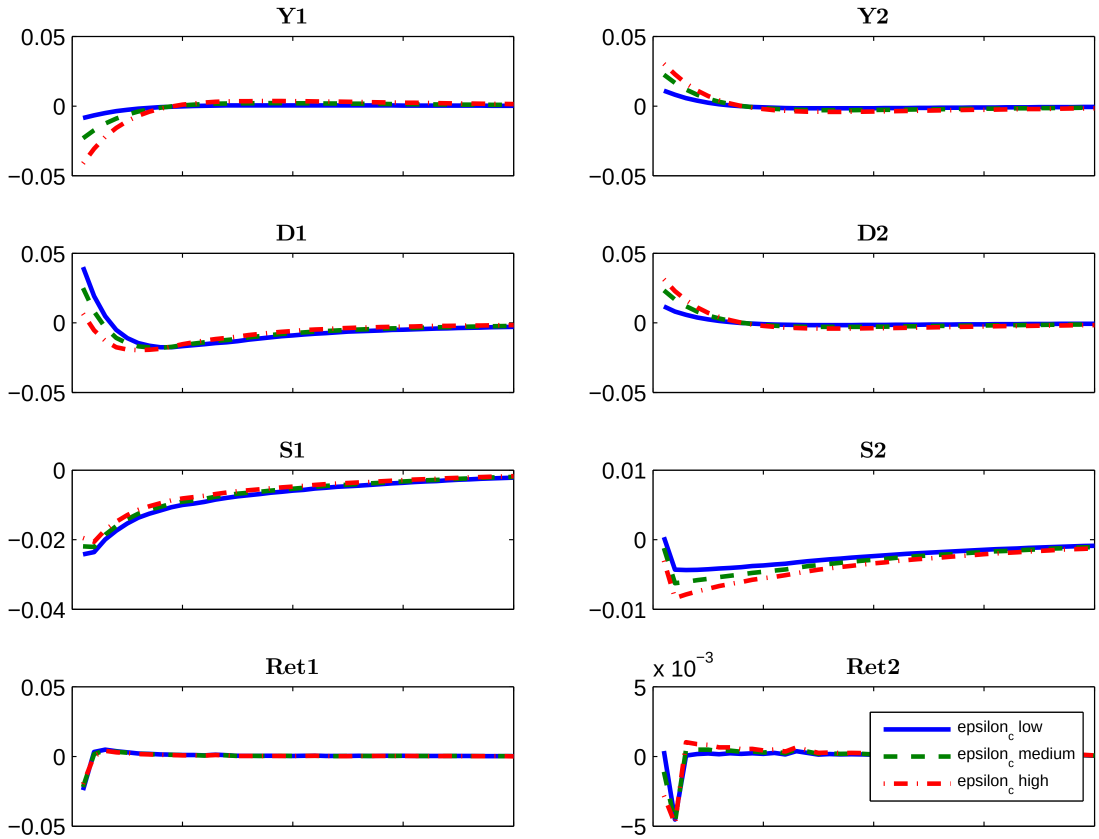
This figure plots the impulse response functions of several macroeconomic variables of the model of Section IV to a one standard deviation monetary policy shock for different values of the elasticity of substitution of across sector consumption varieties, ε_c. ε_c low, medium and high correspond to values of 4, 8 and 12, respectively. Y1 and Y2 are the output of sector one and two, D1 and D2 sector level dividends, S1 and S2 the prices of claims to aggregate sector dividends and Ret1 and Ret2 the returns of these claims.

Figure A.5: **Impulse Response Functions to Technology Shock (varying ε_c)**



This figure plots the impulse response functions of several macroeconomic variables of the model of Section IV to a one standard deviation technology shock for different values of the elasticity of substitution of across sector consumption varieties, ε_c. ε_c low, medium and high correspond to values of 4, 8 and 12, respectively. Y is output, π inflation, w aggregate real wage, λ the marginal utility of consumption, P1 and P2 the relative prices of sectors one and two, X1 and X2 the optimal real reset prices, and DS1 and DS2 the price dispersion in the two sectors.

Figure A.6: **Impulse Response Functions to Technology Shock (varying ε_c)**



This figure plots the impulse response functions of several macroeconomic variables of the model of Section IV to a one standard deviation technology shocks for different values of the elasticity of substitution of across sector consumption varieties, ε_c. ε_c low, medium and high correspond to values of 4, 8 and 12, respectively. Y1 and Y2 are the output of sectors one and two, D1 and D2 sector level dividends, S1 and S2 the prices of claims to aggregate sector dividends and Ret1 and Ret2 the returns of these claims.

Table A.1: **Frequency of Price Adjustment by Industry**

This table reports average frequencies of price adjustment at the industry and aggregate levels with standard deviations in parentheses for different measures of the frequency of price adjustment. SA treats missing values as interrupting price spells, for SB, missing values do not interrupt price spells if the price is the same before and after periods of missing values and SC forms the union of the two. Columns (1) to (3) use equally weighted frequencies of price adjustments, U, whereas columns (4) to (6) weight frequencies with associated values of shipments, W. Frequencies of price adjustments are calculated at the firm level using the micro data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. The sample period is July 1963 to June 2011

		SAU	SBU	SCU	SAW	SBW	SCW
		(1)	(2)	(3)	(4)	(5)	(6)
Agriculture	Mean	19.07%	21.77%	21.87%	21.43%	24.74%	24.86%
	Std	-16.77%	17.11%	17.20%	18.45%	18.94%	19.05%
	Max	54.24%	64.83%	65.17%	55.83%	64.83%	65.17%
	Min	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	N		90			86	
Manfacturing	Mean	11.78%	13.00%	13.07%	12.60%	13.87%	13.95%
	Std	-11.35%	11.51%	11.59%	13.00%	13.05%	13.15%
	Max	59.48%	60.32%	60.32%	59.95%	60.32%	60.32%
	Min	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	N		354			346	
Utilities	Mean	19.74%	21.08%	21.24%	19.96%	21.18%	21.33%
	Std	-13.54%	13.20%	13.22%	13.88%	13.63%	13.66%
	Max	53.89%	53.29%	53.29%	52.63%	52.42%	52.42%
	Min	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	N		107			105	
Trade	Mean	20.89%	22.98%	23.09%	21.56%	23.76%	23.87%
	Std	-15.54%	15.02%	15.10%	15.41%	14.73%	14.83%
	Max	60.00%	60.00%	60.00%	60.00%	60.00%	60.00%
	Min	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	N		47			47	
Finance	Mean	13.07%	18.06%	18.18%	13.19%	19.41%	19.56%
	Std	-11.47%	12.63%	12.74%	12.25%	14.47%	14.64%
	Max	45.65%	45.65%	45.65%	46.84%	51.67%	51.67%
	Min	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	N		122			119	
Service	Mean	9.66%	11.46%	11.50%	10.34%	12.08%	12.12%
	Std	-10.08%	10.90%	10.94%	10.92%	11.56%	11.59%
	Max	43.02%	44.65%	45.12%	43.88%	44.86%	45.28%
	Min	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	N		72			69	
Total	Mean	14.23%	16.32%	16.41%	15.02%	17.37%	17.48%
	Std	-13.09%	13.43%	13.50%	14.23%	14.72%	14.82%
	Max	60.00%	64.83%	65.17%	60.00%	64.83%	65.17%
	Min	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	N		792			772	

Table A.2: **Summary Statistics and Correlations for Firm Characteristics and Return Predictors (Benchmark Sample, all firms)**

This table reports time series averages of annual cross-sectional means and standard deviations for firm characteristics and return predictors used in the subsequent analysis in Panel A and contemporaneous correlations of these variables in Panel B for all firms which have been part of the S&P500 between 1994 and 2009 independent of whether they have missing data on the frequency of price adjustment. Size is the natural logarithm of the market capitalization in thousands, BM is the book to market ratio, Beta is the regression coefficient on the market excess return in rolling times series regressions, Lev is financial leverage, CF measures cash flows, Turnover the fraction of shares traded to shares outstanding, spread is the mean bid - ask spread, PCM is the price to cost margin and HHI the Herfindahl - Hirschman index of sales at the Fama & French 48 industry level. Stock level data are from CRSP and financial statement data from Compustat. The sample period is July 1982 to June 2007.

	Size (1)	BM (2)	Beta (3)	Lev (4)	CF (5)	Turnover (6)	Spread (7)	PCM (8)	HHI (9)
	Panel A. Means and Standard Deviations								
Mean	14.55	0.63	1.08	0.39	0.09	0.11	0.01	0.37	0.07
Std	1.31	0.39	0.42	0.24	0.07	0.09	0.01	0.19	0.06
N	765	747	737	759	760	765	765	759	752
	Panel B. Contemporaneous Correlations								
Size									
BM	−0.18								
Beta	−0.19	−0.14							
Lev	0.01	0.25	−0.11						
CF	0.20	−0.43	−0.10	−0.47					
Turnover	−0.18	−0.11	0.42	−0.17	0.03				
Spread	−0.36	0.15	0.14	0.10	−0.16	−0.01			
PCM	0.13	−0.33	0.06	−0.09	0.28	0.08	−0.14		
HHI	−0.02	−0.14	0.08	−0.07	0.12	0.03	0.06	0.04	

Table A.3: **Panel Regressions of Price Stickiness on Firm Characteristics (Benchmark Sample)**

This table reports the results of regressing the frequency of price adjustment, SAU, on various firm characteristics and return predictors. Standard errors are clustered at the firms level and reported in parentheses. Equally weighted probabilities of price adjustments are calculated at the firm level using the micro data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. Size is the natural logarithm of the market capitalization in thousands, BM is the book to market ratio, Beta is the regression coefficient on the market excess return in rolling times series regressions, Lev is financial leverage, CF measures cash flows, Turnover the fraction of shares traded to shares outstanding, Spread is the mean bid - ask spread, PCM is the price to cost margin and HHI the Herfindahl - Hirschman index of sales at the Fama & French 48 industry level. Stock level data are from CRSP and financial statement data from Compustat. The sample period is July 1982 to June 2007.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Size	0.46**									0.98***
	(0.23)									(0.28)
BM		6.91***								7.27***
		(0.79)								(0.87)
Beta			−4.88***							−2.86**
			(1.13)							(1.17)
Lev				8.74***						10.41***
				(1.57)						(1.68)
CF					−6.62					37.53***
					(5.60)					(6.44)
Turnover						−4.25				11.75***
						(3.07)				(3.12)
Spread							0.31			0.54**
							(0.21)			(0.26)
PCM								−10.08***		−8.02***
								(2.30)		(2.39)
HHI									−26.76***	−18.91***
									(5.77)	(5.44)
Observations	14,059	13,823	13,627	13,998	14,009	14,058	14,058	14,007	13,899	13,284
R^2	0.29%	5.11%	2.69%	2.68%	0.10%	0.12%	0.06%	2.19%	1.46%	11.64%

Standard errors in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table A.4: **Summary Statistics of Firm Characteristics and Return Predictors at the Portfolio Level (Benchmark Sample)**

This table reports time series averages of annual mean firm characteristics and return predictors used in the subsequent analysis at the portfolio level. Stocks are assigned to one of five basket based on the frequency of price adjustment, SAU. Equally weighted probabilities of price adjustments are calculated at the firm level using the micro data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. Size is the natural logarithm of the market capitalization in thousands, BM is the book to market ratio, Beta is the regression coefficient on the market excess return in rolling times series regressions, Lev is financial leverage, CF measures cash flows, Turnover the fraction of shares traded to shares outstanding, Spread is the mean bid - ask spread, PCM is the price to cost margin and HHI the Herfindahl - Hirschman index of sales at the Fama & French 48 industry level. Stock level data are from CRSP and financial statement data from Compustat. The sample period is July 1982 to June 2007.

Portfolio	SAU	Size	BM	Beta	Lev	CF	Turnover	Spread	PCM	HHI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Sticky	0.01	14.47	0.58	1.15	0.38	0.08	0.11	0.01	0.39	0.07
S2	0.05	14.67	0.51	1.09	0.33	0.10	0.10	0.01	0.39	0.07
S3	0.10	14.81	0.59	1.10	0.37	0.09	0.09	0.01	0.37	0.08
S4	0.19	14.86	0.68	1.01	0.45	0.09	0.09	0.01	0.36	0.07
Flexible	0.35	14.84	0.79	0.93	0.45	0.09	0.09	0.01	0.32	0.06
S5-S1	0.34	0.37	0.21	-0.21	0.07	0.00	-0.02	0.00	-0.07	-0.02

Table A.5: **Panel Regressions of Annual Stock Returns on Firm Characteristics (Benchmark Sample)**

This table reports the results of regressing annual percentage returns on firm characteristics and return predictors. Standard errors are clustered at the firm level and reported in parentheses. Size is the natural logarithm of the market capitalization in thousands, BM is the book to market ratio, Beta is the regression coefficient on the market excess return in rolling times series regressions, Lev is financial leverage, CF measures cash flows, Turnover the fraction of shares traded to shares outstanding, Spread is the mean bid - ask spread, PCM is the price to cost margin and HHI the Herfindahl - Hirschman index of sales at the Fama & French 48 industry level. Stock level data are from CRSP and financial statement data from Compustat. The sample period is July 1982 to June 2007.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Size	−5.03***									−6.48***
	(0.25)									(0.32)
BM		8.10***								8.94***
		(0.82)								(1.08)
Beta			4.69***							2.00*
			(0.68)							(1.03)
Lev				−3.07**						2.07
				(1.34)						(1.98)
CF					−1.25					30.84
					(5.27)					(7.86)
Turnover						27.06***				16.43***
						(3.50)				(4.65)
Spread							−1.57***			−5.93***
							(0.35)			(0.44)
PCM								2.31		10.08***
								(1.56)		(2.18)
HHI									16.08***	15.22**
									(5.12)	(6.42)
Year Fixed Effects	N	N	N	N	N	N	N	N	N	N
Observations	14,026	13,791	13,594	13,965	13,976	14,026	14,026	13,974	13,866	13,253
R^2	3.82%	0.77%	0.26%	0.04%	0.00%	0.51%	0.17%	0.01%	0.06%	24.78%

Standard errors in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table A.6: **CAPM Regressions (Benchmark Sample)**

This table reports results for the unconditional CAPM. Stocks are assigned to one of five baskets based on the frequency of price adjustment, SAU and returns are equally weighted at the portfolio level. Equally weighted probabilities of price adjustments are calculated at the firm level using the micro data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. α is the intercept and β the slope of times series regressions of monthly portfolio excess returns on a constant and the excess return of the CRSP value weighted index. OLS and Fama and MacBeth (1973) standard errors are reported in parentheses and Newey and West (1987) standard errors in brackets. The sample period is July 1982 to June 2007.

	Sticky	S2	S3	S4	Flexible	S1-S5
α_p	0.56	0.49	0.49	0.48	0.47	0.10
SE_{OLS}	(0.10)***	(0.09)***	(0.10)***	(0.10)***	(0.13)***	(0.12)***
SE_{NW}	[0.19]***	[0.13]***	[0.18]***	[0.15]***	[0.18]***	[0.13]***
β_p	1.13	1.08	1.04	0.96	0.87	0.26
SE_{OLS}	(0.02)***	(0.02)***	(0.02)***	(0.02)***	(0.03)***	(0.03)***
SE_{NW}	[0.04]***	[0.04]***	[0.06]***	[0.05]***	[0.07]***	[0.04]***

Standard errors in parentheses

$*p < 0.10, **p < 0.05, ***p < 0.01$

Table A.7: **Long Horizon Predictability: HML and Market (Benchmark Sample)**

This table reports results for m-month forecasting regressions of log excess returns on the zero-cost portfolio of going long the portfolio of stocks with high book to market values of equity and shorting the portfolio of stocks with low book to market values of equity of Fama and French (1993), HML, in Panel A, and the CRSP value weighted excess return in Panel B on the proxy for the consumption wealth ratio of Lettau and Ludvigson (2001). For each regression the table reports OLS standard errors in parentheses, Newey and West (1987) standard errors in brackets, and Hodrick (1992) standard errors in curly brackets. The sample period is July 1982 to June 2007.

Horizon m (Months)	1	6	12	24	36	48	60
Panel A. HML							
$b_{lh}^{(m)}$	−0.13	−0.90	−1.85	−4.17	−6.49	−7.40	−8.41
SE_{OLS}	(0.10)	(0.29)∗∗∗	(0.46)∗∗∗	(0.71)∗∗∗	(0.78)∗∗∗	(0.89)∗∗∗	(1.03)∗∗∗
SE_{NW}	[0.07]∗	[0.35]∗∗∗	[0.83]∗∗	[1.51]∗∗∗	[2.38]∗∗∗	[3.90]∗	[4.46]∗
SE_H	{0.07}∗	{0.44}∗∗	{0.94}∗∗	{2.08}∗∗	{3.54}∗	{5.06}	{5.21}
R^2	0.57%	3.18%	5.38%	11.25%	20.84%	21.59%	21.96%
Panel B. Market Excess Return							
$b_{lh}^{(m)}$	0.05	0.61	1.68	4.77	9.68	14.30	14.69
SE_{OLS}	(0.14)	(0.36)∗	(0.52)∗∗∗	(0.78)∗∗∗	(1.04)∗∗∗	(1.23)∗∗∗	(1.38)∗∗∗
SE_{NW}	[0.10]	[0.49]	[1.01]∗	[2.64]∗	[4.70]∗∗	[5.11]∗∗∗	[5.01]∗∗∗
SE_H	{0.10}	{0.61}	{1.27}	{2.80}∗	{4.97}∗	{8.25}∗	{9.10}
R^2	0.04%	1.00%	3.52%	11.93%	25.00%	34.94%	32.24%

Standard errors in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table A.8: **Calibration**

This table shows in Panel A calibrated parameter values of the model of Section IV and the sectoral distribution of the frequency of price adjustment in Panel B.

Panel A. Calibration Parameter

Parameter	Value	Source
β	0.99	standard
b	0.76	Altig et al. (2011)
γ	5	Jermann (1998)
σ	2.5	Carvalho (2006)
ψ	1	Altig et al. (2011)
ϵ_c	8	Carvalho (2006)
ϵ_{ck}	12	Carvalho (2006)
θ_w	0.825	Erceg et al. (2000)
ϵ_w	8	Altig et al. (2011) / Erceg et al. (2000)
ϕ_π	1.24	Rudebusch (2002)
ϕ_y	0.33/4	Rudebusch (2002)
ρ_a	0.95	Smets and Wouters (2007)
ρ_m	0.90	Coibion and Gorodnichenko (2012)

Panel B. Sectoral Distribution

Sector k	Share	Frequency of Price Adjustment
1	0.2	0.105
2	0.2	0.164
3	0.2	0.277
4	0.2	0.638
5	0.2	0.985

Table A.9: **Long-Horizon Predictability on Simulated Data**

This table reports results for q-quarters forecasting regressions of model implied log excess returns of the zero-cost portfolio of going long the claim to dividends of the sector with low frequencies of price adjustment and shorting the claim to dividends of the sector with high frequencies of price adjustment, L-H on log consumption surplus of the model. For each regression the table reports OLS standard errors in parentheses, Newey and West (1987) standard errors in brackets, Hansen and Hodrick (1980) standard errors in curly brackets and Hodrick (1992) standard errors in angle brackets. The sample length is 250 quarters.

Horizon q (Quarters)	1	2	4	8	12	16	20
$b_{lh}^{(q)}$	−0.14	−0.26	−0.48	−0.79	−0.81	−0.77	−0.68
SE_{OLS}	(0.03)∗∗∗	(0.04)∗∗∗	(0.06)∗∗∗	(0.10)∗∗∗	(0.13)∗∗∗	(0.17)∗∗∗	(0.20)∗∗∗
SE_{NW}	[0.05]∗∗∗	[0.07]∗∗∗	[0.11]∗∗∗	[0.20]∗∗∗	[0.29]∗∗∗	[0.40]∗	[0.50]
SE_{HH}	{0.05}∗∗∗	{0.08}∗∗∗	{0.13}∗∗∗	{0.23}∗∗∗	{0.31}∗∗∗	{0.43}∗	{0.52}
SE_H	⟨0.05⟩∗∗∗	⟨0.10⟩∗∗∗	⟨0.17⟩∗∗∗	⟨0.26⟩∗∗∗	⟨0.32⟩∗∗	⟨0.36⟩∗∗	⟨0.38⟩∗
R^2	9.34%	14.28%	21.86%	21.80%	13.75%	8.61%	5.05%

Standard errors in parentheses

$*p < 0.10, **p < 0.05, ***p < 0.01$

Table A.10: **Panel Regression of Annual Stock Returns on Price Stickiness and Firm Characteristics (Benchmark Sample, Monthly Overlapping)**

This table reports the results of regressing overlapping annual percentage returns at the monthly frequency on the frequency of price adjustment, SAU, firm characteristics, return predictors and year fixed effects, where indicated. Standard errors are clustered at the firm level and reported in parentheses. Equally weighted probabilities of price adjustments are calculated at the firm level using the micro data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. Size is the natural logarithm of the market capitalization in thousands, BM is the book to market ratio, Beta is the regression coefficient on the market excess return in rolling times series regressions, Lev is financial leverage, CF measures cash flows, Turnover the fraction of shares traded to shares outstanding, Spread is the mean bid - ask spread, PCM is the price to cost margin and HHI the Herfindahl - Hirschman index of sales at the Fama & French 48 industry level. Stock level data are from CRSP and financial statement data from Compustat. The sample period is July 1982 to June 2007.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
SAU	−7.88***	−6.14***	−12.49***	−5.23***	−7.93***	−7.99***	−8.35***	−7.56***	−7.93***	−7.35***	−4.66**
	(1.68)	(1.78)	(2.03)	(1.67)	(1.73)	(1.71)	(1.69)	(1.69)	(1.73)	(1.69)	(2.15)
Size		−2.72***									−4.22***
		(0.12)									(0.21)
BM			6.70***								6.23***
			(0.53)								(0.69)
Beta				4.89***							5.95***
				(0.52)							(0.75)
Lev					0.87						1.99
					(0.96)						(1.31)
CF						−9.37**					18.13***
						(4.00)					(5.81)
Turnover							−2.03				−10.74***
							(2.23)				(2.87)
Spread								−1.75***			−5.74***
								(0.16)			(0.25)
PCM									−0.70		7.45***
									(1.28)		(1.66)
HHI										10.32***	6.37
										(3.41)	(4.51)
Observations	264,662	264,662	260,096	256,393	261,913	262,757	256,941	264,657	262,636	247,781	239,309
R^2	0.06%	1.84%	0.83%	0.63%	0.06%	0.08%	0.07%	0.43%	0.06%	0.08%	4.81%
Observations	285,503	285,503	280,335	277,689	282,834	283,786	277,572	285,498	283,654	280,179	262,864
R^2	0.07%	1.68%	0.81%	0.33%	0.07%	0.09%	0.08%	0.41%	0.07%	0.10%	4.51%

Standard errors in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table A.11: **Panel Regressions of Annual Stock Returns on Price Stickiness and Firm Characteristics (Benchmark Sample, Durability)**

This table reports the results of regressing annual percentage returns on the frequency of price adjustment, SAU, firm characteristics, return predictors and year fixed effects, where indicated. Standard errors are clustered at the firm level and reported in parentheses. Equally weighted probabilities of price adjustments are calculated at the firm level using the micro data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. Size is the natural logarithm of the market capitalization in thousands, BM is the book to market ratio, Beta is the regression coefficient on the market excess return in rolling times series regressions, Lev is financial leverage, CF measures cash flows, Turnover the fraction of shares traded to shares outstanding, Spread is the mean bid - ask spread, PCM is the price to cost margin, HHI the Herfindahl - Hirschman index of sales at the Fama & French 48 industry level and Dur the durability measure of Bils et al. (2012). Stock level data are from CRSP and financial statement data from Compustat. The sample period is July 1982 to June 2007.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
SAU	−10.18***	−11.07***	−7.98***	−12.97***	−7.87***	−11.01***	−10.98***	−9.87***	24.65***	−9.53***	−10.74***	−11.52***	−8.57***
	(2.14)	(2.25)	(2.42)	(2.47)	(2.30)	(2.29)	(2.28)	(2.24)	(1.06)	(2.22)	(2.27)	(2.47)	(2.96)
Size			−4.34***										−5.00***
			(0.28)										(0.34)
BM				3.31***									3.97***
				(0.83)									(1.18)
Beta					5.30***								2.74***
					(0.72)								(1.06)
Lev						1.02							4.60 * *
						(1.35)							(1.88)
CF							−10.56*						13.40
							(5.49)						(8.30)
Turnover								52.49***					33.72***
								(3.82)					(5.02)
Spread									−0.10***				−7.99***
									(0.02)				(0.61)
PCM										5.87***			6.28***
										(1.63)			(2.17)
HHI											2.95		11.29*
											(4.70)		(6.41)
Dur												0.08	−1.42***
												(0.32)	(0.41)
Year Fixed Effects	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	14,026	14,026	14,026	13,791	13,594	13,965	13,976	14,026	14,026	13,974	13,866	12,236	11,770
R^2	0.11%	19.83%	21.85%	19.94%	20.36%	19.72%	19.74%	21.35%	20.91%	19.80%	19.41%	18.75%	23.99%

Standard errors in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table A.12: **Panel Regressions of Annual Stock Returns on Price Stickiness and Firm Characteristics (Benchmark Sample, Double Clustered)**

This table reports the results of regressing annual percentage returns on the frequency of price adjustment, SAU, firm characteristics, return predictors, and year fixed effects, where indicated. SStandard errors are clustered at the firm level or firm-year level and reported in parentheses. Equally-weighted probabilities of price adjustments are calculated at the firm level using the micro data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. Size is the natural logarithm of the market capitalization in thousands, BM is the book-to-market ratio, Beta is the regression coefficient on the market excess return in rolling times-series regressions, Lev is financial leverage, CF measures cash flows, Turnover is the fraction of shares traded to shares outstanding, Spread is the mean bid - ask spread, PCM is the price-to-cost margin, and HHI is the Herfindahl - Hirschman index of sales at the Fama & French 48 industry level. Stock-level data are from CRSP and financial statement data are from Compustat. The sample period is July 1982 to June 2007.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
SAU	−10.18***	−11.07***	−7.98***	−12.97***	−7.87***	−11.01***	−10.98***	−9.87***	−10.31***	−9.53***	−10.74***	−6.46 * *	−6.46*
	(1.06)	(2.25)	(2.42)	(2.47)	(2.30)	(2.29)	(2.28)	(2.24)	(2.32)	(2.22)	(2.27)	(2.69)	(3.49)
Size			−4.34***									−4.87***	−4.87***
			(0.28)									(0.31)	(1.01)
BM				3.31***								3.88***	3.88
				(0.83)								(1.07)	(2.74)
Beta					5.30***							1.23	1.23
					(0.72)							(0.91)	(3.74)
Lev						1.02						4.80***	4.80
						(1.35)						(1.78)	(3.36)
CF							−10.56*					5.67	5.67
							(5.49)					(7.51)	(11.39)
Turnover								52.49***				35.06***	35.06*
								(3.82)				(4.80)	(18.89)
Spread									−5.55***			−7.60***	−7.60***
									(0.54)			(0.57)	(1.27)
PCM										5.87***		8.00***	8.00*
										(1.63)		(1.96)	(4.12)
HHI											2.95	11.28 * *	11.28
											(4.70)	(5.54)	(10.16)
Year Fixed Effects	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm-Year
Observations	14,026	14,026	14,026	13,791	13,594	13,965	13,976	14,026	14,026	13,974	13,866	13,253	13,253
R^2	0.11%	19.83%	21.85%	19.94%	20.36%	19.72%	19.74%	21.35%	20.91%	19.80%	19.41%	24.82%	24.82%

Standard errors in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table A.13: **Panel Regressions of Annual Stock Returns on Price Stickiness and Firm Characteristics (Benchmark Sample, Within Industry)**

This table reports the results of regressing annual percentage returns on the frequency of price adjustment, SAU, firm characteristics, return predictors, year fixed effects and industry fixed effects, where indicated. FF10 and FF17 indicate industry dummies according to the Fama & French 10 and 17 industry definition. Standard errors are clustered at the firm level and reported in parentheses. Equally weighted probabilities of price adjustments are calculated at the firm level using the micro data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. The sample period is July 1982 to June 2007.

	Baseline	Agriculture	Manufacturing	Utilities	Trade	Finance	Services	Dummies	Dummies	Dummies
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
SAU	−11.07***	−15.4 **	−7.38*	−9.73 **	−9.13	−2.50	−12.16	−7.93***	−5.73 **	−4.66*
	(2.25)	(6.85)	(4.08)	(4.14)	(8.92)	(4.78)	(19.37)	(2.40)	(2.59)	(2.53)
Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry Fixed Effects	N	N	N	N	N	N	N	Y	FF10	FF17
Observations	14,026	764	6,932	2,075	1,058	2,270	927	14,026	14,008	14,008
R^2	19.83%	26.88%	20.24%	25.34%	39.26%	44.46%	21.62%	20.10%	20.09%	19.94%

Standard errors in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table A.14: **Panel Regressions of Annual Stock Returns on Price Stickiness and Firm Characteristics (Benchmark Sample, Unwinsorized)**

This table reports the results of regressing annual percentage returns on the frequency of price adjustment, SAU, firm characteristics, return predictors and year fixed effects, where indicated. Standard errors are clustered at the firm level and reported in parentheses. Equally weighted probabilities of price adjustments are calculated at the firm level using the micro data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. Size is the natural logarithm of the market capitalization in thousands, BM is the book to market ratio, Beta is the regression coefficient on the market excess return in rolling times series regressions, Lev is financial leverage, CF measures cash flows, Turnover the fraction of shares traded to shares outstanding, Spread is the mean bid - ask spread, PCM is the price to cost margin and HHI the Herfindahl - Hirschman index of sales at the Fama & French 48 industry level. Stock level data are from CRSP and financial statement data from Compustat. The sample period is July 1982 to June 2007.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SAU	−11.36***	−12.26***	−8.63***	−13.17***	−6.86**	−12.56***	−12.06***	−10.83***	−11.76***	−11.72***	−11.57***	−6.23*
	(2.87)	(3.00)	(3.14)	(3.16)	(2.98)	(3.01)	(3.00)	(2.85)	(3.05)	(2.94)	(2.98)	(3.30)
Size			−5.70***									−5.77***
			(0.45)									(0.45)
BM				1.90**								1.86*
				(0.97)								(1.12)
Beta					9.04***							1.94
					(1.08)							(1.24)
Lev						2.88						4.17*
						(1.98)						(2.29)
CF							−23.31*					0.95
							(14.17)					(9.84)
Turnover								61.87***				45.46***
								(7.03)				(7.76)
Spread									−2.19***			−4.97***
									(0.84)			(1.12)
PCM										0.69		3.02***
										(0.67)		(0.75)
HHI											1.22	7.23
											(4.62)	(4.62)
Year Fixed Effects	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	14,026	14,026	14,026	13,791	13,594	13,965	13,976	14,026	14,026	13,974	13,866	13,253
R^2	0.10%	13.85%	16.44%	14.44%	14.67%	13.77%	13.90%	16.24%	14.26%	13.74%	13.47%	19.92%

Standard errors in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table A.15: **Mean Portfolio Returns (Alternative Measures of Price Stickiness)**

This table reports time series averages of annual equally weighted portfolio raw returns for various sample periods with Newey and West (1987) standard errors in parentheses. Stocks are assigned to one of five baskets based on the frequency of price adjustment. SA treats missing values as interrupting price spells, for SB, missing values do not interrupt price spells if the price is the same before and after periods of missing values and SC forms the union of the two. Equally (U) and value of shipment weighted (W) probabilities of price adjustments are calculated at the firm level using the micro data underlying the Producer Price Index constructed by the Bureau of Labor Statistics.

	Sticky (1)	S2 (2)	S3 (3)	S4 (4)	Flexible (5)	S1-S5 (6)
			Panel A. Annual Mean Returns (SBU)			
07/1982 - 06/2014	21.56***	19.8***1	19.77***	18.97***	18.49***	3.06*
	(3.75)	(2.81)	(2.88)	(3.23)	(2.52)	(1.72)
07/1982 - 06/2007	24.05***	21.48***	21.65***	21.50***	20.46***	3.59 **
	(3.00)	(2.50)	(2.49)	(2.46)	(2.41)	(1.78)
			Panel B. Annual Mean Returns (SCU)			
07/1982 - 06/2014	21.53***	19.79***	19.80***	18.97***	18.49***	3.04*
	(3.76)	(2.78)	(2.90)	(3.23)	(2.52)	(1.71)
07/1982 - 06/2007	24.04***	21.43***	21.66***	21.53***	20.46***	3.58 **
	(3.03)	(2.46)	(2.54)	(2.42)	(2.41)	(1.77)
			Panel C. Annual Mean Returns (SAW)			
07/1982 - 06/2014	21.15***	19.91***	19.97***	18.88***	18.06***	3.08*
	(3.36)	(3.04)	(2.99)	(3.08)	(2.47)	(1.78)
07/1982 - 06/2007	23.54***	21.58***	21.95***	21.35***	19.75***	3.78 **
	(2.52)	(2.81)	(2.50)	(2.29)	(2.60)	(1.73)
			Panel D. Annual Mean Returns (SBW)			
07/1982 - 06/2014	21.64***	18.78***	19.93***	18.78***	18.76***	2.89*
	(3.45)	(2.79)	(2.80)	(3.32)	(2.55)	(1.74)
07/1982 - 06/2007	24.01***	20.24***	21.80***	21.39***	20.63***	3.38*
	(2.67)	(2.58)	(2.42)	(2.41)	(2.65)	(1.85)
			Panel E. Annual Mean Returns (SCW)			
07/1982 - 06/2014	21.62***	18.85***	19.93***	18.79***	18.75***	2.87*
	(3.46)	(2.81)	(2.80)	(3.37)	(2.52)	(1.70)
07/1982 - 06/2007	24.05***	20.23***	21.80***	21.44***	20.57***	3.47*
	(2.64)	(2.62)	(2.42)	(2.44)	(2.65)	(1.92)

Standard errors in parentheses

$*p < 0.10, **p < 0.05, ***p < 0.01$

Table A.16: **Mean Portfolio Returns (SAU, S&P500)**

This table reports time series averages of annual equally weighted portfolio raw returns for various sample periods with Newey and West (1987) standard errors in parentheses. Stocks are assigned to one of five baskets based on the frequency of price adjustment, SAU. Equally weighted probabilities of price adjustments are calculated at the firm level using the micro data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. Panel A includes only firms which have been part of the S&P500 index at the end of June 1994 whereas Panel B focuses on firms which have been part of the S&P500 index at the end of June 2006.

	Sticky (1)	S2 (2)	S3 (3)	S4 (4)	Flexible (5)	S1-S5 (6)
	Panel A. S&P500 Constituents as of 06/30/1994					
07/1982 - 06/2014	18.41***	18.01***	18.36***	17.06***	15.71***	2.70*
	(3.54)	(3.29)	(2.83)	(3.09)	(2.65)	(1.58)
07/1982 - 06/2007	20.30***	19.39***	19.87***	18.86***	17.26***	3.04 **
	(3.33)	(3.16)	(2.88)	(2.99)	(3.12)	(1.38)
	Panel B. S&P500 Constituents as of 06/30/2006					
07/1982 - 06/2014	22.94***	20.51***	20.26***	19.39***	18.22***	4.72 **
	(4.38)	(3.46)	(3.21)	(3.86)	(2.63)	(1.97)
07/1982 - 06/2007	25.67***	22.57***	22.44***	22.32***	20.50***	5.17 **
	(3.56)	(3.01)	(2.41)	(2.70)	(2.15)	(2.12)

Standard errors in parentheses

$*p < 0.10, **p < 0.05, ***p < 0.01$

Table A.17: **Panel Regressions of Annual Realized Volatilities on Price Stickiness and Firm Characteristics (Benchmark Sample)**

This table reports the results of regressing annual realized volatilities on the frequency of price adjustment, SAU, firm characteristics, return predictors and year fixed effects, where indicated. Standard errors are clustered at the firm level and reported in parentheses. Equally weighted probabilities of price adjustments are calculated at the firm level using the micro data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. Realized volatilities are calculated as the square root of the sum of daily squared returns. Size is the natural logarithm of the market capitalization in thousands, BM is the book to market ratio, Beta is the regression coefficient on the market excess return in rolling times series regressions, Lev is financial leverage, CF measures cash flows, Turnover the fraction of shares traded to shares outstanding, Spread is the mean bid - ask spread, PCM is the price to cost margin and HHI the Herfindahl - Hirschman index of sales at the Fama & French 48 industry level. Stock level data are from CRSP and financial statement data from Compustat. The sample period is July 1982 to June 2007.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SAU	−10.08∗∗∗	−9.94∗∗∗	−7.41∗∗	−7.72∗∗	−0.56	−7.01∗∗	−9.84∗∗∗	−8.00∗∗∗	−10.82∗∗∗	−8.73∗∗∗	−8.76∗∗∗	−6.46∗∗
	(3.22)	(3.16)	(2.91)	(3.10)	(2.29)	(3.07)	(3.18)	(2.17)	(2.88)	(3.12)	(3.15)	(2.69)
Size			−3.55∗∗∗									−4.87∗∗∗
			(0.27)									(0.31)
BM				−3.70∗∗∗								3.88∗∗∗
				(0.88)								(1.07)
Beta					18.53∗∗∗							1.23
					(0.78)							(0.91)
Lev						−8.71∗∗∗						4.80∗∗∗
						(1.54)						(1.78)
CF							−9.80∗					5.67
							(5.67)					(7.51)
Turnover								84.73∗∗∗				35.06∗∗∗
								(2.65)				(4.80)
Spread									6.28∗∗∗			−7.60∗∗∗
									(0.52)			(0.57)
PCM										4.42∗∗		8.00∗∗∗
										(2.11)		(1.96)
HHI											12.39∗∗	11.28∗∗
											(5.14)	(5.54)
Year Fixed Effects	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	14,057	14,057	14,057	13,821	13,625	13,996	14,007	14,057	14,057	14,005	13,897	13,253
R^2	0.59%	22.94%	30.25%	24.35%	45.51%	24.57%	23.15%	44.40%	30.44%	23.26%	23.32%	24.82%

Standard errors in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table A.18: **Summary Statistics and Correlations for Firm Characteristics and Return Predictors (Full Sample)**

This table reports time series averages of annual cross-sectional means and standard deviations for firm characteristics and return predictors used in the subsequent analysis in Panel A and contemporaneous correlations of these variables in Panel B. SAU measures the frequency of price adjustment. Equally weighted probabilities of price adjustments are calculated at the firm level using the micro data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. Size is the natural logarithm of the market capitalization in thousands, BM is the book to market ratio, Beta is the regression coefficient on the market excess return in rolling times series regressions, Lev is financial leverage, CF measures cash flows, Turnover the fraction of shares traded to shares outstanding, Spread is the mean bid - ask spread, PCM is the price to cost margin and HHI the Herfindahl - Hirschman index of sales at the Fama & French 48 industry level. Stock level data are from CRSP and financial statement data from Compustat. The sample period is July 1982 to June 2014.

	SAU	Size	BM	Beta	Lev	CF	Turnover	Spread	PCM	HHI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A. Means and Standard Deviations									
Mean	0.14	15.03	0.63	1.06	0.40	0.09	0.14	0.01	0.37	0.07
Std	0.13	1.25	0.38	0.43	0.24	0.06	0.10	0.01	0.19	0.06
N	540	540	530	523	538	539	540	540	538	535
	Panel B. Contemporaneous Correlations									
Size	0.08									
BM	0.24	−0.17								
Beta	−0.16	−0.21	−0.12							
Lev	0.15	−0.01	0.20	−0.13						
CF	−0.03	0.20	−0.45	−0.08	−0.45					
Turnover	0.00	−0.22	−0.05	0.44	−0.11	0.02				
Spread	0.02	−0.35	0.18	0.18	0.08	−0.18	0.06			
PCM	−0.15	0.13	−0.32	0.06	−0.09	0.29	0.07	−0.12		
HHI	−0.13	0.00	−0.20	0.09	−0.06	0.15	0.01	0.02	0.03	

Table A.19: **Panel Regressions of Annual Stock Returns on Price Stickiness and Firm Characteristics (Full Sample)**

This table reports the results of regressing annual percentage returns on the frequency of price adjustment, SAU, firm characteristics, return predictors and year fixed effects, where indicated. Standard errors are clustered at the firm level and reported in parentheses. SAU treats missing values as interrupting price spells. Equally-weighted probabilities of price adjustments are calculated at the firm level using the micro data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. Size is the natural logarithm of the market capitalization in thousands, BM is the book to market ratio, Beta is regression the coefficient on the market excess return in rolling times series regressions, Lev is financial leverage, CF measures cash flows, Turnover the fraction of shares traded to shares outstanding, Spread is the mean bid - ask spread, PCM is the price to cost margin and HHI the Herfindahl - Hirschman index of sales at the Fama & French 48 industry level. Stock level data are from CRSP and financial statement data from Compustat. The sample period is July 1982 to June 2014.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SAU	−8.11***	−8.97***	−6.12***	−10.91***	−6.86***	−9.00***	−8.88***	−9.09***	−8.34***	−7.88***	−8.49***	−4.50*
	(1.88)	(2.02)	(2.17)	(2.18)	(2.07)	(2.06)	(2.05)	(2.00)	(2.07)	(2.00)	(2.03)	(2.39)
Size			−3.90***									−4.66***
			(0.25)									(0.27)
BM				3.32***								3.21***
				(0.70)								(0.89)
Beta					3.74***							1.87**
					(0.60)							(0.76)
Lev						1.12						3.42**
						(1.16)						(1.55)
CF							−8.09**					9.53
							(4.59)					(6.56)
Turnover								22.95***				7.22**
								(3.02)				(3.51)
Spread									−5.67***			−7.86***
									(0.54)			(0.56)
PCM										4.01***		7.59***
										(1.38)		(1.71)
HHI											5.84	11.32**
											(4.16)	(5.07)
Year Fixed Effects	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	17,243	17,243	17,243	16,926	16,691	17,176	17,192	17,243	17,243	17,187	17,069	16,251
R^2	0.07%	24.10%	25.74%	24.21%	24.39%	24.03%	24.04%	24.54%	25.04%	24.07%	23.82%	27.69%

Standard errors in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

A Tough Act to Follow:
Contrast Effects in Financial Markets*

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Abstract

We present evidence of contrast effects in financial markets: investors mistakenly perceive information in contrast to what preceded it, leading to significant distortions in market reactions to firm earnings announcements. Earnings news today seems more (less) impressive if yesterday's earnings surprise was bad (good). Consistent with contrast effects, we find that the stock price reaction to an earnings announcement is negatively related to the earnings surprise announced by large firms in the previous day. In addition, 1) return reactions are inversely affected by earnings surprises released yesterday, but not by earnings released further in the past or the future, 2) a similar inverse relation exists for firms that release earnings sequentially within the same day, and 3) the mispricing reverses over the long run. We present a number of tests to show that our results cannot be explained by a key alternative explanation involving information transmission from the previous earnings announcement. Further, the results cannot be explained by strategic timing, changes in risk, or trading frictions.

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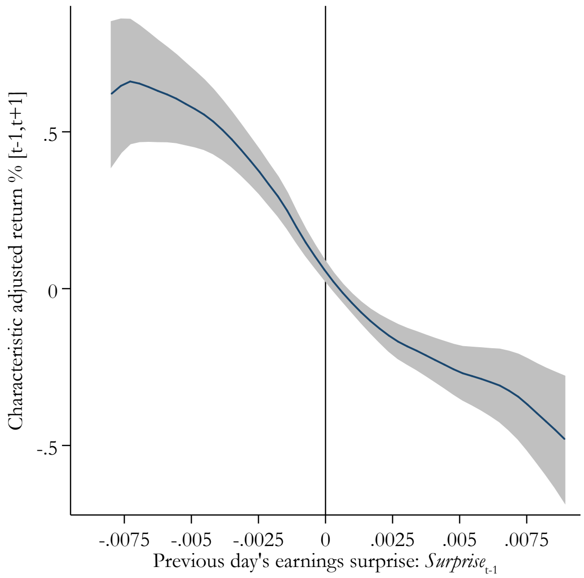
Figure 1



Return of firms that announced earnings today vs. the value-weighted average earnings surprise of large firms that announced earnings in the previous trading day (conditional on own earnings surprise).

> ***Socrates:*** *Could you tell me what the beautiful is?*
> ***Hippias:*** *For be assured Socrates, if I must speak the truth, a beautiful maiden is beautiful.*
> ***Socrates:*** *The wisest of men, if compared with a god, will appear a monkey, both in wisdom and in beauty and in everything else. Shall we agree, Hippias, that the most beautiful maiden is ugly if compared with the gods?*
>
> -Plato

People often interpret information by contrasting it with what was recently observed. For example, Pepitone and DiNubile (1976) show that subjects judge crimes to be less severe following exposure to narratives of very egregious crimes. Kenrick and Gutierres (1980) show that male students rate female students to be less attractive after viewing videos of beautiful actresses. References to such "contrast effects" are also pervasive in our popular culture. People complain about having "a tough act to follow" when they are scheduled to perform following a great performance. Writers use literary foils to exaggerate a character's traits through juxtaposition with a contrasting character. Fashion designers use shoulder pads and peplum hips to create the illusion of a comparatively smaller waist. In all of these cases, contrast effects bias our perception of information. We perceive signals as higher or lower than their true values depending on what else was recently observed.

Contrast effects have the potential to bias a wide variety of important real-world decisions. They may distort judicial perceptions of the severity of crimes, leading to unfair sentencing. At firms, comparisons with the previously reviewed candidate could lead to mistakes in hiring and promotion decisions. An unconstrained firm may make mistakes in investment choices by passing on a positive NPV project because it does not look as good as other options or investing in a negative NPV project because it looks better than even worse alternatives. Finally, at the household level, contrast effects could cloud key decisions such as mate choice and housing search.

In these examples, contrast effects potentially lead to costly mistakes, but it may be difficult for researchers to cleanly measure the bias. Measurement is complicated by the possibility that the decision-makers face unobserved quotas or resource constraints that make comparisons across multiple cases optimal. In addition, researchers often lack of precise data on how decision-makers perceive information. Possibly because of these challenges, most of the existing research on contrast effects has focused on controlled laboratory experiments. Evidence from the field is more limited. Outside of the lab, Bhargava and Fisman (2014) show contrast effects in mate choice using a speed dating field experiment and Simonsohn and Loewenstein (2006) and Simonsohn (2006) show contrast effects in consumer housing and commuting choices.

Our paper tests whether contrast effects operate in another important real world setting: financial markets. The financial setting is particularly interesting because we can test whether contrast effects distort equilibrium prices and capital allocation in sophisticated markets. Full-time professionals making repeated investment decisions involving high stakes may be less prone to such a bias than individuals making infrequent dating or real estate decisions. Moreover, the limited field evidence examines contrast effects in household decision-making, but prices in financial markets are determined through interactions among many investors. Thus, cognitive biases among a subset of investors may not affect market prices given the disciplining presence of arbitrage. And yet, if contrast effects influence prices in financial markets, it would represent an important form of mis-pricing: prices react not only to the absolute content of news, but also to a bias induced by the relative content of news.

In this paper, we test whether contrast effects distort market reactions to firm earnings announcements. Quarterly earnings announcements represent the main recurring source of firm-specific news released by publicly-traded US firms. Prior to the earnings announcement, financial analysts and investors form expectations of what they believe earnings will be. Earnings surprises, i.e., the extent to which actual earnings exceed or fall short of those expectations, are associated with large stock price movements because they represent new information that shifts expectations of firm prospects.

We explore how the stock price reaction to an earnings announcement made by a firm today depends on the level of the earnings surprises announced by other large firms in the previous day. Earnings announcements are typically scheduled weeks before the announcement, so whether a given firm announces following positive or negative surprises by another firm is likely to be uncorrelated with the firm's fundamentals. The theory of contrast effects predicts a *negative* relation between the return reaction to today's earnings surprise and yesterday's surprise, holding today's earnings surprise constant. The intuition is that news today will not seem as impressive if yesterday's earnings surprises were very positive. Conversely, today's earnings surprise will seem more impressive if yesterday's earnings surprises were very disappointing.

The downward sloping pattern in Figure 1 illustrates our main finding. The figure shows a local linear plot of returns surrounding a firm's earnings announcement relative to the value-weighted average earnings surprise announced by large firms in the previous trading day. The figure demonstrates a strong negative relation: controlling for today's earnings news, the return reaction to today's earnings announcement is inversely related to yesterday's earnings surprise. The effect is sizable–a change in yesterday's earnings surprise from the worst to the best decile corresponds to a 43 basis point lower return response to today's earnings announcement.

We explore the basic relation in Figure 1 and demonstrate that it is robust. Using regression analysis, we show that the negative pattern holds regardless of whether we control for the level of today's earnings surprise or how we measure yesterday's earnings surprise: the surprise relative to various measures of analyst expectations or return-based measures. Unlike many anomalies which focus on small-cap firms, we find that contrast effects significantly distort the returns of large firms. A contrast effects trading strategy using portfolios comprised of only firms in the top quintile of size yields four factor daily alphas of 10-15 basis points on days in which the strategy can be implemented, yielding abnormal returns of 7-13% per year. We also examine contrast effects within industry. We find that the effect for large firms is strong both within and across industries, although contrast effects primarily operate through within-industry comparisons for smaller firms.

We present three additional pieces of evidence in support of the contrast effects hypothesis. First, the returns distortion reverses over the long run, which is consistent with contrast effects causing mispricing that is eventually corrected. Second, returns for firms announcing today are negatively related to earnings surprises released by other firms on $t-1$, but are not significantly related to lagged earnings surprises on $t-2$ and $t-3$ or future earnings surprises on $t+1$ and $t+2$. This is consistent with the transitory nature of contrast effects as found elsewhere, in which individuals react primarily to the most recent observation. It also shows that our results are due to the precise ordering of earnings announcements rather than slower-moving time trends. Third, we find similar contrast effects among earnings released sequentially within the same day. Morning earnings surprises have a strong negative impact on the returns of firms that announce in the afternoon. Conversely, the returns of firms that announce in the morning are not impacted by afternoon earnings surprises.

While our findings are consistent with the theory of contrast effects, one may be concerned that we are capturing information transmission from earlier earnings announcements. For concreteness, suppose that firm A announces a positive earnings surprise on day $t-1$ and firm B is scheduled to announce earnings on day t. Empirically, we find that B tends to experience low returns, conditional on its actual earnings surprise. Can information transmission explain this empirical pattern?

We first show that explanations based on a positive correlation in news, where A's positive surprise is good news for B, cannot account for the results because we examine B's *cumulative* *return* from $t-1$ to $t+1$ (starting at market close on $t-2$ before A announces). If there is positive correlation in news, A's positive surprise should predict positive cumulative returns for firm B, not the negative pattern we find in the data. Thus, to account for the results, an information transmission explanation requires negative correlation in news where A's positive surprise is bad news for B (e.g., A competes with B for resources). In this case, B should experience negative returns on $t-1$ when A first announces. We find no support for negative information transmission in the data. Empirically, A's earnings surprise has no predictive power for B's earnings surprise after we account for slower moving time trends at the month level. Further, the market does not behave as if news relevant to firm B is released on day $t-1$, as we find no relation between A's earnings surprise and B's return on day $t-1$.

One may still be concerned that the results are due to a negative correlation in news and a *delayed* reaction to information. For example, A's $t-1$ positive surprise may contain negative news for B, but the market does not react to this information until day t, when B is featured in the media as it announces its earnings. Note that this type of delayed reaction is only a concern if A's earnings surprise contains news about B's prospects other than B's earnings. If A's announcement simply provided information for B's earnings, this predicts a zero relationship between A's earnings surprise and B's cumulative return after controlling for B's actual earnings. Delayed reaction and information transmission more generally are also inconsistent with two important features of the data. First, we find that return reactions are distorted by salient surprises in $t-1$, but not by slightly earlier surprises in $t-2$ or $t-3$. If earlier announcements convey information, one would expect similar effects for these earlier salient surprises. Second, any information transmission, delayed or not, should not lead to the long-run reversals observed in the data. These reversals are instead suggestive of corrections of a short-term bias.

Altogether, we show that most plausible variants of the information transmission story cannot explain our results. The remaining information transmission story that we cannot rule out is the following: A's $t-1$ announcement contains information for B, but the market does not react to this information until day t. On day t, there is a biased response to this information which reverses over time. Further, A's news is negatively correlated with B's prospects (beyond B's earnings), and such information is only released at day $t-1$ but not by firms announcing on days $t-2$ or $t-3$. While we cannot rule out such a story, we believe that the well-founded psychological motivation based on contrast effects offers the more parsimonious explanation of our findings.

Another potential concern is that firms may advance or delay their earnings announcements or manipulate the earnings announcement itself through discretionary accruals (e.g., Sloan, 1996; DellaVigna and Pollet, 2009; and So, 2015). However, such strategic manipulation will only bias our results if they alter firm earnings as a function of the earnings surprises released by other firms on day $t-1$. Firms publicly schedule when they will announce their earnings and almost always do so at least a week before they actually announce (Boulland and Dessaint, 2014). The earnings *surprises* of other firms are, by definition, difficult to predict because they measure surprises relative to expectations. Therefore, it is unlikely that firms can strategically schedule to follow other firms with more or less positive surprises. Further, manipulation of the earnings number itself takes time and is unlikely to occur within a single day as a reaction to other firms' earnings surprises. To directly test strategic timing, we separately examine earnings announcements that moved or stayed relative to the calendar date of the firm's announcement for the same quarter in the previous year. We find similar results for the restricted sample of stayers.

A final potential concern is that earnings surprises on day $t-1$ impacts the risk or trading frictions associated with the announcement on day t, so the return difference is compensation for risk or trading frictions. Fixed firm-specific loadings on risk factors cannot explain our results because we use characteristic adjusted returns (raw return minus the return of a portfolio of similar firms in terms of size, book-to-market, and momentum) in our analysis. To explain our results, a more negative earnings surprise yesterday must increase day-specific trading frictions or betas on risk factors. We instead find that risk loadings, return volatility, volume, and other measures of liquidity do not vary by the earnings surprise in $t-1$.

One of the main contributions of our paper is to further the understanding of how psychological biases found in the lab manifest in real-world settings (e.g., Levitt and List 2007b,a; Chen, Moskowitz, and Shue 2014). Our findings suggest that contrast effects persist outside the laboratory in a market setting where prices are determined by interactions among many investors including potentially deep-pocketed arbitrageurs. Our findings also contribute to the literature on biased reactions to earnings announcements, which has shown that investors underreact to the firm's own earnings news (Ball and Brown, 1968; Bernard and Thomas, 1989,1990; and Ball and Bartov, 1996), predictable seasonal information (Chang et al., 2014), and information in the timing of announcements (DellaVigna and Pollet, 2009; So, 2015; Boulland and Dessaint, 2014). Relative to the existing research, we show how prices are affected by the announcements of *other* firms that announced recently. Further, much of the research in behavioral finance documents price distortions among small firms. We show that contrast effects affect even the largest firms.

Our evidence also underscores how important decisions are often distorted by comparisons to benchmarks that should be irrelevant. Thus, our research is related to a large theory literature on context-dependent choice and reference points (e.g., Kahneman and Tversky, 1979; Koszegi and Rabin 2006, 2007).[1] In particular, our empirical results are broadly consistent with recent models of relative thinking by Cunningham (2013), Bordalo, Gennaioli, and Shleifer (2015), and Bushong, Rabin, and Schwartzstein (2015), although our setting lacks specific features of these models such as choice sets over goods. Investors in our financial setting also resemble FAST thinkers in Bordalo, Gennaioli, and Shleifer (2015), who have both partial recall and biased reactions to what is recalled.

Finally, our findings are related to research in behavioral finance examining investor behavior based on how positions performed since they were purchased (Shefrin and Statman, 1985; Odean, 1998), how exciting certain stocks are relative to others in the market (Barber and Odean, 2008), and how a position compares to the other holdings in an investor's portfolio (Hartzmark, 2015). Relative to this literature which focuses on the trading patterns of individual investors, we test how contrast effects in the perception of news affect equilibrium market prices for large cap stocks.

[1] While closely related to this literature, contrast effects (as typically described in the psychology literature) refer to a simple directional phenomenon in which larger values of the recently observed signal makes the next signal appear smaller in comparison, and vice versa. Most descriptions of contrast effects do not require discontinuous or kinked responses around a reference point (as in prospect theory) or a choice framework to identify which reference points to use or where to allocate attention.

1 Data

1.1 Sources

We use the I/B/E/S detail history file for data on analyst estimates of what a specific firm's earnings will be upon announcement. We examine the quarterly forecasts of earnings per share and merge this to information on daily stock returns from CRSP and firm-specific information from Compustat. Data on the market excess return, risk-free rate, SMB, HML and UMD portfolios as well as size cutoffs all come from the Kenneth French Data Library.

Our analysis uses data on the date of the earnings announcement from the I/B/E/S file. DellaVigna and Pollet (2009) highlight a potential concern regarding earnings announcement dates as reported in I/B/E/S: some recorded dates coincide with the date that each earnings announcement was first published in the Wall Street Journal, which may occur one day after the date in which the earnings was announced through other means. Our main analysis uses I/B/E/S announcement dates because we hope to capture when investors pay attention to earnings announcements. Especially early in the sample (which contains the bulk of the errors), the date of publication in the Wall Street Journal as listed in I/B/E/S may be a better measure of when each firm's earnings announcement is most salient. Nevertheless, we show in the Section 7 that our results are very similar utilizing the DellaVigna and Pollet (2009) date correction. The results are also similar in the more recent sample period, which has a much lower rate of date-related errors.

For most of our analysis, we examine daily returns that have been characteristic-adjusted, following the procedure in Daniel, Grinblatt, Titman, and Wermers (1997). Specifically, using CRSP daily returns, we sort stocks into NYSE quintiles based on size, book value of equity divided by market value of equity (calculated as in Fama and French, 1992), and momentum calculated using returns from $t-20$ to $t-252$ trading days (an analogue to a monthly momentum measure from months $m-2$ to $m-12$). We then match each stock's return to a portfolio of stocks that match each of these three quintiles. Our measure of the characteristic-adjusted return is a stock's return on day t minus the return of the characteristic-matched portfolio on day t.

1.2 Measuring earnings surprise

A key variable in our analysis is the surprise for a given earnings announcement.[2] Broadly defined, earnings surprise is the difference between the announced earnings and the expectations of investors prior to the announcement. To measure surprise, we need an estimate of the expectations of investors. We follow a commonly-used method in the accounting and finance literature and measure expectations using analyst forecasts prior to announcement. This measure is available for a long time-series and does not require us to take a stand on specific modeling assumptions (for example, assuming a random walk with drift as in Bernard, 1992). Analysts are professionals who are paid to forecast future earnings. While there is some debate about what their goal is and how unbiased they are (e.g., McNichols and O'Brien (1997); Lin and McNichols (1998); Hong and Kubik (2003); Lim (2001); and So, 2013), our tests only require that such a bias is not correlated with the surprises of other firms in the day before a firm announces earnings. Given that we only use forecasts made before the $t-1$ firm announces (forecasts from day $t-2$ or earlier), such a bias is unlikely to exist.

Similar to DellaVigna and Pollet (2009), we take each analyst's most recent forecast, thereby limiting the sample to only one forecast per analyst, and then take the median of this number within a certain time window for each firm's earnings announcement. In our base specification, we take all analyst forecasts made between two and fifteen days prior to the announcement of earnings. We choose fifteen days to avoid stale information yet still retain a large sample of firms with analyst coverage. To show that these assumptions are not driving the results, we present variations of this measure in Section 7 utilizing longer windows of 30 and 45 days prior to announcement and also using the direct return reaction to the announcement as a measure of earnings surprise.

To make the magnitude of the surprise comparable across firms, we follow DellaVigna and Pollet (2009) and scale the difference between the actual surprise and the median analyst forecast by the

[2] We follow the literature on earnings announcements in characterizing earnings news as the surprise relative to expectations. We focus on surprise rather than levels because whether a given level of earnings is good or bad news depends on firm-specific circumstances that are captured by measures of investor expectations. In addition, stock prices should reflect current information – the stock market return response to earnings announcements represents the change in valuation of the firm which should depend on the change in earnings relative to expectations. Moreover, the financial press typically reports earnings announcement news in terms of how much earnings beat or missed forecasts. Therefore, the earnings surprise is likely to be the measure of earnings news that is most salient to investors.

share price of the firm from three trading days prior to the announcement. Thus, our estimate of the earnings surprise for firm i on day t can be written as:

$$surprise_{it} = \frac{\left(actual\ earnings_{it} - median\ estimate_{i,[t-15,t-2]}\right)}{price_{i,t-3}} \tag{1}$$

To examine the impact of contrast effects, we need a measure of the surprise occurring on the previous day taking into account that multiple firms may have announced earnings. The ideal variable would focus on the earnings announcements in $t-1$ that were salient as this would be the most likely comparison group in the minds of investors when they consider and evaluate the current day's announced earnings. While we do not have an exact measure of the salient surprise in $t-1$, we utilize a number of proxies and focus most of our analysis on large firms. A firm's market capitalization is related to how much attention that firm receives. One measure we use is simply the surprise of the largest firm to announce on day $t-1$. A second measure, which we use as our baseline, is the value-weighted surprise among all large firms announcing on day $t-1$. We define large firms as those with market capitalization (measured three days before the firm's announcement) above the NYSE 90th percentile of market capitalization in each month. If multiple large firms announced earnings on the previous trading day, we take the value-weighted average of these firms' surprise measures, using each firm's market capitalization three days prior to the firm's announcement. Thus our baseline measure of yesterday's salient surprise is:

$$surprise_{t-1} = \frac{\sum_{i=1}^{N}(mkt\ cap_{i,t-4} \times surprise_{i,t-1})}{\sum_{i=1}^{N} mkt\ cap_{i,t-4}} \tag{2}$$

To reduce the influence of outliers, we winsorize $surprise_{it}$ at the 1st and 99th percentile and take the weighted average to create our $surprise_{t-1}$ measure. After creating $surprise_{t-1}$, we again winsorize at the 1st and 99th percentiles. In addition, in Section 7, we present alternative formulations where we value-weight all firms that announced in $t-1$ or take the equal-weighted average among all large firms.

In later regression analysis, each observation represents an earnings announcement by firm i on day t. In a slight abuse of notation, we omit the i subscript and refer to the firm's own earnings surprise today as $surprise_t$ and the salient earnings surprise released by other large firms on the previous trading day as $surprise_{t-1}$.

1.3 Summary statistics

Table 1 describes the data used in our baseline specification. Our sample begins in 1984 and ends in 2013. For our main analysis, we examine how the return reaction for a firm that announces earnings on day t relates to the salient earnings surprise of other firms released on day $t-1$, controlling for the firm's own earnings surprise. Thus, to be included in the sample, a firm must have at least one analyst forecast in our dataset between days $t-2$ and $t-15$ prior to the announcement. In addition, we require a non-missing measure of $surprise_{t-1}$, which means at least one firm above the 90th percentile of market-capitalization announced their earnings on day $t-1$ and at least one analyst forecasted earnings for this firm between days $t-16$ and $t-3$. After applying these filters and requiring the firm with an announcement on day t to have non-missing characteristic adjusted returns, we are left with 76,062 unique earnings announcements.

Examining the characteristic adjusted returns row, we see that days with an earnings announcement are associated with positive characteristic adjusted returns of 16 basis points, or raw returns of 17 basis points. This is the earnings announcement premium described in Beaver (1968), Frazzini and Lamont (2007), and Barber et al. (2013). Table 1 also shows that the typical earnings surprise is approximately zero (a mean of -0.0003 and a median of 0.0002). The market cap row shows the mean market capitalization in our sample is roughly \$7 billion, while the 25th percentile of market cap is \$440 million, implying that we have many small firms in our sample. Nevertheless, our baseline analysis will focus on larger firms because we value-weight each observation. We find a similar pattern when examining analyst coverage (number of forecasts from $t-15$ to $t-2$). For many firms, we see only one analyst forecast and the median number of forecasts is two, while the mean number of forecasts is nearly four. Thus, a small number of firms are covered heavily by many analysts. The final row describes the number of firms above the 90th percentile that announced on the previous trading day that are used to construct the $surprise_{t-1}$ variable. The median of this variable is 6 with a mean of 7.5, so in general multiple firms comprise the $surprise_{t-1}$ measure.

2 Results

2.1 Baseline results

In our baseline specifications, we test how the price response to a given earnings surprise is impacted by the earnings surprise announced by large firms on the previous trading day. A major determinant of the price response to any earnings announcement will of course be the level of earnings surprise that the firm actually announces. The theory of contrast effects predicts that, conditional on the level of surprise today, the return response to a given earnings announcement will be inversely related to yesterday's salient earnings surprise. Thus, our baseline specification allows for a direct impact of earnings surprise, contrast effects, and controls for time effects as follows:

$$char.\ adj.\ return_{i,[t-1,t+1]} = \beta_0 + \beta_1 \cdot surprise_{t-1} + surprise\ bin_j + \delta_{ym} + \varepsilon_{it} \tag{3}$$

The dependent variable is firm i's three-day characteristic adjusted return from $t-1$ to $t+1$. In later sections, we discuss why including $t-1$ in our return window helps to rule out an alternative explanation involving information transmission of positively correlated news. This returns measure is regressed on controls for firm i's own earnings surprise as well as $surprise_{t-1}$. We impose as little structure as possible on the price response to the firm's own earnings surprises by creating twenty equally sized bins based on the size of the earnings surprise. Grouping the surprise level as dummy variables means we non-parametrically allow each magnitude of surprise to be associated with a different level of average return response. δ_{ym} represents year-month fixed effects. In all regressions, unless otherwise noted, we value-weight each observation using the firm's market capitalization three days prior to the firm's announcement, scaled by the average market capitalization in that year, in order to focus on the more economically meaningful firms.[3] We cluster the standard errors by date.

$Surprise_{t-1}$ is our measure of yesterday's earnings announcement surprise and the coefficient β_1 is our main measure of contrast effects. The contrast effect hypothesis predicts that, all else equal, if yesterday's salient surprise was more positive, any given surprise today will appear worse by comparison. If yesterday's salient surprise was more negative, today's surprise will appear better. Thus, contrast effects predict a negative coefficient on β_1.

Table 2 shows the estimates of β_1 and strongly supports the hypothesis that there are significant contrast effects in the returns response to earnings. For our first estimate of the salient earnings surprise, we use the earnings surprise of the largest firm to announce in the previous day. To make sure this firm is salient, we include only observations where the firm is above the 90th percentile of the NYSE market capitalization cutoff. The coefficient is -0.501 and highly significant.

Examining only the largest firm is a coarse measure of the salient earnings surprise from the previous day if there were multiple large firms that announced. For example, if both Apple and Goldman Sachs announced earnings on the same day, it makes sense that both announcements would be salient events to a large number of investors and neither announcement should be wholly ignored. Column 3 of Table 2 measures $surprise_{t-1}$ using the equal-weighted mean of all firms that announced in the previous day and were above the 90th percentile of market capitalization. We estimate a significant β_1 of -0.896. Finally, Column 5 uses the value-weighted mean of the earnings surprise of all firms that announced yesterday, leading to a significant β_1 of -0.781. This value-weighted measure implicitly assume that the relative market cap of large firms that announced on $t-1$ is a good proxy for the relative salience of their announcements.

In the even-numbered columns of Table 2, we add year-month fixed effects and find that the estimates drop slightly in magnitude, but remain highly significant, suggesting that aggregate time trends cannot explain our results. In later tables, we use the value-weighted salient surprise with year-month fixed effects in Column 6 as our baseline specification.

[3] Average market capitalization has increased over time. To avoid overweighting observations simply because they occur in more recent years, we scale market capitalization by the average in each year. In untabulated results, we find that omitting this scaling leads to materially similar results.

Using the estimated β_1 of -0.721 from Column 6, we estimate that an increase in yesterday's salient earnings surprise from the average earnings surprise in the worst decile (-0.22%) to the average in the best decile (0.37%) is associated with lower returns of 43 basis points. To get a sense of magnitudes, we can compare this result to one of the more robust anomalies in asset pricing: the earnings announcement premium (Frazzini and Lamont, 2007; Barber et al., 2013). With no information other than the fact that earnings will be announced on a given day (typically known well in advance of the date), an equal-weighted strategy going long stocks with earnings announcements earns abnormal returns in our sample of about 10 basis points on the day of announcement and 17 basis points from $t-1$ to $t+1$. Thus, the impact of contrast effects is of a similar magnitude to, if not greater than, other well-known return anomalies related to earnings announcements.

Table 2 shows the regression analog to the local linear plot in Figure 1, Panel A, which we discussed in the Introduction. The figure shows that contrast effects induce a negative relation between the return reaction to today's earnings surprise and yesterday's salient surprise. We can alternatively visualize contrast effects as a vertical shift in the typical return response to a given level of the firm's own earnings surprise. In Figure 3, Panel A, we graph the value-weighted average return response on the y-axis against the earnings surprise announced on day t on the x-axis. The figure shows that when a firm announces better news it tends to experience higher returns.

In Panel B, we show how $surprise_{t-1}$ shifts the normal return reaction to the firm's own earnings surprise. In blue, we show the return response for firms that announce following a very positive $surprise_{t-1}$ (top decile). The red line shows the return response for firms that announce following a very negative $surprise_{t-1}$ (bottom decile). Unsurprisingly, for both groups, there is a strong positive relation between a firm's returns around announcement and the firm's own earnings surprise. More importantly, the figure shows that the blue line lies consistently below the red line, demonstrating that the return response to a firm's own earnings surprise is shifted down significantly if yesterday's surprise was in the highest decile as compared to the lowest decile. The figure also shows that the magnitude of the contrast effect is fairly uniform across the support of earnings surprises released today. In other words, very good salient surprises yesterday makes all earnings surprises today look less impressive, and the magnitude of this difference does not differ substantially based on the level of surprise released today.

Overall, we find empirical results strongly consistent with the main prediction of the contrast effects hypothesis. In the next three sections, we present additional evidence in support of contrast effects.

2.2 Lead and lag effects

Previous tests of contrast effects in laboratory or non-financial settings have shown that subjects tend to contrast the current observation with the observation that occurred directly prior rather than other earlier observations. For example, in the context of speed dating, Bhargava and Fisman (2014) finds that the appearance of the person whom you spoke with directly prior to the current person has a large impact on the current dating decision, but that this effect is limited to the prior subject only. Thus, if a similar type of contrast effect accounts for the pattern that we observe in Table 2, the effect should be strongest for salient surprises that occurred at day $t-1$, and weaker for those on days $t-2$ and $t-3$.

The first column of Table 3 Panel A examines this hypothesis by adding further lags of surprises on $t-2$ and $t-3$ to our base specification. To ensure that our return measure allows for a response to information covering the entire time period (see Section 3), we examine the characteristic adjusted return from $t-3$ to $t+1$ as the dependent variable.

We find a strong and significant negative relation between the previous day's salient surprise and the return response to firms announcing today. Meanwhile, we find very little relation between returns and earlier surprises on $t-3$ and $t-2$. The pronounced negative correlation with respect to $t-1$ is also inconsistent with most alternative explanations of the empirical results (explored in later sections). These other explanations do not predict that the specific short-term ordering of past earnings announcements will impact the return reaction. Thus, the results support the hypothesis that contrast effects are responsible for the strong negative coefficient found on the $surprise_{t-1}$.

Next, we examine how return reactions to firms announcing today are affected by future surprises announced on days $t+1$ and $t+2$. We use characteristic adjusted returns from $t-1$ to $t+2$ as our dependent variable, to allow for the return reaction of a company that announces on day t to respond to these future earnings announcements. While our empirical specification allows for such an effect, it may be less likely to occur because it would require that investors revise their initial perceptions of day t announcements in light of subsequent earnings announcements released in the following two days. In Column 2 of Table 3 Panel A, we find no significant relation as the coefficients on the surprises at $t+1$ and $t+2$ are small, vary in sign and are insignificant.

Almost any empirical exercise involves the worry that there is a mechanical relation due to specification choice. In addition to providing a test for the transitory nature of contrast effects, Table 3 Panel A Columns 1 and 2 offer a placebo test for this concern. If the negative coefficient on $surprise_{t-1}$ is mechanically due to our choice of specification, then the coefficients on $t-2$ or $t+1$ should be similarly biased. Given that we do not find such a relation, we feel confident that our empirical choices are not mechanically driving the result.

2.3 Same-day contrast effects

The analysis presented so far has examined contrast effects across consecutive days. We can also examine contrast effects within the same day. We present the following analysis as supplementary evidence to our baseline estimates because data on the within-day timing of earnings announcements is only available for announcements after 1995. Further, some firms do not preschedule the exact hour of announcement even though they do pre-commit to the exact date of announcement.

Nevertheless, we can explore whether the within-day data support the contrast effects hypothesis. We use the fact that firms generally announce earnings either slightly before market open or slightly after market close. We expect the earnings surprises of large firms that announce in the morning to have a negative impact on the return response for firms that announce later in the afternoon. Earnings surprises of large firms that announce in the afternoon could also have a negative impact on the (2-day) return response for firms that announce earlier in the morning. While our empirical specification would capture such an effect, it may be less likely to occur because it would require that investors revise their initial perceptions of morning earnings announcements in light of subsequent earnings announcements released in the afternoon.

To explore same-day contrast effects, we first categorize firms as announcing before market open (prior to 9:30 am) or after market close (after 4:00pm).[4] We measure the salient earnings surprise as described previously, but with two changes. First, for each day t, we calculate two salient surprises: the surprise of large firms that announced before market open ($AM\ surprise_t$) and the surprise of large firms that announced after market closure ($PM\,surprise_t$). Second, for our return measure we examine the return measured from the close on $t-1$ to the close on $t+1$ as this window includes both the response to the AM or PM surprises as well as the response to the firm's own announcement (as discussed in later sections, this return window helps to rule out an information transmission story involving positive correlation in same-day news).

We start by regressing the returns of firms that announce their earnings after market close on $AM\,surprise_t$, with the same controls described in Equation 3. Table 3 Column 3 shows a coefficient of -1.29 on the AM surprise variable. This same-day measure of contrast effects is slightly larger than the across-days measures estimated in earlier tables. Thus, if anything, the contrast effect is slightly larger when measured intra-day than when measured across days.

Next, we explore whether PM surprises have a negative impact on the return response for firms that announce earlier in the morning. Note, the return window (which extends to $t+1$), does not preclude such an effect as investors could revise their response to morning announcements due to new information released in the afternoon. If, on the other hand, investors only perceive information relative to what was viewed previously, and do not revise their valuations, then we should find no effect of PM surprises on return reactions to morning announcements. In Column 4 of Table 3 Panel A, we find a negative but small and insignificant coefficient on the $PM\ surprise_t$. Thus, within the same day, investors exhibit behavior consistent with contrast effects, but only significantly with respect with previously observed salient surprises.

[4]We exclude firms announcing in the interim time period (roughly 8% of the value-weighted average of firms).

2.4 Long run reversals

If contrast effects are a psychological bias that leads to mispricing, then the negative coefficient on $surprise_{t-1}$ represents a deviation from the fundamental return response to a firm's earnings news. This mispricing should reverse over time if prices eventually converge to fundamental value. Table 3 Panel B examines the return patterns subsequent to the earnings announcement and finds evidence consistent with contrast effects causing mispricing that is reversed in the long run. All columns in the table estimate our baseline specifications, using different return horizons as our dependent variable. The first column examines the characteristic adjusted return from $t-1$ to $t+1$ while Column 2 examines the return from $t+2$ to $t+25$. Over this period we see that the large negative coefficient in Column 1 is reversed slightly. As indicated by Column 3, which examines the return from $t-1$ to $t+25$, the overall contrast effect is still apparent but no longer statistically significant. Extending the window further, Column 4 shows that from $t+2$ to $t+50$, there is large and significant return reversal relative to the original change in prices from $t-1$ to $t+1$. If we include the initial announcement period as in Column 5, we find that $surprise_{t-1}$ has a close-to-zero impact on long run returns from $t-1$ to $t+50$. This suggests that contrast effects leads to mispricing that is fully reversed within the next couple of months after the earnings announcement.

3 Information transmission

While our empirical findings are consistent with the theory of contrast effects, one may be concerned that information transmission from the earlier earnings announcement might account for the empirical patterns we observe.[5] We use a simple example to discuss the implications of various theories of information transmission. For this example, assume that firm A announces a positive earnings surprise on day $t-1$ and firm B is scheduled to announce earnings on day t. Our empirical evidence implies that following A's positive surprise, B is likely to experience low returns conditional on its actual earnings surprise. Can information transmission explain this empirical pattern?

[5] For example, Anilowski, Feng, and Skinner (2007) and Barth and So (2014) study "bellwether" firms whose news convey information about other firms.

We begin by showing that an information transmission story involving *positive* correlation in news cannot explain our results. If there is positive correlation in news, then A's positive surprise is good news for B (e.g., good news for B's earnings or future investment opportunities). If so, B should experience positive returns on day $t-1$ when this good news is released. Then, B might experience lower returns on day t for a given level of earnings surprise (measured using analyst forecasts made prior to $t-1$) because its good news was released early, on day $t-1$. However, A's positive surprise should not negatively affect B's *cumulative return* from $t-1$ to $t+1$. Our results cannot be explained by positive correlation in news because our analysis uses B's cumulative returns (measured starting at market close in $t-2$, before A announces). Positive correlation in news implies a positive correlation between $A's$ surprise and B's cumulative returns, not the negative relation we observe in the data.

Thus, for information transmission to explain our results, there must be *negative* correlation in news, so A's positive surprise is bad news for B (e.g., A competes with B for resources). A negative correlation in news could generate a negative empirical relation between A's surprise and B's cumulative return. However, we show that negatively correlated information transmission, or information transmission of any form, is unlikely to account for our results for two reasons. First, we show that $surprise_{t-1}$ does not predict day t earnings surprises after accounting for slower moving time trends. Second, markets do not react as though negatively (or positively) correlated information is released on day $t-1$ through the salient surprises of other firms.

In Table 4 Panel A, we examine whether $surprise_{t-1}$ predicts the earnings surprises of firms scheduled to announce in the following day. Column 1 regresses the earnings surprise on day t (i.e., the surprise relative to analyst forecasts made on or before $t-2$) on the salient surprise released on day $t-1$. We find that there is a positive and significant relation. However, Column 2 indicates that this is wholly driven by slower-moving time variation. The correlation disappears after we control for year-month fixed effects. Columns 3 and 4 utilize bin measures of surprise (rather than the level measure used in the first two columns) to ensure the results in Columns 1 and 2 are not driven by outliers or the specific scaling. We again find no relation once monthly time variation has been accounted for. Patterns in surprises are related to fluctuations in slow-moving general economic conditions, not the day-to-day fluctuations in earnings surprise.

These results show that A's earnings surprise does not predict B's earnings surprise. Therefore, if A's positive surprise contains negative news about B, it must contain negative news about B's prospects other than just B's earnings.[6] If markets are efficient, then B's stock price should decline on $t-1$ when this information is first released. In Panel B of Table 4, we test whether the market responds as if the salient surprise on day $t-1$ conveys information for the firm scheduled to release earnings on day t. In Columns 1 and 2 (with and without year-month fixed effects), we find no significant relation between $suprise_{t-1}$ and the $t-1$ returns of firms that will announce the next day. Columns 3 and 4 examine open-to-open returns to make sure that we account for market reactions to earnings released after market close on $t-1$. The results are materially unchanged. There is no evidence of either positively or negatively correlated information transmission. The market does not behave as if there is information released by firm A that is relevant for firm B on day $t-1$.

In the previous table, we found insignificant and close-to-zero estimates of information transmission. However, the analysis could be aggregating a subsample in which information is transmitted with other cases where no information is transmitted, thereby adding noise to the analysis and attenuating our estimates. To check that our results are not driven by a subsample of observations where the market believes information is transmitted, we look at cases for which the market reacted as if no information was transmitted in $t-1$. In this sample, we expect to find no evidence consistent with contrast effects if the results are actually driven by information transmission.

In Columns 1 and 2 of Table 5, we examine only firms that announce on day t with a characteristic adjusted return of less than 1% in absolute magnitude on day $t-1$. Within this subsample, in which close-to-zero information is transmitted on day $t-1$, we continue to find a significant negative relation between cumulative returns around announcement and the $t-1$ salient surprise. We estimate a coefficient of -0.627 for $suprise_{t-1}$, which is very close to the -0.721 we find when

[6] A secondary reason why A's positive surprise must contain negative news about B's prospects other than just B's earnings to match our results is that we directly control B's earnings surprise relative to previous analyst forecasts in our baseline regressions. If A's surprise only revealed information about B's earnings surprise, we should estimate a zero coefficient on yesterday's salient surprise after controlling for B's actual earnings surprise.

examining the entire sample. Column 2 repeats the analysis for firms where the return reaction on $t-1$ was even smaller, at less than 0.5% in absolute value and finds a similar pattern. Finally, in Column 3, we restrict the sample to observations for which no *negatively* correlated information was transmitted on $t-1$ (i.e., we exclude negative return reactions to positive salient surprises and positive return reactions to negative salient surprises). We focus on negatively correlated information transmission because positively correlated information predicts the opposite empirical pattern for cumulative returns to that observed in the data. We again find similar results using this limited sample. Altogether, we show that limiting the sample to observations where the market reacts as if no information, or no negatively correlated information, was released on day $t-1$ yields similar results to the rest of the sample. This suggests that we are capturing contrast effects rather than information transmission with our empirical tests.

At this point, one may still be concerned that *delayed* reaction to information transmission could explain the empirical results. A's $t-1$ positive earnings surprise may contain negative news for B, but the market does not react to this information until t. Rational investors may react with a delay if the interpretation of A's news for B's prospects depends on the level of B's earnings surprise. For example, A's good news may be bad news for B, but only if B's own earnings surprise is high. We test for such interaction effects in Table 5 Panel B by interacting $suprise_{t-1}$ with various measures of the firm's own earnings surprise: the raw level, 20 bins, and quintiles for the firm's own earnings surprise. In each of the three specifications, we find no evidence of strong interaction effects. Further, we continue to find a negative direct relation between returns and the previous day's salient surprise, even after we allow for interaction effects. These results show that yesterday's salient surprise negatively impacts the returns reaction to today's earnings announcement, and the extent of this distortion does not depend significantly on the level of today's earnings surprise.

Absent the interaction effects, boundedly rational investors may still react to A's information about B with a delay because investors do not think about firm B until day t when B becomes more salient due to news coverage surrounding its earnings announcement. Note that this type of delayed reaction is only a concern if A's $t-1$ news is negatively correlated with news for B (positive correlation would predict the opposite relation to what we observe in the data). In addition, delayed information transmission is only a concern if A's news contains news about B's prospects other than B's earnings (if A's earnings news simply provided information for what B's earnings surprise will be at t, this predicts a zero relation between A's earnings surprise and B's cumulative return after controlling for B's actual earnings surprise).

Delayed reaction and information transmission more generally are also inconsistent with two important features of the data. First, we find that return reactions are distorted by salient surprises in $t-1$, but not by slightly earlier surprises in $t-2$ or $t-3$. If previous announcements convey information, one would expect similar effects for these earlier surprises. Second, any information transmission, delayed or not, should not lead to long-run reversals. Our finding of long run reversals is more consistent with corrections of mispricing induced by contrast effects bias.

Altogether, we show that most plausible variants of the information transmission story cannot explain our results. While it is impossible to rule out all information stories, what remains is a very specific and complex information transmission story which must contain the following elements:

1. $A's$ $t-1$ positive surprise must contain negative information for B.
2. The negative information relates to B's prospects other than just B's earnings.
3. $B's$ returns reaction does not depend on the interaction between $A's$ surprise and B's surprise, so rational investors should not wait until day t to react to information released on day $t-1$. Nevertheless, the market does not react to this information until day t.
4. When the market does react to this information on day t, it reacts in a biased manner, leading to a long run reversal.
5. The relevant information for firm B is only contained in $t-1$ salient surprises, but not in earlier salient surprises released on $t-2$ or $t-3$.

While this complex information transmission explanation is impossible to reject, we feel that our contrast effects hypothesis offers a more parsimonious explanation of the empirical results that is based on a well-known and intuitive psychological phenomenon.

4 Contrast effects without conditioning on today's surprise

So far, we have shown that the return response to a given earnings announcement is inversely related to yesterday's salient earnings surprise, *conditional* on the level of surprise today. Controlling for the firm's own earnings surprise in our baseline regression primarily serves to increase the explanatory power of the regression and reduce noise in the estimation procedure. In general, we showed in Section 3 that the earnings surprise of the firm announcing on day t is not correlated with the earnings surprises of other firms released in the previous day, after controlling for slower moving time trends. Therefore, we should continue to find a negative relation between the return response to a given earnings announcement and yesterday's salient earnings surprise, *unconditional* on the firm's own surprise today. Omitting the firm's own earnings surprise as a control variable should lead to more noise in our regression fit, but should not systematically bias the coefficient on $surprise_{t-1}$.

Table 6 Panel A presents results without controlling for the announced earnings surprise. We continue to find a robust negative coefficient on yesterday's salient surprise, although the R^2 decline as expected. Column 1 examines the impact without year-month fixed effects and finds a coefficient of -0.481 while Column 2 adds the fixed effects and finds a coefficient of -0.757. The numbers are not statistically different than the results where we controlled for the announced level of earnings surprise in Table 2 Columns 5 and 6. Figure 2 Panel B shows the graphical analogue of these tests using a local linear regression. Similar to the pattern in Panel A, we see a strong negative relation between $surprise_{t-1}$ and the characteristic adjusted return response to the earnings announced on day t.

One important implication of not conditioning on a firm's announced earnings surprise is that there is no longer a look-ahead bias when we examine the return response. We can predict day t and future returns using information available on day $t-1$. Thus, it would be possible to trade based on the magnitude of the previous day's salient earnings surprise and earn predictably higher or lower returns on firms that release earnings the next day. To accurately measure return responses without any look-ahead bias, we modify our regression specification slightly. First, we exclude year-month fixed effects because they are estimated using future days within the same month. Second, we change our return window from $[t-1, t+1]$ to $[t, t+1]$ so it does not include returns on $t-1$. Finally, we move from close-to-close returns (the conventional return measure in the finance literature) to open-to-open returns. To implement a strategy using close-to-close returns, one needs to know $surprise_{t-1}$ as of market close on day $t-1$. However, many firms announce earnings immediately after market close. To make our regression more closely resemble a trading strategy without lookahead bias, we examine returns from market open to market open (calculated as in Lou, Polk, and Skouras, 2015).

Table 6 Panel A shows that our results are similar using these adjustments. The odd-numbered columns exclude year-month fixed effects. Column 3 and 4 examine open-to-open returns from $t-1$ to $t+1$ while Columns 5 and 6 limit the return period from t to $t+1$. We estimate coefficients of -0.672 without year-month fixed effects and -0.898 with year-month fixed effects, both highly significant. If anything, the return results are larger when the returns examined are actually tradable.

This finding is also shown in graphical form in Figure 4. In Panel A, the maroon line represents the average cumulative characteristic adjusted returns of a simple strategy that buys firms announcing earnings today if the salient surprise in $t-1$ was negative. The navy line represents the cumulative returns of a strategy that buys firms announcing earnings today if the salient surprise in $t-1$ was positive. We find that the maroon line lies above the navy, indicating that it pays to buy firms announcing today if yesterday's salient surprise was negative. Panel B examines return reactions following more extreme salient surprises released on $t-1$ (above the 75th percentile or below the 25th percentile based on the distribution of $surprise_{t-1}$ in the previous quarter). The gap between the maroon and navy lines increases and we find that the average return after announcement is significantly higher when $surprise_{t-1}$ was in the lowest quartile than when $surprise_{t-1}$ was in the highest quartile.

As discussed earlier, we usually observe positive returns on earnings announcement days. This is the earnings announcement anomaly, as shown in Frazzini and Lamont (2007) and Barber et al. (2013). The magnitude of the coefficients in Table 6 and the fact that the navy line in Figure 4 is not significantly positive shows that contrast effects are strong enough to counteract the impact of the earnings announcement premium.

As a final robustness check, we examine whether it is possible to construct a calendar-time trading strategy based on contrast effects that generates abnormal returns. The purpose of this trading strategy is not to find the maximum alpha attainable to traders, but rather to show the robustness of our results to a different specification. Calendar time asset pricing offers a different risk adjustment than the characteristic adjusted returns used elsewhere in the paper. In addition, the trading strategy uses daily diversified value-weighted portfolios that more closely resemble what investors might hold. The strategy equal-weights trading days (and value-weights multiple earnings announcements within the same day) while the baseline regressions value-weight each earnings announcement.

The trading strategy is a daily long-short strategy. On days where the salient surprise at $t-1$ was low (below a certain cutoff), we buy firms scheduled to announce on day t and short the market, holding this portfolio for days t and $t+1$. On days where the salient surprise at $t-1$ was high (above a certain cutoff), we go long the market and short firms scheduled to announce on day t. Again, we hold this portfolio on days t and $t+1$. Each daily portfolio is value-weighted based upon the market capitalization of the firms announcing earnings on each day. Following the asset pricing literature which assumes that investors will only invest if they are able to diversify their holdings across several firms, we require at least five stocks to announce per day for the strategy to be active in Columns 1 and 2. We relax this restriction in Columns 3 and 4. We focus our trading strategy on large firms in the top quintile of the market that account for our findings (see Table 9). We utilize Fama-French regressions in which portfolios returns are regressed on the market, size, book to market and momentum factors.

Table 6 presents the results. First, we examine the trading strategy utilizing the cutoff of zero: if $surprise_{t-1}$ is not positive, we go long firms that announce earnings on day t and short the market.

If $surprise_{t-1}$ is positive, we short announcers on day t and go long the market. We find a significant daily alpha of 11 basis points. Next, we use more extreme cutoffs in forming our portfolios and go long when $surprise_{t-1}$ is below the 25th percentile (relative to the distribution of salient surprises in the previous quarter) and short if $surprise_{t-1}$ is above the 75th percentile. With these more extreme cutoffs, we expect contrast effects to be more pronounced. Consistent with this, we see a larger daily alpha of 20 basis points with a t-statistic greater than 3. In Columns 3 and 4 we allow portfolios with fewer than five stocks per day, which increases the exposure to idiosyncratic risk, but allows an increase in the number of days in which the trading strategy can be implemented. We see a similar pattern with slightly lower alphas for both choices of cutoffs.

We can compound these daily alphas to estimate the annual alpha of a contrast effects trading strategy (shown in the bottom row of the table). If the trading strategy could be implemented every trading day, 15 basis points per day would yield an annual abnormal return of nearly 45%. However, firms tend to cluster earnings announcement around earnings seasons and not all trading days contain earnings announcements. The trading strategy can only be implemented if there exists a non-missing salient surprise in the relevant cut-off categories in the previous trading day. For example, in the first column which assumes that investors only trade when they are able to diversify across five or more stocks, we can implement the strategy an average of 51 trading days per year (roughly 20% of total trading days) which yields an abnormal annual return of 6%. The slightly lower alphas from the last two columns of Table 6 can be earned on more trading days per year, leading to higher annual abnormal returns of between 11% to 13%.

5 Strategic timing of earnings announcements

Previous research has shown that firms may advance or delay their earnings announcements relative to the schedule used in the previous year or manipulate the earnings announcement itself (e.g., through adjustment of discretionary accruals). However, these types of strategic manipulation will only bias our results *if they alter firm earnings announcements as a function of the earnings surprises* *released by other firms on day* $t-1$. Such short-run manipulation within a single trading day is unlikely to occur. Firms typically publicly schedule when they will announce their earnings more than a week before they actually announce (Boulland and Dessaint, 2014). The earnings *surprises* of other firms are, by definition, difficult to predict because they measure surprises relative to expectations. Therefore, it is unlikely that firms can strategically schedule to follow other firms with more or less positive surprises. Further, manipulation of the earnings number itself takes time and is unlikely to occur within a single day as a reaction to the earnings surprises made by other firms on day $t-1$.

To directly test strategic timing, we separately examine earnings announcements that moved or stayed the same relative to the calendar date of the announcement for the same quarter in the previous year. Firms typically report their earnings on roughly the same day every year, with small changes, e.g., to announce on the same day of the week (So, 2015). Thus, in order for strategic timing to explain our results, it must be the firms that deviate from their normal earnings announcement date that drive our results. We follow So (2015) and examine the calendar date a firm announces its earnings versus the firm's announcement date for the same quarter one year ago. We categorize firms as having moved their earnings date forward or backwards if it differs from their previous same-quarter date by five or more days. We find roughly 80% of firms keep the date the same, 10% move it forward by more than 5 days and 10% move it backwards.

We examine these sets of firms in Table 7 Panel A and find that strategic timing cannot account for the negative relation between return reactions and salient surprises at $t-1$. Firms that did not greatly move their announcement date have a large negative coefficient of -0.778 that is statistically significant at the 1% level. Firms that moved their announcements forward or backwards have insignificant estimates of contrast effects with large standard errors. Under the strategic timing hypothesis, we should have found that firms that shifted their earnings announcement data accounted for the negative relation, while firms that kept their normal announcement dates displayed no significant relation. Instead, we observe the opposite pattern.

6 Risk and trading frictions

Another possible concern is that firms become more exposed to systematic risk factors based on the earnings surprise announced by other firms the previous day. Because our analysis uses characteristic adjusted returns, differences in firm-specific stable loadings on standard risk factors are unlikely to explain our results. In order to account for our results, it must be that the previous day's salient earnings surprise shifts a firm's exposure to risk on its announcement day. A more negative surprise yesterday leads to higher loadings on risk factors today, and then investors demand a higher return as compensation for the increased risk.

Table 7 Panel B tests for such a channel. We modify our base specification so the characteristic adjusted return is regressed on four factors (market excess return, SMB, HML, and momentum) along with interactions of those factors with $surprise_{t-1}$. The emphasis of this test is on the interaction term. If a firm's covariation with market factors is systematically larger when there are more negative surprises on the previous day, we would expect to see large negative coefficients for these interaction terms. Examining characteristic adjusted returns in Column 1 and raw returns in Column 2, we find no support for this hypothesis. Only one coefficient is marginally significant, but it is positive, and only one of the eight estimates is directionally negative. Thus fixed or time-varying loadings on standard risk factors are unlikely to account for our results.

Another possible concern is that our findings are due to a liquidity premium. For a liquidity premium to explain our results, it must be that a more negative salient surprise yesterday predicts lower liquidity for firms announcing today, so that the the higher return is compensation for the lower liquidity. In Table 7 Panel B, we show that yesterday's salient surprise does not appear to be correlated with today's volume or bid-ask spread, two proxies for liquidity.[7]

An alternative version of a liquidity story relates to capital constraints. Suppose there is limited capital to be invested in the purchase of stocks and on day $t-1$, a firm releases especially good

[7] In addition to our standard set of control variables, we also include firm fixed effects to account for the substantial heterogeneity in liquidity across different firms. The firm fixed effects means that we are identifying changes in within-firm announcement day liquidity as a function of variation in the salient earnings surprise released by other firms in the previous day.

news. Capital may flow into this firm, so that there is less capital available to invest in other firms, leading to a lower price response when a firm announces at t. We first note that this story is unlikely to apply in our context because even a large firm announcing on $t-1$ will be small relative to the substantial amount of liquid capital invested in US large cap stocks. We can also test this story directly. A capital constraints story implies that there should be lower returns for all other firms, not only for the firms announcing on day t. In untabulated results, we find that, if anything, there is a positive correlation between the $surprise_{t-1}$ and the market return (excluding firms announcing on days $t-1$ and t) which suggests that liquidity issues due to limited capital do not account for the results.

Finally, we check that our results cannot be explained by a risk premium associated with tail risk. For example, if a lower salient surprise in $t-1$ leads to greater crash risk for firms scheduled to announce on day t, rational investors will demand a premium to compensate them for this crash risk. Figure 5 shows the distribution of returns for the highest and lowest quintile of $surprise_{t-1}$. There does not appear to be a significant difference in either tail of the two distributions, suggesting that the empirical results are not be explained by a rational fear of extreme negative returns based on the previous day's salient surprise.

7 Robustness and heterogeneity

7.1 Alternative measures

This section examines whether our results are robust to alternative choices in the construction of the variables used in the baseline analysis. One concern is that analyst forecasts may not represent market expectations (because they are stale or because analysts are biased or uninformed). If so, our measure of $surprise_{t-1}$ may not capture true market surprise. Therefore, we utilize an alternative measure, the value-weighted $[t-2, t]$ characteristic adjusted return for large firms that announced on day $t-1$. Our returns-based measure of the salient surprise on $t-1$ is:

$$return\ surprise_{t-1} = \frac{\sum_{i=1}^{N}\Big(mkt\ cap_{i,t-4} \times char.\ adj.\ return_{i,[t-2,t]}\Big)}{\sum_{i=1}^{N} mkt\ cap_{i,t-4}} \tag{4}$$

Table 8 Panel A Column 1 uses this measure and finds a similar result as in our baseline. We find a significant coefficient of -0.051 on the new $return\ surprise_{t-1}$ measure. The average return response in the lowest and highest deciles of salient return surprise is -3.9% and 4.3%, respectively. Thus, an increase from the lowest to the highest decile for $return\ surprise_{t-1}$ is on average associated with a decrease in returns of 42 basis points.

In Table 2, firms above the 90th percentile of market capitalization were used to calculate $surprise_{t-1}$. To examine the robustness of the results to the choice of the size cutoff, Columns 2 and 3 of Table 8 Panel A measure yesterday's value-weighted average surprise using all firm's above the 85th and 95th percentiles of market capitalization, respectively. Both measures yield similar values to the measure using the 90th percentile cutoff. The next column value-weights all firms that announced earnings on $t-1$ in the calculation of the salient surprise, regardless of market capitalization. This causes the coefficient on salient surprise to decrease in absolute magnitude, although it remains significant. The reduced magnitude is consistent with the earnings announcements of small firms yesterday receiving less attention and being noticed by fewer people. Including smaller firms in the measure of salient surprise may add noise to the estimate of what yesterday's salient earnings surprise actually was.

As discussed earlier in Section 1.1, our main analysis uses I/B/E/S dates which, in the early years of our sample, sometimes records the date when the earnings announcement was first published in the Wall Street Journal rather than when the information was released through other means (usually one day earlier). Our goal is to capture when investors pay attention to earnings announcements. Especially in the early years of our sample (which contain the bulk of the errors), the Wall Street Journal publication date as listed in I/B/E/S may be a better measure of when each firm's earnings announcement became most salient. In Column 5 of Table 8 Panel A, we show that our results are very similar utilizing the alternative DellaVigna and Pollet (2009) date correction, which compares the announcement date listed in I/B/E/S with that in Compustat.[8]

Until this point, all analyst-based measures of earnings surprise have been constructed with forecasts from $t-15$ to $t-2$. The first two columns of Table 8 Panel B measure earnings surprise using analyst forecasts from $t-30$ to $t-2$ and from $t-45$ to $t-2$. Including more stale forecasts causes the coefficient on salient surprise to decline in absolute magnitude to -0.534 and -0.348, respectively. These results are consistent with more stale forecasts being worse measures of the actual earnings surprise, although the results also reflect the inclusion of a number of small firms with one forecast occurring more than 15 days before their announcement.

In Column 3, we scale $surprise_{t-1}$ by the sum of the squared size weights of each firm comprising the weighted-mean calculation. The accounts for the fact that the weighted average over a greater number of firms has a smaller standard deviation. We find materially similar results. Finally, in Column 4, we equal-weight each observation. In all previous results, we value-weighted regressions using the $t-3$ market cap of the firm announcing earnings today. Using equal-weights, we find a negative but insignificant coefficient on $surprise_{t-1}$. This is consistent with later results in Sections 7.2 and 7.3, in which we show that our measure of contrast effects is driven by investors comparing the earnings surprises of large firms to those of other large firms. Contrast effects also strongly affect the return response for smaller firms, but the comparisons primarily occur within an industry.

7.2 Size and analyst coverage

In our baseline analysis, we focus on large firms both in terms of the measure of yesterday's surprise and in terms of weighting observations for firms announcing earnings today (all regressions are value-weighted unless otherwise noted). We focus on earnings surprises released by large firms in

[8]For the DellaVigna and Pollet (2009) date correction, we only include announcements contained in both datasets where the date is the same or is different by no more than one trading day. We then use the following rules: 1) If I/B/E/S has a time stamp for the time of the announcement within the day, we use the I/B/E/S date. 2) If the announcement dates in Compustat and I/B/E/S agree, we use this date if it is on or after January 1, 1990 and the previous trading date if it occurred prior to January 1, 1990. 3) If the Compustat date is the trading day before the I/B/E/S date, we use the Compustat date. 4) If the I/B/E/S date is the trading day before the Compustat date, we use the I/B/E/S date.

$t-1$ because their earnings surprises are likely to be more salient to investors. In Table 9, we explore how the magnitude of the contrast effect varies with the size of the firm releasing earnings today. The first column breaks the coefficients down by size quintile of the firm releasing earnings on day t. We find that the smaller quintiles have the expected negative coefficients, but these coefficients are smaller in magnitude and insignificant, while the largest (fifth) quintile is driving the results. Our findings are not driven only by small firms as is the case with many other asset pricing anomalies.

However, it is important to note that these results do not prove that contrast effects are weak for small firms. Rather, we could measure strong contrast effects for large firms announcing today because investors tend to contrast large firms releasing earnings today with other large firms that released earnings yesterday. Investors of smaller firms may tend to contrast the earnings of small firms with that of other similar firms that released earnings yesterday. However, because multiple firms release earnings on $t-1$, it is difficult for us, as econometricians, to identify which firms are salient to investors for each small firm announcing earnings today. This is a point that we explore in detail in Section 7.3, where we show that contrast effects are sizable and significant for smaller firms once we look within industries.

The second column explores heterogeneity in the number of analysts covering firms that release earnings today. In general, the more interest the market has in a given firm, the more analysts will cover that firm's earnings announcement. We examine contrast effects separately for firms covered by one analyst, two analysts, and three or more analysts. We find a monotonic increase in contrast effects of 0.004 for firms with one analyst, -0.661 for two analysts, and -0.825 for three or more analysts. The only statistically significant estimate is that for firms with three or more analysts. These results again show that our findings are not driven by small firms with little analyst coverage. However, we again caution that these results do not imply that investors in firms with little analyst coverage do not suffer from contrast effects. Rather, these investors may contrast these smaller, niche firms with a specific set of other similar small firms that we have difficulty identifying.[9]

[9]We face the additional measurement challenge that the earnings surprises of small firms are measured with greater error because our measure of market expectations is likely to be noisier due to reduced analyst coverage. This implies that we may control for the actual earnings surprises of small firms with more error.

Finally we explore how our results vary over time. We examine the effect separately decade by decade and find that our results have not declined in recent years. The effect grows monotonically from -0.526 in the 1980s, -0.586 in the 1990s, -0.725 in the 2000s, and -0.906 after 2010. While the estimates for each time period are not significantly different from one-another, they do show that our findings are not driven only by the early period of our sample and have, if anything, grown stronger over time. In addition, the large estimate of contrast effects in the 2000s and after shows that our results are unlikely to be driven by date recording errors in the early period in I/B/E/S.

7.3 Industry contrast effects

As discussed in the previous section, while we find stronger evidence of contrast effects among larger firms, it remains possible that contrast effects also strongly affect the returns of smaller firms. Investors may compare smaller firms to a subset of similar firms that announced in the previous day. If so, our baseline empirical specification will underestimate the true magnitude of contrast effects for small firms announcing on day t because we measure the salient surprise in $t-1$ as the value-weighted average of earnings surprises among large firms that announced in $t-1$.

It is difficult to know what the right comparison group is for any firm, but one reasonable possibility is other firms in the same industry. In this section, we explore how contrast effects depend on whether the firms announcing today and yesterday belong to the same industry. We find that contrast effects for large firms are strong both within and across industries, while contrast effects primarily operate through within-industry comparisons for smaller firms.

In Table 10, we modify our baseline specification to include two measures of $suprise_{t-1}$: one based on other firms announcing in the same industry as the firm announcing on day t and one based on other firms in different industries. To form these two salient surprise measures, we continue to use the value-weighted average surprises of firms above the 90th percentile of market capitalization, under the assumption that, even within industry, larger firms are more likely to be more salient.[10] We present results using the very broad Fama French 5 industry classification as well as the slightly

[10]In untabulated results, we find a similar pattern if we expand the definition of salient surprise to allow for the inclusion of smaller firms that announced on $t-1$.

narrower Fama French 12 industry classification.[11] We also caution that companies may be related in a variety of ways that matter to investors, and these relations will be imperfectly captured by any industry classification system. Thus, the results are based on a noisy proxy of what we think investors are paying attention to.

A limited number of large firms (median of 6) announce earnings on $t-1$ and there are usually fewer firms in the same industry as the firm announcing on day t than firms in different industries. This implies that the standard deviation of the different-industry salient surprise will be relatively smaller, as the average of a larger sample has a smaller standard deviation. To make the magnitudes of the coefficients on the $t-1$ salient surprises in the same- and different-industry samples comparable, we scale each salient surprise by the sum of the squared size weights of each firm comprising the weighted-mean calculation. While this scaling makes the coefficients for the same and different industry salient surprises comparable to one another, the magnitude of these coefficients should not be compared to those in other tables. In addition, if no firm announced within the same (different) industry on $t-1$, we set the relevant $surprise_{t-1}$ variable to zero and include a dummy variable equal to one when the same (different) industry $surprise_{t-1}$ is missing for that observation.

Table 10 Columns 1 and 2 modifies our baseline specification to use the two separate measures of salient surprise on day $t-1$. Column 1 is value-weighted by the market capitalization of the firm announcing earnings today while Column 2 is equal-weighted. Thus, Column 1 overweights larger firms relative to Column 2. We find that, when large firms are overweighted, the magnitude of the contrast effect is similar within and across industries. When smaller firms are weighted more heavily as in Column 2, the contrast effect is large and significant only within the same industry and there is a small and insignificant contrast effect for firms in different industries. In Column 3, we allow for different effects for large firms (above median market capitalization) and small firms (below the median) announcing on day t. We find that small firms exhibit a large contrast effect when compared to other firms in the same industry, but not to firms in different industries. The

[11] We do not use more narrowly-defined industry classification systems because a limited set of firms announce earnings on $t-1$. If we use very narrowly-defined industries, we often lack another firm announcing within the same industry.

contrast effect for large firms is approximately equal within and across industries. We find a similar pattern in Columns 3 through 6, when we move from the Fama French 5 to the Fama French 12 industry classification system. However, the differences by firm size are not statistically significant, as indicated by the p-values at the bottom of the table. One possible explanation is that industry classification is a coarse proxy for the comparison groups actually used by investors.

Overall, these results are consistent with a world in which investors in smaller firms pay more attention to previous announcements by other firms in the same industry. Meanwhile, investors in larger firms pay attention to the recent earnings announcements of other large firms, regardless of industry similarity.

8 Conclusion

We present evidence of contrast effects in sophisticated financial markets: investors mistakenly perceive information in contrast to what preceded it. We examine stock price reactions to earnings announcements of publicly-traded US firms. The scheduling of when earnings are to be announced is usually set several weeks before the announcement, so whether a given firm announces following positive or negative surprises by other firms is likely to be uncorrelated with the firm's fundamentals. We find that the reaction to an earnings announcement is inversely related to the level of earnings surprise announced by large firms in the previous day. This implies that market prices react to the relative content of news instead of only reacting to the absolute content of news.

The existing empirical literature on contrast effects comes from laboratory settings and the limited field evidence focuses on households making infrequent dating or real estate decisions. Our results show that contrast effects affect equilibrium prices and capital allocation in sophisticated markets. In this setting, professionals make repeated investment decisions based on earnings announcements and market prices are determined through the interactions among many investors.

Our results suggest that contrast effects have the potential to bias a wide variety of important real-world decisions, including judicial sentencing, hiring and promotion decisions, firm project choice, and household purchase decisions. In addition to causing decision errors, contrast effects may also provide a psychological basis for preferences, such as internal habit formation, that are assumed in many influential models in macroeconomics and finance. Under internal habit formation, individuals value gains in consumption relative to previous experience rather than only its absolute level. These preferences could arise because past high levels of consumption lead individuals to perceive any amount of current consumption as lesser in comparison.

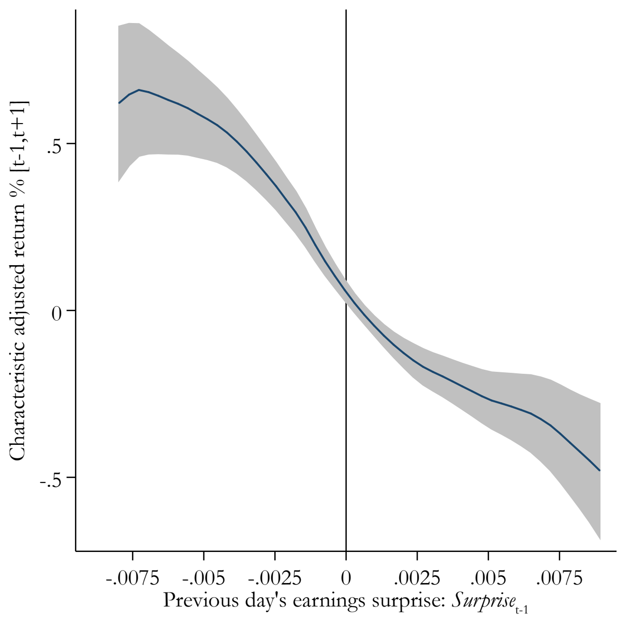
To attain a clean measure of contrast effects, we chose a financial setting in which firms publicly commit to the date of an earnings news announcement several weeks ahead of time. However, our results imply that, in other settings, strategic agents with discretion over the timing of information disclosure may schedule the release of news in order to take advantage of contrast effects bias. For example, a firm with very bad news to release may try to release that news after another firm releases even worse news, so that its own news does not appear very negative in comparison. Such strategic manipulation of market biases may be a promising direction for future research.

Figure 2

Return Reaction to Earnings $Surprise_{t-1}$

This graph shows the relationship between the characteristic adjusted returns from $[t-1, t+1]$ of firms that announced earnings on day t and the salient surprise ($surprise_{t-1}$) announced by other firms on day $t-1$ (calculated as the value-weighted earnings surprises of large firms that announced earnings on day $t-1$), estimated using a value-weighted local linear regression with the optimal bandwidth. We define a "large" firm as a firm with market capitalization at $t-4$ exceeding the 90th percentile cutoff of the NYSE index in that month. Gray areas indicate 90 percent confidence intervals. Panel A reports returns residuals after controlling for 20 bins in terms of the firm's own earnings surprise. Panel B reports unconditional returns without controlling for the firm's own earnings surprise, demeaned by the value-weighted average return in the sample.

Panel A: Conditional on Own Earnings Surprise



Panel B: Unconditional

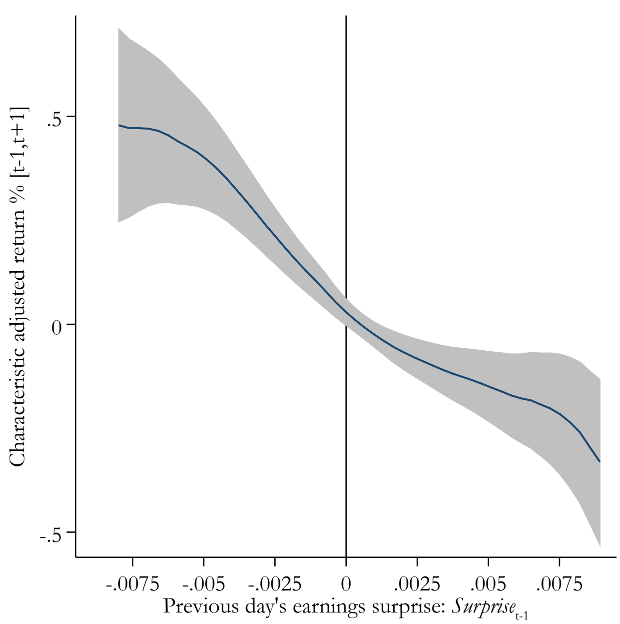
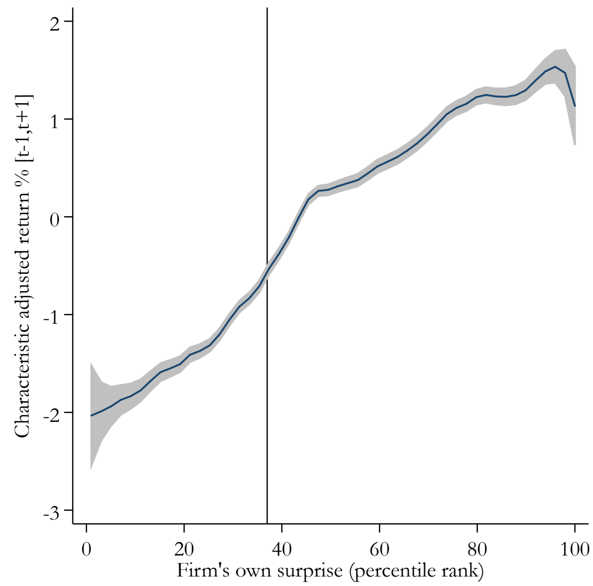


Figure 3
Return Reaction to Own Earnings Surprise

This graph shows the return reaction to a firm's own earnings surprise, and how that varies with $surprise_{t-1}$. Each line plots the value-weighted characteristic adjusted return $[t-1, t+1]$ of firms that announced earnings on day t against the percentile ranks of the the firm's own earnings surprise, estimated using a value-weighted local linear regression with the optimal bandwidth. Panel A examines the entire sample, unconditional on $surprise_{t-1}$. Panel B shows two subsamples: return reactions following $surprise_{t-1}$ in either the lowest or highest deciles. Gray areas indicate 90 percent confidence intervals.

Panel A: Unconditional on $\boldsymbol{Surprise_{t-1}}$



Panel B: Top and Bottom Decile of $\boldsymbol{Surprise_{t-1}}$

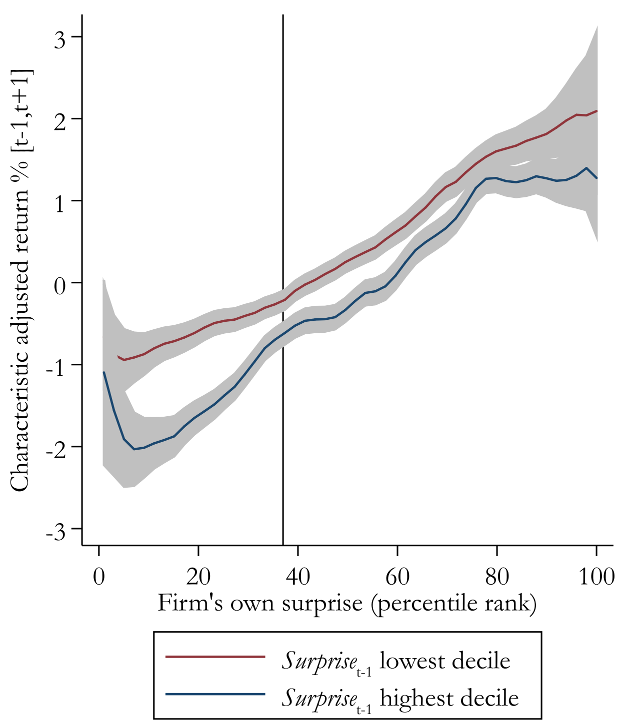
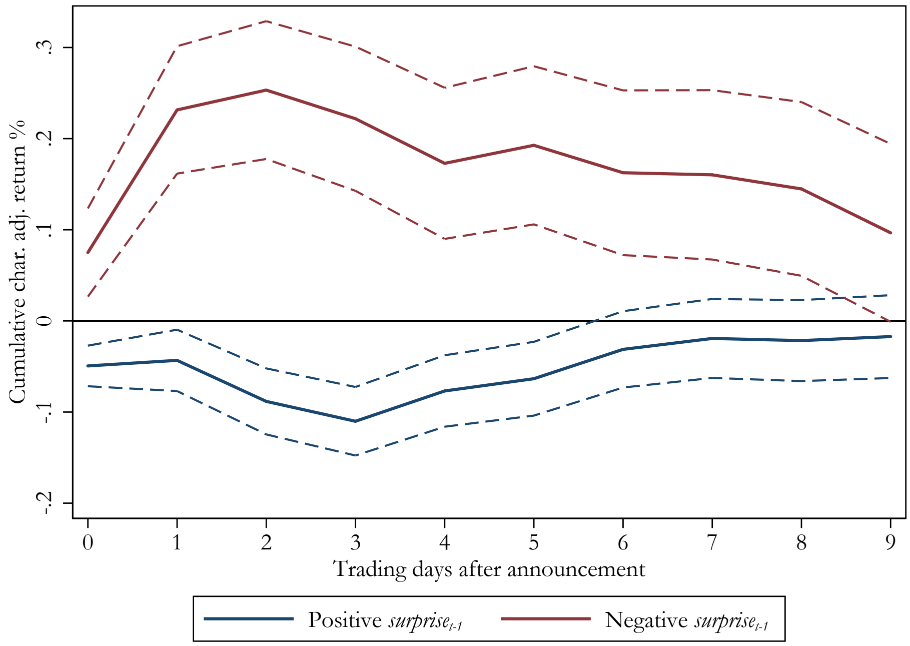


Figure 4
Cumulative Characteristic Adjusted Returns

This graph plots the cumulative value-weighted characteristic adjusted returns starting at market open on day t of firms that announce on day t, conditional on $surprise_{t-1}$. In Panel A, we examine subsamples where $surprise_{t-1}$ was negative or positive. In Panel B, we examine subsamples whether $surprise_{t-1}$ was below the 25th percentile or above the 75th percentile relative to its distribution over the previous quarter. The dotted lines indicate 90 percent confidence intervals.

Panel A: Positive vs. Negative $Surprise_{t-1}$



Panel B: Above 75th Percentile vs. Below 25th Percentile $Surprise_{t-1}$

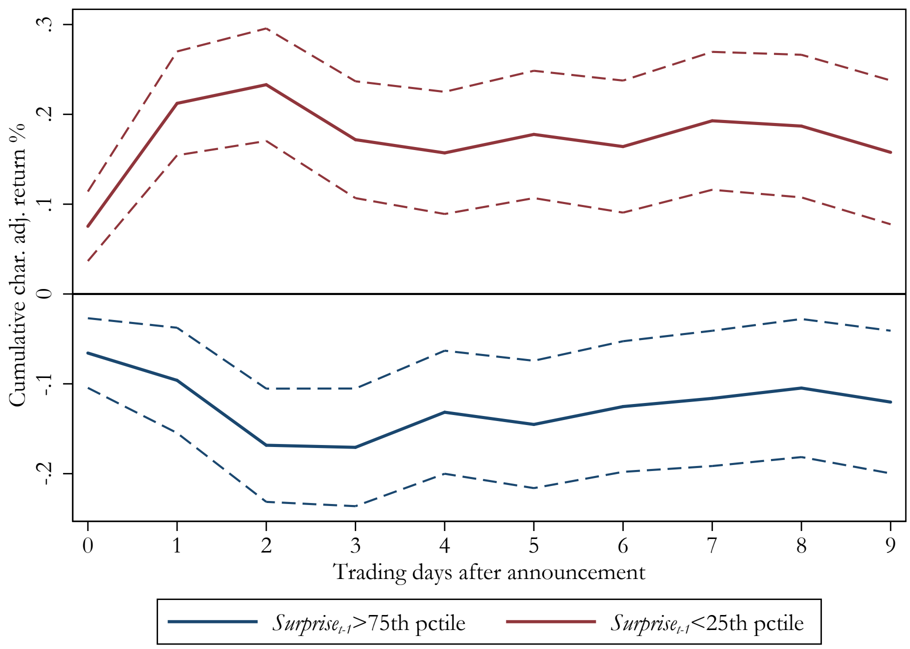


Figure 5
Distribution of Returns by $\boldsymbol{Surprise_{t-1}}$

This graph shows the distribution of characteristic adjusted returns $[t-1, t+1]$ of firms that announced earnings on day t split into two samples based on $surprise_{t-1}$. The red line contains firms that announced the day after a $surprise_{t-1}$ in the highest quintile while the blue lines contains firms that announced after a $surprise_{t-1}$ in the lowest quintile. Distributions are estimated using a kernel density estimator.

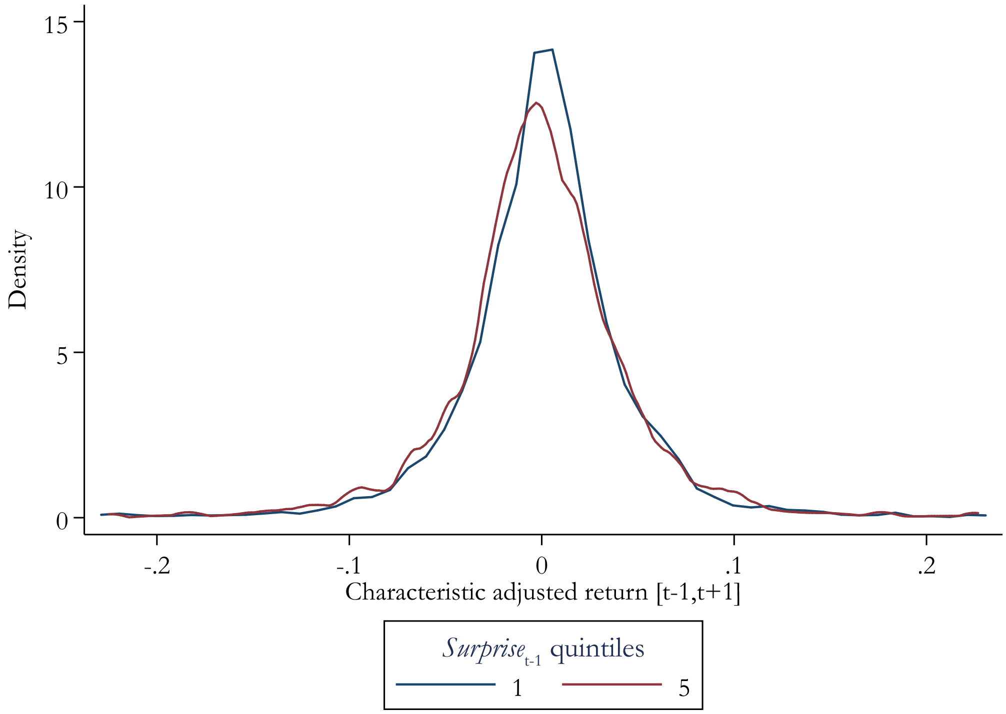


Table 1
Summary Statistics

This table presents summary statistics for the main variables used in our analysis using data from 1984 to 2013. The earnings surprise is measured as $(actual - forecast)/price_{t-3}$ where $forecast$ is the median of each analyst's most recent forecast that is released within 15 days of the announcement, excluding t and $t-1$. Characteristic adjusted returns are the return of a firm minus the return of a portfolio matched on quintiles of market capitalization, book-to-market ratio, and momentum. $Surprise_{t-1}$ is our baseline measure of the salient surprise released by other firms in the previous trading day. It is calculated as the value-weighted earnings surprise of all large firms that announced in the previous trading day. We define a "large" firm as a firm with market capitalization three days before its earnings is announced that exceeds the 90th percentile cutoff of the NYSE index in that month.

	N	Mean	SD	P25	P50	p75
Own earnings surprise	76062	-0.0003	0.0138	-0.0003	0.0002	0.0015
Characteristic adjusted return [t-1, t+1]	76062	0.0016	0.0671	-0.0297	0.0007	0.0330
Raw return [t-1, t+1]	76062	0.0017	0.0503	-0.0181	0.0000	0.0211
Volume	75899	3071	15700	132	545	2061
Market Cap$_{t-3}$ ($M)	76062	7679	24100	441	1491	5069
Number of analysts [t-15, t-2]	76062	3.727	3.674	1	2	5
$Surprise_{t-1}$	76062	0.0005	0.0017	0.0000	0.0004	0.0010
Number of surprises [t-1], large firms	76062	7.546	5.782	3	6	12

Table 2
Baseline Results

This table explores the relation between return reactions for firms that announce earnings today and the earnings surprises of other firms that announced in the previous trading day. The characteristic adjusted return from $[t-1, t+1]$ for announcing firms is regressed on various measures of the salient earnings surprise from $t-1$ and additional controls. Characteristic adjusted returns are the return of a firm minus the return of a portfolio matched on quintiles of market capitalization, book-to-market ratio, and momentum. Surprises for the firms announcing today and in the previous trading day are measured as $(actual - forecast)/price_{t-3}$ where $forecast$ is the median of each analyst's most recent forecast that is released within 15 days of the announcement, excluding t and $t-1$. We define a "large" firm as a firm with market capitalization three days before its earnings is announced that exceeds the 90th percentile cutoff of the NYSE index in that month. Columns 1 and 2 measure $surprise_{t-1}$ as the earnings surprise of the largest firm (conditional on it being a large firm) announced in the previous trading day. Columns 3 and 4 measure $surprise_{t-1}$ using the equal-weighted earnings surprise of all large firms that announced in the previous trading day. Columns 5 and 6 measure $surprise_{t-1}$ as the value-weighted earnings surprise of all large firms that announced in the previous trading day. All regressions include controls for 20 equally sized bins in terms of the earnings surprise of the firm that announced today. Even-numbered columns also include controls for year-month fixed effects. We refer to Column 6 as our baseline specification in later tables. Observations are value-weighted by the $t-3$ scaled market capitalization of the firm announcing earnings today. Standard errors are clustered by date. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Characteristic adjusted return $[t-1, t+1]$					
	(1)	(2)	(3)	(4)	(5)	(6)
$Surprise_{t-1}$ of largest firm	-0.501***	-0.338**				
	(0.141)	(0.153)				
$Surprise_{t-1}$ large firms, EW mean			-0.896***	-0.779***		
			(0.211)	(0.225)		
$Surprise_{t-1}$ large firms, VW mean					-0.781***	-0.721***
					(0.184)	(0.197)
Own $surprise_t$ controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	No	Yes	No	Yes	No	Yes
R^2	0.0530	0.0742	0.0535	0.0747	0.0534	0.0747
Observations	76062	76062	76062	76062	76062	76062

Table 3
Additional Support for Contrast Effects

This table provides further evidence of contrast effects. Panel A Columns 1 and 2 examine the impact of $t-3$, $t-2$, $t-1$, $t+1$, and $t+2$ salient surprises. The dependent variable in Columns 1 and 2 is the characteristic adjusted return over the windows $[t-3,\, t+1]$ and $[t-1,\, t+2]$, respectively. Dummy variables are included for instances where there is a missing salient surprise of the indicated day. p-values are from the test of whether the $t-1$ coefficient is equal to the indicated coefficient. Panel A Columns 3 and 4 explore contrast effects within the same day. We classify an earnings announcement as "AM" or "PM" based on whether it was released before market open or after market close. Column 3 regresses the $[t,\, t+1]$ characteristic adjusted returns of firms that released PM announcements on the value-weighted surprises of large firms that released AM announcements. Column 4 regresses the $[t,\, t+1]$ characteristic adjusted returns of firms that released AM announcements on the value-weighted surprises of large firms that released PM announcements. Panel B shows the relation between $surprise_{t-1}$ and long run return reactions. Return windows are as labeled in column headers. All other variables and weights are as defined in Table 2. Standard errors are clustered by date. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Lags and Leads and Same-Day Contrast Effects

	Longer lags and leads		Own PM announcement	Own AM announcement
	(1)	(2)	(3)	(4)
$Surprise_{t-3}$	-0.288			
	(0.184)			
$Surprise_{t-2}$	0.244			
	(0.224)			
$Surprise_{t-1}$	-0.725***	-0.723***		
	(0.216)	(0.242)		
$Surprise_{t+1}$		0.0117		
		(0.291)		
$Surprise_{t+2}$		-0.194		
		(0.327)		
AM surprise of others			-1.256**	
			(0.566)	
PM surprise of others				-0.404
				(0.285)
p-value: (t-3) = (t-1)	0.0819			
p-value: (t-2) = (t-1)	0.000795			
p-value: (t+1) = (t-1)		0.0467		
p-value: (t+2) = (t-1)		0.185		
Own $surprise_t$ controls	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
R^2	0.0739	0.0656	0.146	0.0988
Observations	76042	76052	19364	17901

Panel B: Long Run Return Windows

	$[t-1, t+1]$	$[t+2, t+25]$	$[t-1, t+25]$	$[t+2, t+50]$	$[t-1, t+50]$
	(1)	(2)	(3)	(4)	(5)
$Surprise_{t-1}$	-0.721***	0.156	-0.580	1.097**	0.389
	(0.197)	(0.362)	(0.375)	(0.544)	(0.549)
Own $surprise_t$ controls	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes
R^2	0.0747	0.0202	0.0388	0.0254	0.0338
Observations	76062	75886	75886	74795	74795

Table 4
Information Transmission

This table explores whether $surprise_{t-1}$ conveys information about firms that will announce earnings today. Panel A examines whether $surprise_{t-1}$ predicts the earnings surprise that will be announced on day t. The dependent variable in Columns 1 and 2 is the earnings surprise of the firm that announces on day t. The dependent variable in Columns 3 and 4 is the bin (1 through 20, equally sized) for the earnings surprise of the firm that announces on day t. Panel B explores the day $t-1$ return reaction of the firm scheduled to announce on day t to $surprise_{t-1}$. The dependent variable is the $t-1$ characteristic adjusted return for the firm scheduled to announce on day t, measured as close-to-close returns in Columns 1 and 2 and open-to-open returns in Columns 3 and 4. All other variables and weights are as defined in Table 2. Standard errors are clustered by date. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Surprise Predictability

	$Surprise_t$		20 bins in $surprise_t$	
	(1)	(2)	(3)	(4)
$Surprise_{t-1}$	134.2***	-26.45	0.165***	0.0117
	(32.63)	(27.17)	(0.0605)	(0.0601)
Own $surprise_t$ controls	No	No	No	No
Year-month FE	No	Yes	No	Yes
R^2	0.00290	0.0653	0.00218	0.0320
Observations	76062	76062	76062	76062

Panel B: Return Response to Potential Information Release

	Close-to-close char adj ret $[t-1]$		Open-to-open char adj ret $[t-1]$	
	(1)	(2)	(3)	(4)
$Surprise_{t-1}$	0.0295	-0.0758	0.106	0.0529
	(0.105)	(0.102)	(0.123)	(0.118)
Own $surprise_t$ controls	Yes	Yes	Yes	Yes
Year-month FE	No	Yes	No	Yes
R^2	0.00000998	0.0221	0.000133	0.0216
Observations	76062	76062	61867	61867

Table 5
Further Tests of Information Transmission

Panel A explores contrast effects within the subsample of observations for which information transmission from $surprise_{t-1}$ to firms announcing on day t is unlikely to have occurred. In Column 1, the sample is restricted to observations for which the $t-1$ characteristic adjusted returns of the firm announcing earnings today moved by less than 1% in either direction and Column 2 restricts the sample to cases where the return moved by less than 0.5%. Column 3 examines the sample with no negatively correlated information transmission, i.e., we exclude negative (positive) return reactions to positive (negative) $surprise_{t-1}$. Panel B examines whether contrast effects are related to an interaction between $surprise_{t-1}$ and the announced surprise on day t. Column 1 measures the surprise today using the level, Column 2 measures it using 20 equally sized bins, and Column 3 uses quintiles. For brevity, we report only the interaction effects, but all direct effects are included in the regressions. The dependent variable in Panel A is the open-to-open $[t, t+1]$ characteristic adjusted return of the firm announcing earnings on day t. The dependent variable in Panel B is the same as in our baseline specification–the close-to-close $[t-1, t+1]$ characteristic adjusted return of the firm announcing earnings on day t. All other variables and weights are as defined in Table 2. Standard errors are clustered by date. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Sample with No Evidence of Information Transmission

	$\lvert Ret_{t-1}\rvert < 0.01$	$\lvert Ret_{t-1}\rvert < 0.005$	No neg corr info transmission $[t-1]$
	(1)	(2)	(3)
$Surprise_{t-1}$	-0.627***	-0.614*	-1.289***
	(0.242)	(0.340)	(0.275)
Return type	Open-open	Open-open	Open-open
Own $surprise_t$ controls	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes
R^2	0.101	0.133	0.0870
Observations	27451	15082	31212

Panel B: Interaction Effects

	Characteristic adjusted return $[t-1, t+1]$		
	(1)	(2)	(3)
$Surprise_{t-1}$	-0.765***	-1.095***	-0.888*
	(0.204)	(0.423)	(0.526)
$Surprise_{t-1}$ x own surprise	19.36		
	(26.62)		
$Surprise_{t-1}$ x own surprise (20 bins)		0.0417	
		(0.0375)	
$Surprise_{t-1}$ x own surprise quintile 2			-0.181
			(0.702)
$Surprise_{t-1}$ x own surprise quintile 3			0.247
			(0.702)
$Surprise_{t-1}$ x own surprise quintile 4			0.554
			(0.684)
$Surprise_{t-1}$ x own surprise quintile 5			0.249
			(0.737)
Year-month FE	Yes	Yes	Yes
R^2	0.0304	0.0717	0.0715
Observations	76062	76062	76062

Table 6
Unconditional Relation (Not Controlling for Own Surprise)

Panel A presents regressions similar to those in Table 2, except that they exclude the firm's own surprise as control variables. Odd-numbered columns also exclude year-month fixed effects. All other variables and weights are as defined in Table 2. Standard errors are clustered by date. Panel B presents the abnormal returns to portfolios formed based upon $surprise_{t-1}$. On days where $surprise_{t-1}$ is below a cutoff, we long stocks with an earnings announcement on day t and short the market and do the opposite when $surprise_{t-1}$ is above a cutoff. The position is held for days t to $t+1$. We include only stocks with a market capitalization above the 80th percentile of the NYSE. Columns 1 and 2 include only portfolios where there are at least 5 stocks with earnings announcements on each day while Columns 3 and 4 include any day with at least one stock announcing earnings. Columns 1 and 3 utilize a cutoff of 0 for $surprise_{t-1}$, while Columns 2 and 4 utilize a cutoff of being below the 25th or above the 75th percentile of $surprise_{t-1}$, respectively. We compute abnormal returns from a four factor model by regressing portfolio returns on the market, SMB, HML and UMD risk factors. Each portfolio is value-weighted by the stocks announcing earnings on day t. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Unconditional Results

	Close-to-close $[t-1, t+1]$		Open-to-open $[t-1, t+1]$		Open-to-open $[t, t+1]$	
	(1)	(2)	(3)	(4)	(5)	(6)
$Surprise_{t-1}$	-0.481***	-0.757***	-0.537***	-0.820***	-0.672***	-0.898***
	(0.177)	(0.203)	(0.202)	(0.226)	(0.191)	(0.223)
Own $surprise_t$ controls	No	No	No	No	No	No
Year-month FE	No	Yes	No	Yes	No	Yes
R^2	0.000393	0.0225	0.000467	0.0207	0.000805	0.0215
Observations	76062	76062	61840	61840	61840	61840

Panel B: Abnormal Returns to Trading Strategy

	5 or more stocks		Any number of stocks	
	(1)	(2)	(3)	(4)
Alpha %	0.109**	0.199***	0.101**	0.153***
	(0.0448)	(0.0540)	(0.0492)	(0.0560)
MktRf	-0.0113	-0.00318	-0.0836**	-0.0339
	(0.0364)	(0.0409)	(0.0416)	(0.0465)
SMB	0.0711	-0.0981	0.0855	0.0368
	(0.0717)	(0.0823)	(0.0831)	(0.0927)
HML	0.103	0.136	0.123	0.222**
	(0.0775)	(0.0867)	(0.0845)	(0.0928)
UMD	0.0584	0.0283	-0.0139	0.00316
	(0.0505)	(0.0578)	(0.0568)	(0.0624)
Long cutoff: $Surprise_{t-1}$	< 0	$< 25^{th}$ pctile	< 0	$< 25^{th}$ pctile
Short cutoff: $Surprise_{t-1}$	> 0	$> 75^{th}$ pctile	> 0	$> 75^{th}$ pctile
Observations	1300	846	2183	1554
Annual return %	7.36	8.78	11.61	12.65

Table 7

Strategic Timing of Earnings Announcements, Changes in Risk and Trading Frictions

This table tests whether the negative relation between return reactions and $surprise_{t-1}$ is driven by changes in the scheduling of announcements or changes in risk or trading frictions. In Panel A, $\Delta date$ is the difference between the day of the current earnings announcement and the previous year's same-quarter earnings announcement (e.g., for a firm announcing on March 15, 2004 that previously announced on March 12, 2003, $\Delta date = 3$). Panel B Columns 1 and 2 test whether the negative relation is driven by changes in risk, as measured by the betas of the market, SMB, HML, and UMD risk factors. We regress the characteristic adjusted return (Column 1) or the raw return (Column 2) on the four factors, year-month fixed effects, $surprise_{t-1}$, and the interaction between $surprise_{t-1}$ and the four factors. Panel B Columns 3 and 4 test whether the negative relation is driven by changes in liquidity, measured as the log of daily dollar volume in Column 3 and the log of the bid-ask spread in Column 4. Measures of liquidity vary greatly across firms so Columns 3 and 4 include firm fixed effects. All other variables and weights are as defined in Table 2. Standard errors are clustered by date. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Strategic Timing of Earnings Announcements

	Characteristic adjusted return $[t-1, t+1]$	
	(1)	(2)
$Surprise_{t-1}$ x abs(Δ date)<=5	-0.778***	
	(0.222)	
$Surprise_{t-1}$ x abs(Δ date)>5	-0.346	
	(0.497)	
$Surprise_{t-1}$ x Δ date<-5		0.900
		(0.713)
$Surprise_{t-1}$ x abs(Δ date)<=5		-0.784***
		(0.222)
$Surprise_{t-1}$ x Δ date>5		-0.791
		(0.659)
Own $surprise_t$ controls	Yes	Yes
Year-month FE	Yes	Yes
R^2	0.0755	0.0758
Observations	70272	70272

Panel B: Changes in Risk and Trading Frictions

	Char adj ret $[t-1, t+1]$	Raw ret $[t-1, t+1]$	Log(volume)	Log(bid-ask)
	(1)	(2)	(3)	(4)
$Surprise_{t-1}$	-0.778***	-1.061***	3.087	1.411
	(0.200)	(0.250)	(4.825)	(5.532)
Mkt-rf x $surprise_{t-1}$	0.120	-1.508		
	(7.424)	(9.274)		
SMB x $surprise_{t-1}$	-22.99	-18.79		
	(16.61)	(23.35)		
HML x $surprise_{t-1}$	11.10	42.40		
	(23.99)	(29.35)		
UMD x $surprise_{t-1}$	23.80*	51.61***		
	(13.66)	(16.25)		
Own $surprise_t$ controls	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
R^2	0.0758	0.216	0.891	0.754
Observations	76062	76062	75910	68909

Table 8

Alternative Measures of Surprise

This table shows that our baseline results are robust to alternative measures and sample restrictions. All variables and weights are as defined in Table 2, except for the following changes. Panel A Column 1 measures the salient surprise in $t-1$ as the value-weighted average of the return response to the $t-1$ earnings announcements of other firms above the 90th percentile of market capitalization. In Columns 2 and 3, $surprise_{t-1}$ is calculated using firms that announced in $t-1$ that exceeded the 85th and 95th percentile size cutoffs of the NYSE index in that month, respectively. In Column 4, $surprise_{t-1}$ is calculated using the value-weighted surprise of all firms that announced in the previous trading day, regardless of size. Column 5 uses announcement dates based on the filters from DellaVigna and Pollet (2009). Panel B Columns 1 and 2 calculate own surprise and $surprise_{t-1}$ using the median of each analyst's most recent forecast released with the past 30 or 45 days, respectively, excluding days t and $t-1$. Column 3 scales $surprise_{t-1}$ by the sum of the squared size weights of each firm comprising the weighted-mean calculation of $surprise_{t-1}$. Column 4 re-estimates the baseline regression, but equal-weights each observation instead of of value-weighting. Standard errors are clustered by date. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Different Value-Weighted Measures

	Characteristic adjusted return $[t-1, t+1]$				
	(1)	(2)	(3)	(4)	(5)
Return $surprise_{t-1}$, VW mean	-0.0510**				
	(0.0218)				
$Surprise_{t-1}, > 85^{th}$ pctile		-0.782***			
		(0.182)			
$Surprise_{t-1}, > 95^{th}$ pctile			-0.715***		
			(0.212)		
$Surprise_{t-1}$, all firms				-0.473***	
				(0.137)	
$Surprise_{t-1}$, adjusted dates					-0.652***
					(0.206)
Own $surprise_t$ controls	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes
R^2	0.0742	0.0749	0.0715	0.0541	0.0782
Observations	75044	79875	66609	76062	62438

Panel B: Different Forecast Windows, Scaling, and Weighting

	Characteristic adjusted return $[t-1, t+1]$			
	(1)	(2)	(3)	(4)
$Surprise_{t-1}$, forecasts[t-30,t-2]	-0.534***			
	(0.176)			
$Surprise_{t-1}$, forecasts[t-45,t-2]		-0.348**		
		(0.161)		
$Surprise_{t-1}$, scaled SD			-0.355***	
			(0.100)	
$Surprise_{t-1}$, EW regression				-0.213
				(0.159)
Own $surprise_t$ controls	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
R^2	0.0664	0.0664	0.0746	0.0737
Observations	121617	150232	76062	76062

Table 9
Heterogeneity

This table shows how contrast effects vary by the size and analyst coverage of the firm announcing today. In Column 1, $surprise_{t-1}$ is interacted with indicators for five quintiles for the size (as measured in $t-3$, using quintile cutoffs of the NYSE index in that month). In Column 2, $surprise_{t-1}$ is interacted with indicators for the number of analysts covering the firm announcing earnings today (the number of distinct analysts that released forecasts in the past 15 days excluding day t and $t-1$). In Column 3, we estimate separate effects for each decade in the sample. All direct effects of size quintiles or number of analysts are included in the regression. All other variables and weights are as defined in Table 2. Standard errors are clustered by date. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Characteristic adjusted return $[t-1, t+1]$		
	(1)	(2)	(3)
$Surprise_{t-1}$ x size quintile 1	-0.369		
	(0.474)		
$Surprise_{t-1}$ x size quintile 2	-0.361		
	(0.450)		
$Surprise_{t-1}$ x size quintile 3	-0.284		
	(0.399)		
$Surprise_{t-1}$ x size quintile 4	0.203		
	(0.293)		
$Surprise_{t-1}$ x size quintile 5	-0.813***		
	(0.214)		
$Surprise_{t-1}$ x (num analysts = 1)		0.00369	
		(0.514)	
$Surprise_{t-1}$ x (num analysts = 2)		-0.661	
		(0.420)	
$Surprise_{t-1}$ x (num analysts >= 3)		-0.825***	
		(0.220)	
$Surprise_{t-1}$ x 1980s			-0.526
			(0.348)
$Surprise_{t-1}$ x 1990s			-0.586
			(0.615)
$Surprise_{t-1}$ x 2000s			-0.725**
			(0.282)
$Surprise_{t-1}$ x 2010s			-0.906**
			(0.368)
Own $surprise_t$ controls	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes
R^2	0.0750	0.0750	0.0747
Observations	76062	76062	76062

Table 10
Industry Match

This table explores how contrast effects vary with industry match between the firm announcing earnings today and the firm announcing in the previous trading day. $Surprise_{t-1}\,same\,industry$ is the salient earnings surprise in $t-1$, calculated using only firms in the same industry as the firm announcing today. $Surprise_{t-1}\,dif\,industry$ is the salient earnings surprise in $t-1$, calculated using only firms in a different industry as the firm announcing today. To make the magnitudes of the coefficients on the $t-1$ salient surprises comparable, we scale each salient surprise by the sum of the squared size weights of each firm comprising the weighted-mean calculation. Small (large) firm is a dummy variable equal to one if the $t-3$ size of the firm announcing earnings today is below (above) the median NYSE market capitalization in that month. p-values are for the test of whether a given same-industry coefficient is equal to its different-industry analogue. All other variables and weights are as defined in Table 2. Standard errors are clustered by date. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Fama French 5 Industries			Fama French 12 Industries		
	(1)	(2)	(3)	(4)	(5)	(6)
$Surprise_{t-1}$ same industry	-0.340***	-0.308***		-0.268*	-0.331**	
	(0.128)	(0.114)		(0.155)	(0.139)	
$Surprise_{t-1}$ dif industry	-0.339**	-0.0246		-0.326**	-0.0472	
	(0.144)	(0.112)		(0.133)	(0.0985)	
$Surprise_{t-1}$ same industry x small firm			-0.457**			-0.566**
			(0.224)			(0.275)
$Surprise_{t-1}$ dif industry x small firm			-0.199			-0.244
			(0.208)			(0.195)
$Surprise_{t-1}$ same industry x large firm			-0.336**			-0.258
			(0.131)			(0.159)
$Surprise_{t-1}$ dif industry x large firm			-0.343**			-0.328**
			(0.147)			(0.135)
Regression weights	Value	Equal	Value	Value	Equal	Value
p-value: same=dif	0.995	0.109		0.788	0.106	
p-value: same=dif, small firms			0.431			0.369
p-value: same=dif, large firms			0.974			0.755
Own $surprise_t$ controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0748	0.0739	0.0749	0.0745	0.0738	0.0745
Observations	76062	76062	76062	76062	76062	76062

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