Product Price Change Timing and Stock Returns

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Abstract

I show that firms with low price change frequency conditional on macroeconomic shocks earn a risk premium. I build a multisector model in which firms face heterogeneous nominal rigidities. Firms with higher price change frequencies after macroeconomic shocks are less exposed to systematic cash-flow risk, lowering average equity returns. I create a new dataset that links firms from Compustat to weekly grocery store scanner data. I demonstrate that a common proxy for price change frequency conditional on price gap size, the kurtosis of price changes, carries a risk premium of 6% in the post-2005 period, consistent with the model. This premium cannot be explained by differences in unconditional price change frequency.

1 Introduction

Nominal rigidities amplify firms' cashflow losses after adverse macroeconomic shocks. Firms that do not adjust prices after these shocks are likely to post product prices that are either too low or too high compared to their profit-maximizing price, and experience greater cashflow losses as a result. Investors therefore demand a risk premium to hold these firms' equity.

I show that firms with lower price change frequencies conditional on price gap size earn a risk premium of over 6% per year. How much more likely a firm is to adjust the price of a product when its price gap is large compared to when it is small–a property known as state dependence–affects the cashflow losses a firm experiences after macroeconomic shocks. After a shock, a firm with highly state-dependent pricing will be more likely to adjust its price and reduce cashflow losses than a firm with less state dependent pricing, even if both firms adjust prices at the same unconditional frequency. This makes firms with less state dependence risky, even holding unconditional price change frequency constant.

To build intuition for why a lack of state dependence heightens cashflow risk, consider two single product firms with different types of nominal rigidities. Firm A is randomly allowed to change its price with probability α each period, regardless of how far its optimal price lies from its current price. This firm has no state dependence: the probability of a price change is completely unrelated to the size of its price gap.[1] In contrast, firm B can change its price whenever it wants, but must pay a menu cost κ to do so. The probability firm B changes its price is 0 when the cashflow losses due to its price gap are lower than a threshold determined by κ, and 1 when they

[0]Researcher's own analyses calculated based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

[1]This type of pricing behavior can occur when firms incur substantial administrative costs associated with collecting data on optimal prices. In the firm Zbaracki et al. 2004 focus on, for example, pricing data are collected over several months during a "pricing season" each year. This leads the firm to change its price at regular intervals regardless of its products' price gaps.

exceed this threshold. Because the probability of this firm's price changes is entirely predicted by its price gap, it has high state dependence.

When there is a large negative macroeconomic shock, both firms' cashflows fall and their optimal prices move away from their posted price. If the price gap is large enough, firm B pays the menu cost and changes its price, giving it a higher conditional frequency of price changes after large shocks. The menu cost κ acts as an upper bound on the cashflow losses this firm suffers due to its price gap. On the other hand, firm A does not have a higher price change frequency after such a shock, and its losses due to its price gap can be large if it does not receive a price change. Firm A's lower conditional frequency after large shocks makes its cashflows fall by more in bad states, making it riskier.

The implications for cashflows in the face of nominal shocks for each firm are shown in Figure 1. Productivity is given on the x-axis, and cashflows on the y-axis. The profits of firms without nominal rigidities are shown in blue. The profits of the low state dependence firm A are shown in red, and of the menu cost firm B in violet. When there is a negative productivity shock, cashflows fall for all firms. However, the profits of the menu cost firm fall only slightly more than would a firm with no nominal rigidities–if the shock is large enough, the profits are exactly the profits of the non-rigid firm minus the menu cost κ. The Calvo firm's profits can decrease by far more, with a gap between its profits and the non-rigid firm's that is several times the size of the gap between the menu cost firm's and the non-rigid firm's profits. This greater curvature in profits for the firm with low state dependence makes its cashflows fall by more when negative shocks hit, making investors demand a premium for holding its stock.

To establish the link between state dependence and cashflow risk, I construct a multisector general equilibrium model where firms face heterogeneous probabilities of free price changes and menu costs.[2] The nominal rigidites of each sector range from minimal state dependence with frequent random free price changes and prohibitive menu costs, to maximum state dependence with no random free price changes and

[2]My model is closely related to that of Nakamura and Steinsson 2010, who denote the combination of menu costs and free price changes as "Calvo Plus" nominal rigidities.

low menu costs. I first show that firms with high state dependence are more likely to change prices after monetary policy shocks, even though all firms in the economy have approximately the same unconditional price change frequency. I then show that average equity returns fall with state dependence. The model therefore predicts that firms with a lower state dependence are less likely to change prices after aggregate shocks, and that these firms earn an equity risk premium.

Under a broad class of models, including the model in this paper, state dependence is tightly connected to the kurtosis of a firm's price changes.[3] The kurtosis of a distribution measures the frequency and size of extreme observations compared to the peak of the distribution. If a firm exhibits a high kurtosis of price changes, it closes its price gap frequently when the price gap is small and infrequently when its price gap is moderately sized. High kurtosis firms also occasionally close very large price gaps, indicating several periods of accumulated shocks pass before the firm changes its price. This combination of many small price changes with some very large price changes indicates that the probability of a firm's price change is unrelated to its price gap and that the firm has low state dependence. In contrast, the high state dependence menu cost firm will change its price every time the price gap exceeds a threshold determined by the menu cost, and never when the price gap is below that threshold. This results in a distribution of price changes that is highly concentrated around this threshold with thin tails, leading to a low kurtosis of price changes. I show that higher kurtosis indicates lower state dependence in my model by simulating the distribution of price changes within each sector. The monotonic, negative relationship between kurtosis and state dependence validates the use of kurtosis as an empirical proxy for low state dependence in the context of my model.

To empirically link state dependence to equity returns, I build a new dataset linking firms in Compustat to grocery store scanner data from Nielsen. I merge weekly product-store level prices and sales with financial and accounting variables in Compustat and stock returns from CRSP. I then calculate frequency and kurtosis of price changes for products in my sample, and aggregate these pricing statistics to

[3] See Alvarez, Le Bihan, and Lippi 2016.

the firm level.

I find that firms in the highest tercile of price change kurtosis earn average equity returns that are 6.4% higher than those of firms in the lowest tercile over the 2006-2019 period. This premium is in the same range as other risk premia associated with nominal rigidities, such as the unconditional frequency premium found by Weber 2014 of 4% and the demand elasticitiy premium of 6.2% found by Clara 2019. This premium is not driven by small firms; value-weighted average returns imply firms with high kurtosis of price changes earn a premium of 6.6% above low price change kurtosis firms. Controlling for other variables that commonly predict returns, including unconditional frequency, does not negate the price change kurtosis premium.

The risk premium earned by firms with high kurtosis of price changes is explained by their lower conditional price change frequency after large macroeconomic shocks. In panel regressions I show that firms with higher price change kurtosis are less likely to adjust prices after large monetary policy shocks. These regressions confirm the mechanism in the model where firms with higher state dependence adjust prices more frequently after macroeconomic shocks, reducing their systematic cashflow risk.

In Section 2, I discuss the related literature in macroeconomics and finance. In Section 3, I describe a model where firms facing heterogeneous types of nominal rigidities. In Section 4, I outline the key testable predictions of the model, and discuss how kurtosis of price changes is linked to state dependence. In Section 5 I describe my new dataset linking firms in Compustat to Nielsen's barcode-level data. In Section 6 I present empirical evidence confirming the predictions of the model. Section 7 concludes the paper and discusses future directions for research in product pricing behavior and asset pricing.

2 Literature Review

This paper directly addresses two major strands of the finance and macroeconomics literatures. It extends the work of Weber 2014 and Gorodnichenko and Weber 2016, who link the frequency of price changes to equity risk premia. Weber 2014 finds that firms that adjust prices with lower unconditional frequency earn an equity risk premium. To rationalize this result, he builds a model with a continuum of monopolistically competitive firms that adjust prices at random times (Calvo pricing). These firms are divided into sectors with different frequencies of price changes. Sectors with lower price change frequency are less able to adjust prices in response to macroeconomic shocks, making their cashflows have a higher covariance with these shocks and earning a risk premium.

A closely related paper in this vein in Gorodnichenko and Weber 2016, who show that short-term stock returns are more responsive to monetary policy shocks for firms with less frequent price changes. D'Acunto et al. 2018 and Augustin et al. 2021 study the effect of nominal rigidites on the capital structure and credit risk of firms. Li and Palomino 2014 study the asset pricing implications of monetary policy responses to inflation in the presence of price and wage rigidities. Clara 2019 demonstrates that in the presence of nominal rigidities, firms' demand elasticities are a significant risk factor for equity returns. However, he finds no evidence for a price change frequency premium in the 2011-2017 period.

This paper also has implications for an ongoing debate in the monetary economics literature on sufficient statistics for monetary non-neutrality. Alvarez, Le Bihan, and Lippi 2016 and Alvarez, Lippi, and Oskolkov 2021 show that within a broad class of standard price stickiness models and low inflation environments, the ratio of kurtosis to frequency of price changes is a sufficient statistic to predict the real response within an economy to a once-and-for-all interest rate shock.

The empirical evidence on this topic has so far been ambiguous. Alvarez et al. 2021 use French CPI and PPI microdata to regress price response responses at the sector level on kurtosis and frequency of price changes. They find that sectors with higher kurtosis to frequency ratios have smaller cumulative price responses to interest rate shocks. Gautier, Marx, and Vertier 2022 find that kurtosis and frequency are indeed sufficient statistics for monetary non-neutrality among gasoline providers in France in the period from 2007 to 2018. However, Hong et al. 2021 find no evidence that kurtosis of price changes is associated with differences in price responses to monetary policy shocks across US Producer Price Index (PPI) sectors, while higher frequency is associated with a greater response. My results support the view of Alvarez et al. 2021 and Gautier, Marx, and Vertier 2022 that standard models realistically link pricing moments to monetary non-neutrality.

3 Model

I build a general equilibrium model that links lower state dependence to higher cashflow risk, an equity risk premium, and higher kurtosis of price changes. At the core of the model are firms with heterogeneous menu costs and probabilities of a free (Calvo) price change. The nominal rigidities of this model are a special case of the class of rigidities studied in Alvarez, Le Bihan, and Lippi 2016, in which kurtosis and frequency are sufficient statistics for predicting the real effects of a once-and-for-all monetary policy shock.[4]

Firms face nominal rigidities that combine Calvo-style free price changes and menu costs. The probability of a free price change and the menu cost differ according to a firm's sector k. Each period, a firm receives the opportunity to change its price for free with probability α_k, as in Calvo 1983. If it does not receive a free price change, it can choose to pay a menu cost κ_k to change its price, as in Caplin and Spulber 1987 and Golosov and Lucas 2007. κ_k acts as an upper bound on the losses a firm sustains from its price gap, as the firm will always change its price when expected cashflows losses from its price gap exceed κ_k.

3.1 Households

Households maximize discounted expected utility, which is a function of consumption C_t and labor supplied N_t. The household has CES utility.

[4]Their result is contingent on the strong assumptions that firms have symmetric costs to their price gaps, inflation is 0, and shocks to the price gap are normally distributed. While none of these assumptions hold in my model exactly, I quantitatively demonstrate that lower kurtosis of price changes predicts stronger price responses to monetary policy shocks in Section 4.2.

$$\max_{C_t,N_t} E_0 \sum_{t=0}^{\infty} \beta^t \Big[\frac{C_t^{1-\gamma}}{1-\gamma} - \chi\frac{N_t^{1+\xi}}{1+\xi}\Big]$$

The consumption aggregate is a combination of the goods produced by each firm i:

$$C_t = \left(\int_i C_{i,k,t}^{\frac{\eta-1}{\eta}} di\right)^{\frac{\eta}{\eta-1}}$$

k is the sector firm i belongs to. As describe in the next subsection, firms are ex ante identical except in the types of nominal rigidities they face. η is the elasticity of substitution between goods. I assume the between-sector elasticity of substitution is identical to the within-sector elasticity. This eliminates the need to keep track of the relative price of a sector compared to the economy-wide aggregate price, eliminating a state variable from the model. The household faces a budget constraint

$$P_tC_t + Q_{t+1}B_{t+1} \leq D_t + B_t + W_tN_t$$

Where P_t is the aggregate price index, B_{t+1} are household savings in period t, Q_{t+1} is the price of the risk-free asset, and W_t is the nominal wage. The first order conditions for aggregated consumption, bond holdings, and labor supply are:

$$\partial C_t : C_t^{-\gamma} = \lambda_t P_t$$

$$\partial B_{t+1} : Q_{t+1}\lambda_t = \lambda_{t+1}$$

$$\partial N_t : -\chi N_t^{\xi} + W_t\lambda_t = 0$$

where λ_t is the budget constraint multiplier. Combining these first order conditions, I derive the Euler equation and labor supply equation:

$$\text{Euler}: 1 = E_t \beta \frac{1}{Q_{t+1}} \frac{P_t}{P_{t+1}} \left(\frac{C_{t+1}}{C_t} \right)^{-\gamma}$$

$$\text{Labor Supply}: \chi N_t^{\xi} = \frac{W_t}{P_t} C_t^{-\gamma}$$

I follow Nakamura and Steinsson 2010 and set the Frish labor supply elasticity to infinity: $\xi = 0$. This parameter choice simplifies the labor supply equation to $\frac{W_t}{P_t} = \chi C_t^{\gamma}$. This assumption allows firms to choose their prices without making a prediction about N_t in the current period, making the model more computationally tractable.

Given the optimal choice of aggregated consumption C_t, household demand for each firm's good $C_{i,k,t}$ solves the following cost-minimization problem:

$$\min_{\{C_{i,k,t}\}} \int_i \frac{P_{i,k,t}}{P_t} C_{i,k,t} di$$

such that

$$C_t \leq \left(\int_i C_{i,k,t}^{\frac{\eta-1}{\eta}} di \right)^{\frac{\eta}{\eta-1}}$$

Solving this problem gives the demand curve faced by firm i given aggregate consumption C_t:

$$C_{i,k,t} = \left(\frac{P_{i,k,t}}{P_t} \right)^{-\eta} C_t$$

3.2 Firms

The economy is populated by a continuum of firms i, each of which belongs to a sector k. These firms are ex-ante the same except for the nominal rigidities between sectors. Each firm maximizes the expected discounted value of its real dividends:

$$E_0 \sum_{t=0}^{\infty} M_{0,t} \frac{D_{i,k,t}}{P_t}$$

where nominal dividends $D_{i,k,t}$ are profits from sales of the intermediate good $Y_{i,k,t}$ produced by the firm minus nominal labor costs and a menu cost (scaled by the price level) if the firm decides to change its price:

$$D_{i,k,t} \leq P_{i,k,t} Y_{i,k,t} - W_t N_{i,k,t} - P_t \kappa_k \mathbf{I}_{[\kappa_k \text{ paid}]}$$

The firm hires labor N_t, for which it pays the market wage W_t. The firm's production function has constant returns to scale for labor:

$$Y_{i,k,t} = A_t Z_{i,k,t} N_{i,k,t}$$

A_t is aggregate technology, while $Z_{i,k,t}$ is firm-level, idiosyncratic technology. Each of these technologes follows an exogenous AR(1) process in logs:

$$log(A_t) = \rho^A log(A_{t-1}) + \epsilon_t^A$$

$$log(Z_{i,k,t}) = \rho^Z log(Z_{i,k,t-1}) + \epsilon_t^Z$$

The firm faces the demand curve derived under the household's problem:

$$Y_{i,k,t} = \left(\frac{P_{i,k,t}}{P_t} \right)^{-\eta} C_t$$

Finally, the firm's per-period real dividend payments can be rewritten as

$$D_{i,k,t}^R = \frac{D_{i,k,t}}{P_t} = \left(\frac{P_{i,k,t}}{P_t} - \frac{W_t}{P_t} \frac{1}{Z_{i,k,t} A_t} \right) \left(\frac{P_{i,k,t}}{P_t} \right)^{-\eta} C_t - \kappa_k \mathbf{I}_{[\kappa_k \text{ paid}]}$$

After aggregate shocks occur at the beginning of each period, firms receive a free price change with probability α_k. If they do not receive a free price change, firms choose whether to adjust their price $P_{i,k,t}$ by paying the menu cost κ_k. If the firm changes its price either by getting a free price change or paying the menu cost, it adjusts its price to the value that maximizes expected discounted dividend payments.

3.3 Monetary Authority

Following Nakamura and Steinsson 2010, the central bank sets nominal GDP according to an exogenous process:

$$log\Big(P_tC_t\Big) = log\Big(NGDP_t\Big) = log\Big(NGDP_{t-1}\Big) + \mu_{NGDP} + \epsilon_t^{NGDP}$$

ϵ_t^{NGDP} is a monetary policy shock, which is drawn each period from a normal distribution with mean 0 and standard deviation σ^{NGDP}. This formulation of nominal shocks allows firms to predict only the price level in the current period, as opposed to both the price level and aggregate real output separately. Once the price level P_t is predicted, real output is simply $C_t = \frac{NGDP_t}{P_t}$.

3.4 The Dynamic Problem

Let $\hat{P}_{i,k,t} = \frac{P_{i,k,t}}{P_t}$ denote the firm's real price. At the beginning of each period, productivity and monetary policy shocks ϵ_t^z, ϵ_t^A , and ϵ_t^{NGDP} are realized. The resulting inflation from these shocks moves the firm's real price to its beginning of period value $\hat{P}_{-1}$. The firm then receives a free price change with probability α_k. If it receives a free price change, the firm changes its price to $\hat{P}^*(Z, A, C)$, which maximizes its expected discounted value. If it does not receive a free price change, it then chooses whether to change its price by paying the menu cost κ_k. It makes its decision based on its sector-specific nominal rigidities, real price, idiosyncratic productivity, aggregate productivity, and aggregate real consumption. If it pays the menu cost, the firm changes its price to $\hat{P}^*(Z, A, C)$.

The firm's value is given by:

$$
\begin{aligned}
V^k(\hat{P}_{-1}, Z, A, C) = \alpha_k & \underbrace{\left[\Pi^R(\hat{P}^*(Z, A, C), Z, A, C) + EM'V^k(\hat{P'}_{-1}, Z', A', C')\right]}_{\text{Free price change}} \\
& + (1 - \alpha_k) \max \left[\underbrace{\Pi^R(\hat{P}_{-1}, Z, A, C) + EM'V^k(\hat{P'}_{-1}, Z', A', C')}_{\text{No free price change, does not pay } \kappa_k}, \right. \\
& \left. \underbrace{\Pi^R(\hat{P}^*(Z, A, C), Z, A, C) - \kappa_k + EM'V^k(\hat{P'}_{-1}, Z', A', C')}_{\text{No free price change, pays } \kappa_k} \right] \quad (1)
\end{aligned}
$$

The term after α_k is real profit in the current period, $\Pi^R(\hat{P}^*(Z, A, C), Z, A, C)$, plus the expected discounted future value of the firm, $EM'V^N(\hat{P'}_{-1}, Z', A', C')$, if the firm is given a free random price change. If, with probability $1 - \alpha_k$, the firm does not receive a free price change, the firm chooses whether or not to pay the menu cost. If it chooses not to pay the menu cost, it earns profits at the beginning of period price $\Pi^R(\hat{P}_{-1}, Z, A, C)$ and its discounted expected value at the start of the next period is $EM'V^N(\hat{P'}_{-1}, Z', A', C')$. If it chooses to pay the menu cost, the firm changes its price to the value-maximizing price, earning the same cashflows and expected future value as in the case with a free price change. However, the firm must pay the menu cost κ_k.

3.5 Predicting Consumption and Inflation

When making pricing decisions at the beginning of each period, firms must predict the aggregate price level P_t in the current period. In principle, an infinite number of state variables are required to predict P_t (each firms' beginning of period price and idiosyncratic technology). To make this problem tractable, firms predict inflation using the Krusell-Smith procedure, where a small number of aggregate moments provide an approximation to the variables being predicted. Firms predict log inflation using a linear combination of log aggregate productivity, real consumption, and the nominal GDP shock:

$$log(\hat{\Pi}_t) = \mu_{NGDP} + \zeta_0 + \zeta_1 log(A_t) + \zeta_2 log\Big(\frac{C_{t-1}}{C^{SS}}\Big) + \zeta_3 \epsilon_t^{NGDP} \tag{2}$$

I make an initial guess of ζ_1, ζ_2, and ζ_3 using economic intuition on how optimal prices move in response to changes in supply (aggregate technology A_t) and demand (C_{t-1} and ϵ_t^{NGDP}). I guess that $\zeta_1 < 0$ because higher productivity reduces marginal costs, which makes the profit-maximizing price fall. ζ_2 and ζ_3 are greater than 0 because increases in demand raise the profit-maximizing price.

I simulate the economy with firms predicting inflation based on my initial guesses of ζ_1, ζ_2, and ζ_3. I then regress realized inflation on the three aggregate variables, and simulate the economy based the updated ζ_1, ζ_2, and ζ_3. This process converges at a rule for predicting inflation that very closely approximates realized inflation. In Figure 2 I plot realized vs predicted inflation. Regressing realized inflation on predicted inflation once the coefficients converge yields an R^2 of over 99%.The coefficient on predicted inflation, 0.997, is statistically indistinguishable from 1, while the intercept, 0.000006, is statistically indistinguishable from 0. This tight one-to-one relationship between predicted inflation and realized inflation suggests the rule in Equation 2 provides an accurate approximation to the rational expectations equilibirum inflation.

3.6 Equilibrium

The equilibrium of this economy consists of

1. Aggregate consumption C, aggregate technology A, a distribution of firms $\mathbf{G}$ over idiosyncratic technology Z and real prices $\hat{P}$, and nominal GDP $NGDP_t$.

2. Firm predictions of inflation as a function of observed aggregate variables $\Gamma^{\pi}(A, C_{-1}, \epsilon^{NGDP})$.

3. A firm policy function for its real price $\hat{P} = \mathbf{H}(\hat{P}, Z, A, C)$.

such that

1. The policy function $\mathbf{H}$ maximizes the firm's value given the state variables.

2. Firm pricing decisions based on $\mathbf{H}$, aggregated over distribution of firms $\mathbf{G}$, are consistent with predicted inflation: $\Pi(\mathbf{G}, A, C_{-1}, \epsilon^{NGDP}) = \Gamma^{\pi}(A, C_{-1}, \epsilon^{NGDP})$.

3. The variables Z, A, and $NGDP$ evolve according to their given stochastic processes.

4. The market for labor and the market for goods clear.

3.7 Calibration

I calibrate the model at quarterly frequency drawing on widely accepted moments in the finance and macroeconomics literature. I set the time discount rate β to 0.99. Relative risk aversion γ is set to 5, consistent with Jermann 1998 and Weber 2014. The labor disutility parameter χ is chosen so that in the flexible price steady state the labor supply is 1. I follow Hansen 1985, Rogerson 1988, and Nakamura and Steinsson 2010 to set the inverse frisch labor supply elasticity ξ to 0. The elasticity of substitution between goods η is 4, in line with the estimates of Berry, Levinsohn, and Pakes 1995. Idiosyncratic shock volatiltiy σ_z is set to 0.075, close to the average idiosyncratic volatility of Nakamura and Steinsson 2010. Aggregate productivity shock volatility σ_a is 0.0085, consistent with Weber 2014. The persistence of aggregate productivity σ_a is set to 0.8, similar to persistence in Smets and Wouters 2007. Aggregate monetary policy shock volatiltiy σ_{NGDP} is 0.0065, in line with Nakamura and Steinsson 2010.

I group firms into four sectors with varying types of nominal rigidities. The first sector has firms with purely Calvo pricing. Each subsequent sector has a lower probability of a free price change, but a lower menu cost so that all sectors have approximately the same unconditional frequency of price changes. The final sector has no free price changes. The exact combinations of calvo probabilities α_k and menu costs κ_k are shown in Table 3.

4 Model Predictions

I solve for the optimal price setting policy function given an initial guess of the inflation prediction parameters ζ_1, ζ_2, and ζ_3. Using this policy function, I simulate an economy with 50,000 firms for 5,000 periods. Each period, firms adjust their price according to their policy function, and I record aggregate inflation to fine-tune the inflation prediction rule as discusssed in Section 3.5.

4.1 State Dependence and Kurtosis of Price Changes

I plot histograms of price changes within each sector in Figure 3. The distribution of price changes for firms in the Calvo sector closely mirrors the normal distribution. This is consistent with the intuition that the timing of these firms' price changes is a random draw from a normal distribution of price gaps of combined idiosyncratic productivity, aggregate productivity, and monetary policy shocks.[5]. The last sector has price changes that are heavily concentrated around a bimodal distribution. This behavior is consistent with firms adjusting prices only when their cashflow losses due to their price gap exceeds their menu cost. Sectors 2 and 3 have price change distributions that are a mixture of the pure Calvo and pure menu cost cases.

The kurtosis of price changes accurately reflects the state dependence of the firms in each sector. The Calvo sector with pure random price change timing has the highest kurtosis. As the probability of free price changes and menu costs fall, and state dependence increases, the distribution of price changes becomes more highly concentrated around a bimodal distribution. This lowers the kurtosis of price changes. In this model, lower kurtosis of price changes captures lower α_k and κ_k (holding unconditional frequency constant) and the state dependence of firms' price change timing.

[5]The kurtosis of price changes for these firms is counterfactually low–the highest tercile of kurtosis in my sample is about 6. However, this is easily accounted for by including leptokurtic idiosyncratic productivity shocks, as in Midrigan 2011. Furthermore, this exercise demonstrates that it is not necessary for firms to experience different distributions of shocks to explain the relationship between kurtosis of price changes and equity returns.

4.2 Price Change Frequency after Aggregate Shocks

The mechanism by which state dependence decreases cashflow risk is that firms with a higher state dependence are more likely to change prices after macroeconomic shocks, controlling for their unconditional frequency of price changes. To show this is the case, I regress the frequency of price changes for sector k in period t on the unconditional frequency of sector k and the size of the monetary policy shock $|\epsilon_t^{NGDP}|$:

$$Freq_{k,t} = \beta_1 Freq_k + \beta_2 |\epsilon_t^{NGDP}| + \nu_{i,t}$$

In the first four columns of Table 2, I show the coefficients and standard errors of this regression for each sector. In sector 1 with no state depdendence, the coefficient on $|\epsilon_t|^{NGDP}$ is statistically indistringuishable from 0, consistent with firms in this sector changing prices at random times unrelated to the size of their price gaps. For sectors 2-4, the coefficient on $|\epsilon_t^{NGDP}|$ is increasing and highly significant, demonstrating that firms with higher state dependence are more likely to adjust prices after larger macroeconomic shocks.

Finally, I regress sector price change frequency at time t on the previous two variables plus the kurtosis of price changes for sector k and the interaction between this kurtosis and the monetary policy shock:

$$Freq_{k,t} = \beta_1 Freq_k + \beta_2 |\epsilon_t^{NGDP}| + \beta_3 Kurt_k + \beta_4 |\epsilon_t^{NGDP}| \times Kurt_k + \nu_{i,t}$$

The results are shown in the last column of Table 2. The interaction coefficient is negative and statistically significant: the higher the kurtosis of a sector's price changes, the less its frequency of price changes in period t is affected by the size of the aggregate shock. In particular, if the kurtosis of price changes for the sector is approximately 3, the size of the aggregate shock has no effect on price change frequency–consistent with the Calvo sector's price changing behavior.

4.3 Equity Returns

Finally, I calculate the mean real equity return $\frac{V_t^k\left(\hat{P}_{i,k,t+1},Z_{i,k,t+1},A_{t+1},C_{t+1}\right)}{V_t^k\left(\hat{P}_{i,k,t},Z_{i,k,t},A_t,C_t\right)-D_{i,k,t}/P_t}$ for each firm in the economy. In Table 3, I show the mean frequency and kurtosis of price adjustment for each sector, as well as the average equity return, probability of a free price change, and menu cost. I compute standard errors for frequencies, kurtoses, and mean equity returns, shown in parentheses. The spread for these three statistics between firms in sectors 1 and 4 are shown in the final row, with standard errors again in parentheses.

From sectors 1 to 4, the probabilities of free price changes fall and menu costs fall, resulting in higher state dependence in firm's pricing decisions. While frequency falls slightly, kurtosis falls significantly. The decline in average equity returns from sectors 1 to 4 demonstrates that firms with higher state dependence are less exposed to systematic risk. This difference in risk cannot be explained by frequency alone, as firms in sectors with higher frequencies of price changes earn higher average equity returns.[6] Instead, the proxy for state dependence–kurtosis of price changes–accounts for the significant differences in systematic risk across sectors.

5 Data

I test the relationship between state dependence, conditional price change frequency, and equity returns predicted by the model by constructing a new dataset that links firms in Compustat to granular grocery store pricing data. I use weekly data on prices and quantities from Nielsen to construct firm-level measures of price adjustment frequency and kurtosis. I combine these measures with financial variables from Compustat and equity returns from CRSP. My final sample contains monthly data for 211 firms from 2006 to 2019.

[6]The slight increase in frequency from sectors 1 to 4 cannot explain the cashflow risk implied by equity returns in each sector. Lower unconditional frequency causes higher cashflow risk, as in Weber 2014 and Gorodnichenko and Weber 2016, and therefore implies higher average equity returns.

5.1 Weekly Pricing Data

The Nielsen's Scanner Dataset contains prices of products referenced by 12-digit barcodes (UPC), recorded each week across tens of thousands of supermarkets. UPCs are a very fine level of classification for a good and using them effectively removes concerns about changing prices due to changes in quality.[7] Within each store, the price of each UPC is recorded every week the UPC is present in the store from 2006 to 2019. I refer to a UPC-store combination as a good throughout this paper.

To link UPCs in the scanner data with firms in Compustat, I follow the procedure used by Clara, Corhay, and Kung 2021 and Kim 2020 to link a related dataset, the Nielsen Consumer Panel Data, to Compustat. Each UPC begins with a GS1 prefix which uniquely identifies the brand selling the good. Using a Python webscraping tool, I search for the companies that all 2.4 million UPCs in the Scanner Data belong to in the GS1 Company Database. I then match GS1 company names to Compustat names by comparing bigrams with a fuzzy match in Stata, and manually check the results for false matches. Finally, I manually search through the 200 largest GS1 brands by sales volume and link these to Compustat by hand.

With the UPC to Compustat link, I collect pricing data for goods linked to firms in Compustat. First, I remove good-year combinations where the good's price is not present in every week of the year.[8] I then compute the total sales value of each good that remains in my sample. I then aggregate total sales within the Nielsen data to the firm level, calculating total firm sales across all goods. I extract the weekly pricing data for goods that are at least 0.1% of a firm's total sales volume in Nielsen. In addition, I extract UPC-store combinations where the store's sales of a particular UPC is at least 0.5% of the sales value of the UPC's total sales, and the UPC's total sales across all stores is at least 0.1% of the total value of the firm's sales [9].

[7] Hottman, Redding, and Weinstein 2016 point out that products that are higher-quality versions of old products are almost always given a new UPC.

[8] This is the data cleaning procedure of Karadi, Schoenle, and Wursten 2020, who also use an extremely large dataset of prices, the IRI Marketing dataset. As they and Argente and Yeh 2022 point out, products introduced within a year are more likely to experience idiosyncratic pricing behaviors at their introduction. Removing goods not present in the entire year also makes the sample size more manageable.

[9] This procedure makes it more likely that UPCs with high sales volumes are included in my

The pricing data from Nielsen matched to Compustat contains a total of 47,339,971 weekly price and quantity observations encompassing 262,612 unique goods. A good is in my sample for an average of 3.8 years, and a median of 3 years. [10]

With the weekly prices in hand, I compute the frequency and kurtosis of price changes at the good level. I classify any movement in a good's price greater than \$0.01 as a price change. The frequency of price changes for good j, $Frequency_j$, is the ratio of the number of such price changes divided by the number of weeks j is in my sample. To calculate the kurtosis of price changes for j, I follow the cleaning method used in Alvarez, Le Bihan, and Lippi 2016 and Hong et al. 2021. I compute log price changes $\Delta p_{j,t}$ and drop those changes that are above the 99th percentile for all log changes in my sample. I then demean each price change by the mean log price change of good j. Finally, I divide by the standard deviation of log price changes for good j, creating normalized log price changes $\Delta \hat{p}_{j,t}$. The kurtosis of log price changes for j is computed as

$$Kurtosis_j = \frac{1}{T_j} \sum_{t \in j} \left(\Delta \hat{p}_{j,t} \right)^4$$

where T_j is the number of periods in which a price change occurs for j. With $Frequency_j$ and $Kurtosis_j$ calculated for each good, I then take a weighted average of each statistic to construct firm-level average pricing statistics $Frequency_i$ and $Kurtosis_i$. The weights ω_j are based on j's total sales in the sample divided by the sales of all goods that belong to firm i:

$$Frequency_i = \frac{1}{J} \sum_{j} \omega_j Frequency_j$$

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sample, even if they are geographically dispersed and no specific UPC-store combination within that UPC meets the 0.1% threshold.

[10] The median good in therefore is my sample for 156 months. At a median price change frequency of 0.29, this implies I observe about 45 price changes for the median good. The relatively frequent sampling frequency allows me to compute a more accurate measure of kurtosis than alternative datasets with monthly prices, such as the BLS PPI microdata used in Gilchrist et al. 2017, Augustin et al. 2021, and Weber 2014, at a disaggregated good level.

$$Kurtosis_i = \frac{1}{J}\sum_j \omega_j Kurtosis_j$$

$$\omega_j = \frac{\sum_t P_{j,t} * \text{Units Sold}_{j,t}}{\sum_{j \in J_i}\Big(\sum_t P_{j,t} * \text{Units Sold}_{j,t}\Big)}$$

where Units $\text{Sold}_{j,t}$ is the number of units of j sold in week t, J_i is the set of goods j that firm i sells, and $P_{j,t}$ is the price of good j in week t.

5.2 Financial Data

I merge the pricing statistics with several financial variables to control for potentially confounding factors. The controls are the same as those Weber 2014 uses, and are measured using data from Compustat or CRSP. From Compustat, I compute Book to Market Equity (BM) as the ratio of book equity to market equity. Book equity is the sum of stockholder's book equity (SEQ) plus deferred taxes and investment (TXDB) minus preferred stock book value (PSTK). Market equity is the price of shares at the end of the year (PRCC_F) times the number of shares (CSHO). Market capitalization is the log of market equity. Leverage is the sum of short-term (DLC) and long-term debt (DLTT) divided by total debt plus stockholder equity (SEQ). Cashflows is income before extraordinary items (IB) plus depreciation (DP) divided by total assets (AT). The price-cost margin, a proxy for markups, is sales (SALE) minus cost of goods sold (COGS), all divided by sales. To compute the Herfindal-Hirschman Index (HHI) for the concentration of sales within an industry, I group firms into the 48 Fama French industries in each year. For each year, I take the sum of the squares of each firm share of sales within its industry to create the industry-year HHI.

In addition to these accounting variables, I measure the rolling beta, share turnover, and bid-ask spread using CRSP. The rolling beta for a firm is the coefficient of the regression of its excess return over the past 60 months on the excess return of the Mkt-Rf factor taken from Kenneth French's website (see Fama and French 1993). Turnover is the volume of shares sold (VOL) divided by shares outstanding (SHROUT). Spread is the daily difference between bids and asks for a stock, averaged each month. I also download 3-, 4-, and 5- factor returns from Kenneth French's website. I winsorize all variables at the 1% level. In my main sample, I remove all goods with fewer than 5 price changes to remove low kurtosis measurements spuriously caused by a small number of observations.

The summary statistics for the data are shown in Table 4. The pricing statistics are very much in line with the prior literature studying grocery store prices: Midrigan 2011 finds a mean price change frequency of 0.34 compared to my 0.35, while Alvarez, Le Bihan, and Lippi 2016 find a kurtosis of 4 compared to my mean of 4.08. Correlations between pricing statistics and financial variables are shown in Table 5.

6 Empirical Results

With this dataset in hand, I test the hypotheses of the model that 1. firms with higher state dependence have higher conditional frequencies of price changes after large macroeconomic shocks and 2. this results in lower systematic cashflow risk and average equity returns. As discussed in Section 4.1, a higher kurtosis of price changes captures lower state dependence in my model. Therefore, the model predicts that firms with a higher kurtosis of price changes will have lower conditional price change frequencies after large shocks and higher average equity returns.

6.1 Short Term Price Responses to Monetary Policy Shocks

I first establish that firms with a higher kurtosis of price changes have price change frequencies that are less responsive to the size of an aggregate shock. This result is consistent with the hypothesis that a higher kurtosis of price changes indicates lower state dependence. On average, larger aggregate shocks should move firms' optimal prices by more, widening their price gap. The frequency of price adjustment for firms with high state dependence should therefore exhibit a higher sensitivity to the size of the aggregate shock.

I examine changes in the weekly frequency of price changes at the firm level after monetary policy shocks. For each firm i and week w, I compute the frequency of the firm's price changes as the fraction of goods owned by i whose price changed from week $w-1$ to w. I denote this weekly frequency by $Freq_{i,w}$. I use the monetary policy surprises provided by Acosta and Saia 2020, who extend the series constructed by Nakamura and Steinsson 2018 to cover the 2000-2020 sample. Nakamura and Steinsson 2018 measure movements in the Federal Funds Rate (FFR) in a 30 minute window around FOMC announcements. I denote a Federal Funds Rate surprise occuring after the end of week $w-1$ but before the end of week w as MP_w.

I predict weekly frequency with unconditional frequency, kurtosis, and the absolute size of MP shocks:

$$Freq_{i,w+h} = \delta_y + \beta_{1,h} Freq_i + \beta_{2,h} Kurt_i + \beta_{3,h} |MP_w| + \beta_{4,h} Kurt_i \times |MP_w| + \epsilon_{i,w,h}$$

Where $Freq_i$ and $Kurt_i$ are firm-level frequency and kurtosis of price changes as described in the previous section. $Freq_{i,w+h}$ is the fraction of goods owned by i whose price changed in week $w+h$. I run this regression for $h=0$ (price change frequency the week a FFR shock occurs) to $h=6$ (price change frequency 6 weeks after the shock has occured). δ_y are year fixed effects. The coefficient $\hat{\beta}_4$ captures how a firm's responsiveness to the size of FFR shocks depends on its kurtosis of price changes. If kurtosis is a negative indicator of selection and state dependence, the sign on $\hat{\beta}_4$ should be negative, i.e. a firm with a higher kurtosis of price changes has a weekly price change frequency that is less sensitive to the size of a macroeconomic shock. This is precisely the prediction of the model, shown in Table 2. I cluster standard errors at the firm level.

The coefficients of this regression for each horizon are shown in Panel A of Table 6 and confirm the hypothesized connection between state dependence, kurtosis of price changes, and conditional price adjustment frequency after macroeconomic shocks. The coefficient on unconditional frequency of price changes, $\hat{\beta}_1$, is close to 1 and highly significant. $\hat{\beta}_2$ is positive and statistically significant, consistent with the intuition that a larger aggregate shock increases the frequency of price change for a state dependent firm. This effect is significant for price changes up to a month after the initial MP shock, and attenuates farther out from the shock. Parallel with this effect, $\hat{\beta}_4$ is negative and statistically significant and also attenuates as the horizon increases. The interaction effect is economically significant: a firm with $Kurt_i = 0$ increases its price change frequency the week of a shock by 0.6% for each basis point increase in the size of the MP shock, while a firm with $Kurt_i = 6$ experiences no increase in price change frequency after a shock. These regressions provide strong evidence that higher kurtosis of price changes indicates lower sensitivity of price change probability to macroeconomic shocks, and thus greater cashflow exposure to such shocks.

I rerun this analysis without year fixed effects in Panel B of Table 6. While the coefficient on MP shocks is no longer statistically significant without controlling for year effects, the interaction term $\hat{\beta}_4$ is almost unchanged. As additional robustness checks, I replace firm-level frequency and kurtosis with a firm fixed effect in Table A1. The initial strong effect of kurtosis on the effect of MP shocks on price change frequencies remains, as does the pattern of this effect attenuating as the number of weeks from the initial shock increases.

Overall, these tests provide strong evidence that supports the hypothesis of the model that firms with a higher kurtosis of price changes are less likely to adjust their prices after larger macroeconomic shocks, controlling for unconditional frequency. This greater nominal rigidity in the face of such shocks makes firms with a higher kurtosis of price changes have greater cashflow risk. In Section 6.2, I show that firms with higher kurtoses of price changes earn an equity premium, consistent with the mechanism of the model that links kurtosis to higher cashflow risk.

6.2 Equity Returns

6.2.1 Portfolio Sorts

The first test I perform is single-variable tercile portfolio sorts based on the frequency and kurtosis of price changes. I group firms in my sample into three bins based on each pricing statistic. Within each bin, I compute the monthly average return among firms. I then take the average of each bin's return across time, and compute Newey-West standard errors (Newey and West 1987) with twelve lags for each bin's average return. I also construct a series for the spread between the returns for the high and low bins.

In addition to examining differences in average returns, I control for exposure to the factors in the CAPM and 3-, 4-, and 5- factor models.[11] I regress monthly returns from each bin and the spread on the factors of each model separately to compute the return not explained by exposure to these factors. I then compute the mean returns and standard errors in the same way as described above. In addition to equal-weighted returns, I calculate value-weighted returns for each bin by weighting each firm's return by its market capitalization.

As shown in Table 8, frequency of price changes does not have a clear relationship with equity returns. In none of the equal-weighted or value-weighted sorts is there a significant spread between the bins with high and low frequency. While this result may seem surprising given the main result in Weber 2014, this lack of a relationship is consistent with empirical results in the later Weber 2014 sample and with Clara 2019. In stark contrast to the lack of a relationship between frequency and returns, there is a significant and robust difference in returns between firms with low kurtosis and high kurtosis of price changes. As shown in Table 8, the differences between kurtosis-based spreads for equal-weighted returns is statistically significant at the 5% level and economically meaningful at about 6.4%. The value-weighted spreads continue to be statistically significant and are in the same range of magnitude as the equal-weighted spreads, indicating this result is not driven only by small firms.

6.2.2 Double Sorts

Given the positive correlation between the kurtosis and frequency of price changes seen in Table 5, it is possible that the relationship between kurtosis and average equity returns is confounded by frequency. While this is unlikely given the lack of a relationship between frequency and returns in my sample, I examine the relation-

[11] See Carhart 1997, Fama and French 1993, and Fama and French 2015.

ship between kurtosis and returns controlling for frequency. I first group firms by frequency into terciles, and then by kurtosis within each frequency tercile. The double sort shown in Table 9 suggests that, controlling for frequency of price changes, kurtosis of price changes still positively predicts equity returns. Consistent with the intuition that a greater degree of state dependent pricing reduces cashflow risk more for firms who change prices infrequently, the spread between high kurtosis and low kurtosis firms is largest and statistically significant for the lowest frequency tercile. For firms with more frequent price changes, kurtosis continues to be positively associated with kurtosis, although the effect is smaller and not statistically distinguishable from 0.

I further sort kurtosis conditionally on the financial control variables. For each control variable, I sort firms into terciles. Within each of these control variable terciles, I then sort firms into terciles based on their kurtosis of price changes. I then take the average return among firms in each month based on their conditional kurtosis tercile, and compute the monthly spread. As in the single-variable portfolio sorts, I calculate Newey-West standard errors with 12 lags to find the mean return across time for each of the three conditional kurtosis bins. Table 10 shows the average return in each conditional kurtosis bin as well as the high-low spread. For every control variable, I find a statistically and economically significant difference between the low and high conditional kurtosis bins.

6.2.3 Panel Regressions

To supplement the portfolio sorts, I test the relationship between frequency, kurtosis, and the control variables with a series of panel regressions. The regressions take the form

$$r_{i,t,t+1} = \delta_y + \beta_1 Frequency_i + \beta_2 Kurtosis_i + \Gamma_{i,t}\mathbf{X}_{i,t} + \epsilon_{i,t+1}$$

where δ_y are year fixed effects, β_1 and β_2 are the coefficients on frequency and kurtosis, and $\mathbf{X}_{i,t}$ are the financial control variables. The control variables' timings are chosen so that investors have information on the variables for the duration of the returns they are predicting. Following the convention used in Bretscher et al. 2020, Compustat-based accounting variables (such as leverage) in December of year $y-1$ are used to predict returns from July of year y to June of year $t+1$, and CRSP-based variables (such as market capitalization) are measured in June of year y to predict returns in the same time span.

The regression results are shown in Table 11. The first column regresses returns on frequency and kurtosis without controls or fixed effects. The second column adds fixed effects, and the third one of the control variables. Regressions are run with individual control variables until the right-most column, where all controls and year fixed effects are included in the regression. These panel regressions once again demonstrate the positive relationship between kurtosis of price changes and equity returns. The coefficient on kurtosis, β_2, remains positive and statistically significant regardless of the fixed effects or control variables used.

I repeat these panel regressions with different types of fixed effects in Tables A4, A5, A6, and A7. The point estimates for β_2 remain consistently positive across all panel regressions, although for heavily saturated regressions (such as the inclusion of industry and year fixed effects and control variables), it is no longer statistically significant.

6.2.4 Robust Kurtosis

As pointed out by Alvarez, Le Bihan, and Lippi 2016, Hong et al. 2021, and Berger and Vavra 2018, kurtosis is difficult measure in small samples and sensitive to outliers. To check whether my results are specific to how kurtosis is measured, I compute a measure of robust kurtosis. This measure of kurtosis, proposed by Moors 1988 and described in Kim and White 2004, uses octiles to capture the dispersion of price changes around the first and third quartiles:

$$Kurt_{Moors} = \frac{(\hat{q}_{7/8} - \hat{q}_{5/8}) + (\hat{q}_{3/8} - \hat{q}_{1/8})}{\hat{q}_{6/8} - \hat{q}_{2/8}}$$

I calculate $Kurt_{Moors}$ at the good level, and aggregate to the firm level in the same way I compute firm-level frequency and kurtosis. At the UPC-store level, I find a

Spearman's rank correlation coefficient of 0.3960 between directly measured kurtosis and $Kurt_{Moors}$. I sort firms into terciles by $Kurt_{Moors}$ Table A3 and continue to find a statsitically significant kurtosis premium.

6.2.5 1963-2019 Sample

To test the validity of these results outside my sample, I compare the average returns of firms in each kurtosis tercile from 1963-2019 in Table A2. I find a positive, statistically significant relationship between kurtosis and equity returns over the longer sample. The long-term equity earned by firms with a high kurtosis of price changes is 2.681%, in line with the frequency premium of 2.74 in the 1963-2011 period found by Weber 2014.

6.2.6 Aggregation at UPC Level

The above empirical tests, based on kurtosis of price changes measured at the UPC-store level, provide strong evidence of a kurtosis risk premium. To test whether these results hold when I change the unit at which I calculate the price change statistics, I calculate frequency and kurtosis of price changes at the UPC-level, pooling together price changes across stores. I then calculate $Freq_i$ and $Kurt_i$ by weighting the frequency and kurtosis of each UPC's price changes by the total sales of that UPC in my sample. I redo the portfolio sorts using the new aggregate pricing statistics, shown in Section C.

I continue to find little evidence of a premium associated with frequency of price changes. Instead, the kurtosis of price changes seems to be the key measure relating nominal rigidities to exposure to systematic risk. The sorts on kurtosis continue to show a monotonically positive relationship between kurtosis of price changes and average equity returns. In the value-weighted sorts, this relationship is highly statistically significant. Sorting firms by $Kurt_{Moors}$ gives the same conclusion, with the equal-weighted sorts monotonically increasing and a statistically significant spread between high and low $Kurt_{Moors}$ firms. The double sorts of kurtosis within frequency demonstrate that kurtosis is positively associated with equity returns regardless of frequency, although this relationship is not statisically significant.

6.2.7 Regular Price Changes

Posted prices have a propensity to change frequently but return to their previous values after a short period of time (Eichenbaum, Jaimovich, and Rebelo 2011). Midrigan 2011 argues that the majority of price changes observed in the data are sales, and that filtering sales from regular, non-sale prices is key to predicting the real effects of nominal shocks. I use his two-sided regular price identification algorithm with a window of 13 weeks to build regular price series for each good in my sample (I leave the details of the algorithm to Midrigan 2011) and Kehoe and Midrigan 2015). I then calculate frequency and kurtosis of price changes following the same procedure I use for posted prices, and repeat my empirical tests on regular frequency and kurtosis. I remove all goods with fewer than 5 regular price changes. This restriction reduces my sample substantially from 211 firms to 145 firms.

As documented in Section D, the kurtosis of regular price changes continues to positively predict returns in all tests, although this relationship is no longer statistically significant in the single-variable sorts. This is consistent with evidence from Carvalho and Kryvtsov 2021, who find that sales and temporary prices explain a substantial proportion of the heterogeneity of price selection between different stores within the United States.[12] In light of that result, it is not surprising that removing sales mitigates the relationship between state dependence and cashflow risk. Interestingly, however, kurtosis continues to have statistically significant predictive power on equity returns for firms with the lowest tercile of regular price change frequency, as shown in the double sort. This provides some evidence that there is a modest

[12] Price selection refers to differences between the distribution of prices that change due to monetary policy shocks, and those that would change in the absence of such a shock. High selection implies that the increase in the probability of a price change after a nominal shock is greatest for products whose price gaps are largest; higher selection amplifies price responses to monetary policy shocks and dampens real responses. In my model, selection increases one to one with state dependence. Price changes that occur due to a monetary policy shocks that would not have occured without such a shock are due entirely to the monetary policy shock increasing the cost of the price gap to exceed the menu cost. Therefore, the Calvo sector has no selection, while selection increases across sectors to the pure menu cost case.

effect of kurtosis on cashflow risk even when excluding sales.

I find a negative and statistically significant relationship between frequency of regular price adjustments and returns in the value-weighted sorts. This suggests that among the larger firms in my sample, there is a negative frequency premium when focusing on real prices. This is in line with the results of Weber 2014, who keeps firms in his sample only if they are listed on the S&P, focusing on larger firms. Furthermore, the prices used in the PPI microdata have been found to be almost completely devoid of sales (Nakamura and Steinsson 2008), suggesting that regular prices in my data set provide a closer analogue to the prices Weber 2014 observes. Nonetheless, more work is needed to understand the implications of regular vs posted prices for stock returns.

6.3 Idiosyncratic Shocks

In my model, differences in firms' kurtosis of price changes is due not to a difference in the underlying distribution of firm-specific shocks, but due to differences in the types of nominal rigidities firms face. In reality, it may be the case that firms do not differ in their nominal rigidities and therefore exposure to systematic shocks, but instead that firms all have roughly the same nominal rigidities and differences in the distribution of price changes merely reflect firm-specific differences in idiosyncratic shocks. If this is the case, the kurtosis of the distribution of idiosyncratic shocks should be closely positively related to a firm's kurtosis of price changes.

To test this possibility, I proxy idiosyncratic shocks by idiosyncratic equity returns. I regress each firm's excess returns on systematic factors:

$$r^e_{i,t,t+1} = \alpha_i + \beta_{i,Mkt-Rf} R_{i,t,t+1} + \epsilon^{idiosyncratic}_{i,t,t+1}$$

I find the idiosyncratic returns using the CAPM as well as the 3- 4-, and 5- factor models. I then compute the volatility and kurtosis of $\epsilon^{idiosyncratic}_{i,t,t+1}$ for each firm i. Finally, I examine the correlation and rank correlation between the volatilities and kurtoses of $\epsilon^{idiosyncratic}_{i,t,t+1}$ to the frequency and kurtosis of price changes.

In both linear and rank correlations, I find that firms with higher volatilities of idiosyncratic stock returns have higher price adjustment frequency and lower kurtosis of price changes. This is consistent with the predictions of Calvo Plus-style nominal rigidities: firms with higher idiosyncratic shock volatilities will cross the menu cost price change threshold more frequently than firms with lower volatilities of idiosyncratic shocks. This greater number of price changes around the menu cost threshold reduces kurtosis, and, compared to a firm with the same Calvo probability and menu cost, result in more frequent price changes.

However, there is little evidence that the kurtosis of price changes is driven simply by the differences in distributions of idiosyncratic shocks. Both the linear correlation and rank correlation of kurtosis of price changes to these shocks is statistically indistinguishable from 0, suggesting that the primary driver of the kurtosis of price changes for a firm is not a mechanical by-product of firm-specific shocks, but instead dependent on the type of nominal rigidity faced by the firm.

7 Conclusion

The implications of nominal rigidities for stock returns have recently come into focus in the asset pricing literature. While there is substantial evidence for a frequency premium in prior decades, recent work focusing on the post-2007 period has largely failed to find such a premium. I reconcile these seemingly divergent results by studying the importance of nominal rigidities *conditional* on macroeconomic shocks.

I show that how likely firms are to change prices conditional on their price-related cashflow losses, a property known as state dependence, is a significant determinant of systematic cashflow risk not explained by the unconditional frequency of price changes. I build a multisector model with heterogeneous nominal rigidities to show that firms with higher state dependence have higher frequencies of price changes after large macroeconomic shocks. These firms have cashflows that have a corresponding lower covariance with aggregate shocks, and higher state dependence therefore predicts lower average equity returns. I demonstrate that state dependence can be proxied by the kurtosis of price changes in this model.

I take my model to the data by constructing a new dataset linking firms in Compustat to weekly pricing data from the Nielsen Scanner Data. I find strong evidence that the kurtosis of price changes carries a risk premium, consistent with the model's prediction that lower state dependence increases systematic cashflow risk. Through various portfolio sorts, panel regressions, and robustness checks, firms with a higher kurtosis of price changes consistently earn higher average equity returns. I find this effect is strongest for firms with the lower frequency of price changes, consistent with these firms experiencing higher cashflow risk after macroeconomic shocks. I show that firms with higher kurtosis are less likely to adjust prices after larger monetary policy shocks, confirming the central mechanism of the model that links low state dependence to lower conditional price change frequency after macroeconomic shocks to greater cashflow risk.

This paper raises several avenues of future research into the implications of nominal rigidities for asset pricing. A natural question arising from this work is what determines whether firms have more or less state dependence in their price change timing. The positive correlation between frequency and kurtosis of price changes, as well as the negative correlation between kurtosis and the variance of idiosyncratic stock returns, indicates that firms with more volatile price gaps have greater state dependence. This pattern suggests a link between state dependence and exposure to more volatile shocks, but more work is needed to identify a causal effect. Similarly, the empirical results on regular prices vs posted prices suggest that the interaction between frequency, state dependence, and sales is a fruitful area of research for improving our understanding of nominal rigidities and systematic risk.

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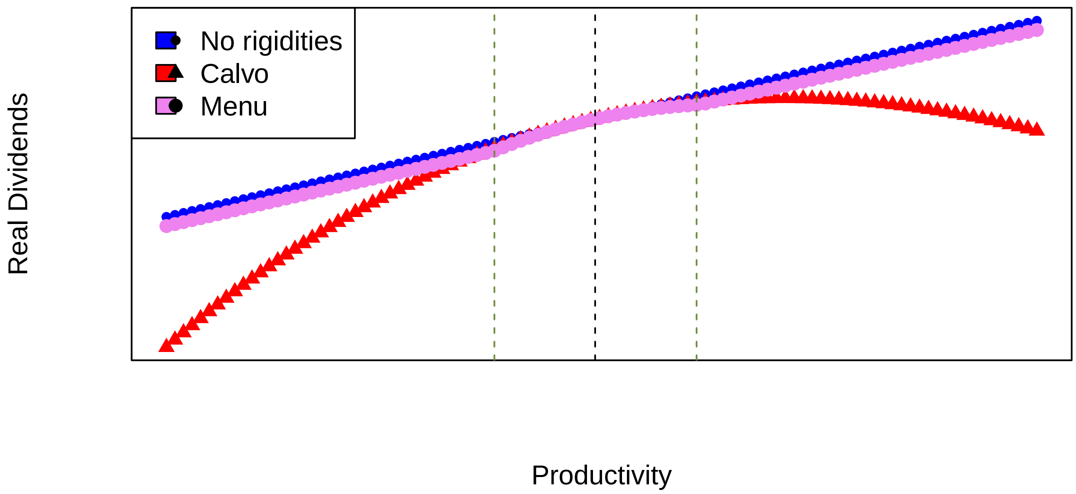
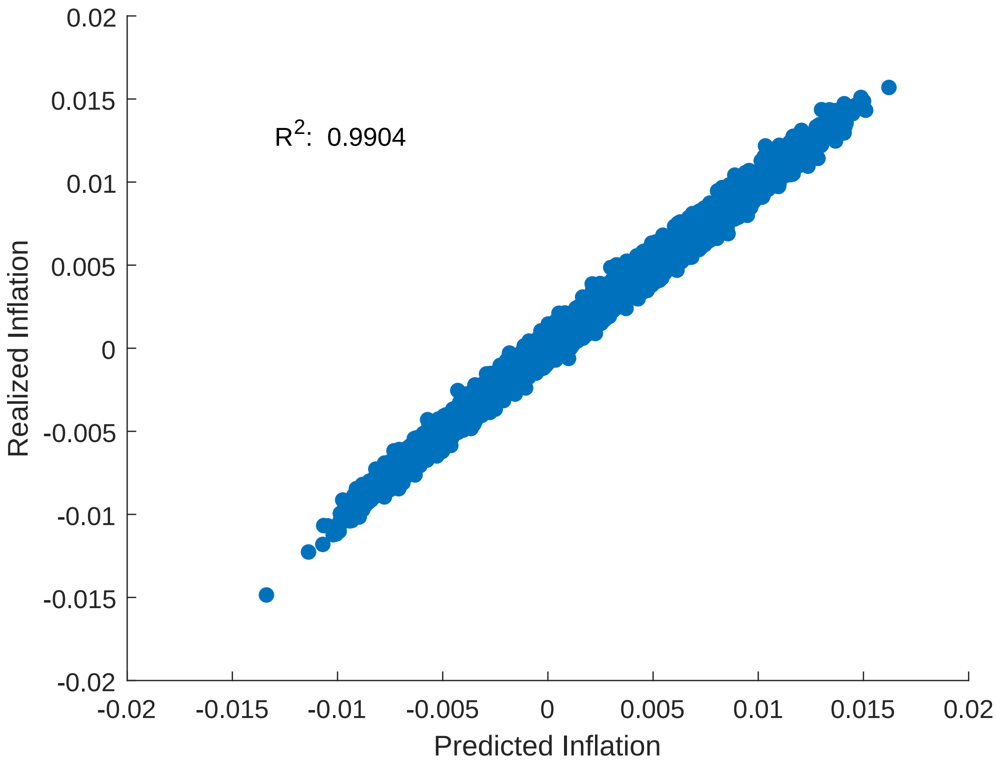
Figure 1: Profits as a function of productivity A_t



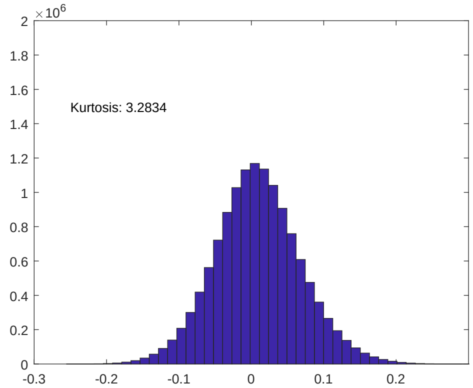
Expected profits as a function of technology for firms with different types of nominal rigidities as a function of productivity. Cashflows for a firm without nominal rigidites are shown in blue circles. Cashflows for a firm with free random price changes are shown in red. Cashflows for a menu cost firm are shown in violet.

Figure 2: Predicted vs Realized Inflation in the Model

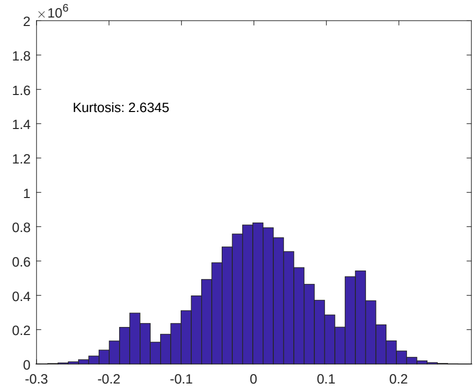


Predicted inflation vs realized inflation in the model. Firm predict inflation according to the rule given in Equation 2. After updating their prices based on this predicted inflation, I calculate realized inflation each period. Each point in the scatterplot represents predicted vs actual inflation in a single period in the simulation of the model.

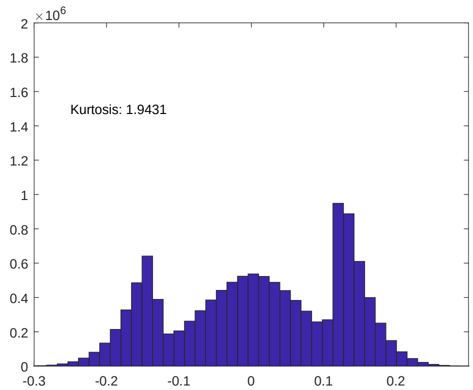
Figure 3: Price Change Histograms



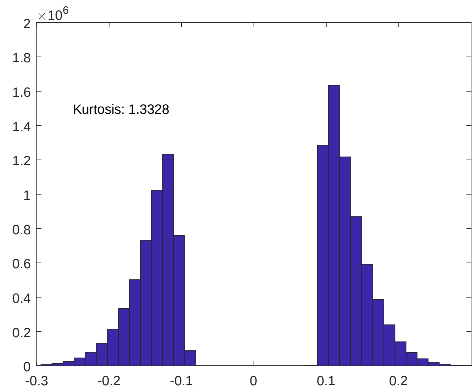
(a) Sector 1



(b) Sector 2



(c) Sector 3



(d) Sector 4

Histograms of price changes from all firms in each sector. The calvo and menu cost parameters, as well as the frequencies and kurtoses of price changes for firms in each sector, are shown in Table 3.

Table 1: Model Calibration

Parameter		
Time Discount Factor	β	0.99
Relative Risk Aversion	γ	5
Disutility from Labor	χ	1.33
Inverse of Frisch Labor Supply Elasticity	ξ	0
Elastity of Demand	η	4
Idiosyncratic Productivity Persistence	ρ_z	0.7
Idiosyncratic Productivity Shock Volatility	σ_z	0.075
Aggregate Productivity Persistence	ρ_a	0.8
Aggregate Productivity Shock Volatility	σ_a	0.0085
Mean Nominal GDP Growth	μ_{NGDP}	0.002
Monetary Policy Shock Volatility	σ_{NGDP}	0.0065

Parameters of the multisector model. These parameters are calibrated according to the values described in Section 3.7.

Table 2: Frequency of Price Changes After Monetary Policy Shocks by Sector

Sector	1	2	3	4	All
α_k	0.23	0.15	0.07	0	
κ_k	1	0.067	0.042	0.021	
$Freq_k$	1.000	0.9998	0.9997	0.9997	0.9385
	(0.0002)	(0.0003)	(0.0004)	(0.0006)	(0.0014)
$\lvert\epsilon_t^{NGDP}\rvert$	-0.0009	0.5808	0.7194	0.7801	2.2879
	(0.0090)	(0.0112)	(0.0133)	(0.0196)	(0.0420)
$Kurt_k$					0.0043
					(0.0001)
$\lvert\epsilon_t^{NGDP}\rvert \times Kurt_k$					-0.6900
					(0.0174)

Frequency of price changes in period t regressed on the unconditional frequency of price changes for sector k and the absolute value of the monetary policy shock at time t, $|\epsilon_t^{NGDP}|$. The first four columns show this regression for each sector. The last column regresses frequency of price changes for sector k in period k on unconditional frequency of k, the monetary policy shock, the kurtosis of price changes for sector k, and the interaction between the monetary policy shock and the kurtosis of price changes.

Table 3: State Dependence and Returns in the Model

α_k	κ_k	Frequency	Kurtosis	Mean Annual Return
0.23	1	0.2300	3.2745	3.6333
		(0.0000)	(0.0000)	(0.0000)
0.18	0.067	0.2218	2.6336	3.3790
		(0.0000)	(0.0000)	(0.0000)
0.12	0.042	0.2103	1.9426	3.2594
		(0.0000)	(0.0000)	(0.0000)
0.00	0.021	0.2084	1.3321	3.1168
		(0.0000)	(0.0000)	(0.0000)
		0.0215	1.9423	0.5166
		(0.0000)	(0.0000)	(0.0002)

Sector-specific pricing moments and equity returns. The first column shows the probability of a free price change for firms in each sector. The second column shows sector menu costs. The third and fourth are the average frequency and kurtosis of price changes at the firm level within each sector. The fifth column shows average annualized equity returns. The final row shows the spread in frequency, kurtosis and average equity returns between firms in the highest vs lowest state dependence sectors. Standard errors are shown in parentheses.

Table 4: Summary Statistics: 2006-2019

	Median	Mean	SD	Min	Max	Firms
			Price Change Statistics			
Frequency	0.291	0.353	0.212	0.026	0.865	211
Kurtosis	3.810	4.077	2.002	1.073	12.076	211
			Financial Variables			
Market Cap	13.906	13.904	2.347	9.112	19.167	210
BM	0.466	0.505	0.368	-0.430	1.972	207
Beta	0.858	0.999	0.657	-0.445	3.462	210
Leverage	0.393	0.438	0.289	0.002	1.822	202
Cashflows	0.077	0.059	0.101	-0.445	0.264	209
Turnover	16.080	18.519	12.246	0.623	72.056	210
Bid-Ask Spread	2.502	4.316	5.487	1.000	41.644	210
Price-Cost Margin	0.352	0.361	0.174	0.044	0.844	209
HH Index	0.071	0.084	0.053	0.025	0.280	209
Annualized Returns	9.857	5.652	25.159	-183.424	79.795	211

Summary statistics for the main sample of firms linked from Compustat/CRSP to the Nielsen Scanner Dataset. Frequency and kurtosis of price changes are computed for price changes at the UPC-store level and aggregated using a weighted average to the firm level. Financial variables are computed annually (if their source is Compustat) or monthly (if from CRSP); see Section 5 for descriptions of how variables are constructed. Summary statistics are shown as unconditional firm averages.

Table 5: Correlations

	Pricing Statistics		Financial Variables									
	Freq	Kurt	Market Cap	BM	Beta	Lev	CF	Turnover	Spread	PCM	HH	Ret
Freq	1.00											
Kurtosis	0.34	1.00										
Market Cap	-0.00	0.18	1.00									
BM	0.03	-0.05	-0.28	1.00								
Beta	0.09	-0.16	-0.20	0.04	1.00							
Leverage	0.09	0.09	0.03	-0.38	-0.06	1.00						
Cashflows	0.08	0.22	0.51	-0.21	-0.18	-0.07	1.00					
Turnover	0.13	0.02	0.21	0.02	0.27	-0.02	0.09	1.00				
Bid-Ask Spread	-0.11	-0.08	-0.46	0.07	-0.15	-0.02	-0.06	-0.40	1.00			
Price-Cost Margin	0.03	0.04	0.29	-0.19	-0.14	-0.01	0.27	-0.08	-0.05	1.00		
HH Index	0.13	0.05	0.02	0.07	-0.00	-0.06	-0.09	-0.01	-0.11	0.10	1.00	
Annualized Returns	0.01	0.09	0.32	-0.10	-0.15	0.03	0.29	0.15	-0.07	0.07	0.01	1.00

Correlations between price change statistics and financial variables at the firm level. Firm variables are computed as average across the 2006-2019 sample.

Table 6: Frequency of Price Changes after Monetary Policy Shocks

Panel A: Year Fixed Effects

$Freq_{i,w+h}$	$h=0$	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$	$h=6$
$Freq_i$	0.883***	0.891***	0.897***	0.885***	0.874***	0.890***	0.879***
	(0.0258)	(0.0273)	(0.0287)	(0.0278)	(0.0262)	(0.0266)	(0.0263)
$\lvert MP_w \rvert$	0.632***	0.496**	0.694***	0.680***	0.681***	0.459**	0.450*
	(0.243)	(0.222)	(0.231)	(0.229)	(0.239)	(0.233)	(0.233)
$Kurt_i$	-0.000335	-0.000503	-0.000836	9.84e-05	0.00212	0.000596	9.18e-05
	(0.00276)	(0.00279)	(0.00284)	(0.00282)	(0.00289)	(0.00286)	(0.00270)
$\lvert MP_w \rvert \times Kurt_i$	-0.110**	-0.114***	-0.121***	-0.102**	-0.118***	-0.101**	-0.0854*
	(0.0455)	(0.0437)	(0.0451)	(0.0464)	(0.0453)	(0.0448)	(0.0453)
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	14,080	14,080	14,080	14,080	14,080	14,080	14,080
R-squared	0.377	0.381	0.379	0.380	0.376	0.376	0.377

Panel B: No Year Fixed Effects

$Freq_{i,w+h}$	$h=0$	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$	$h=6$
$Freq_i$	0.899***	0.909***	0.915***	0.904***	0.892***	0.907***	0.897***
	(0.0240)	(0.0248)	(0.0263)	(0.0259)	(0.0245)	(0.0250)	(0.0245)
$\lvert MP_w \rvert$	0.294	0.258	0.338	0.285	0.321	0.220	0.151
	(0.236)	(0.230)	(0.231)	(0.232)	(0.230)	(0.228)	(0.227)
$Kurt_i$	0.000369	0.000228	-0.000105	0.000906	0.00287	0.00130	0.000777
	(0.00261)	(0.00270)	(0.00273)	(0.00270)	(0.00282)	(0.00281)	(0.00257)
$\lvert MP_w \rvert \times Kurt_i$	-0.110**	-0.113**	-0.120***	-0.102**	-0.119**	-0.0988**	-0.0834*
	(0.0454)	(0.0438)	(0.0452)	(0.0466)	(0.0460)	(0.0452)	(0.0458)
Year FE	N	N	N	N	N	N	N
Observations	14,080	14,080	14,080	14,080	14,080	14,080	14,080
R-squared	0.337	0.337	0.338	0.332	0.332	0.334	0.333

*** p<0.01, ** p<0.05, * p<0.1

The fraction of goods whose price changed in week $w+h$ for each firm regressed on the absolute value of monetary policy surprises, denoted by $|MP_w|$, and the interaction between the monetary policy surprise and firm kurtosis, $|MP_w| \times Kurt_i$. Monetary policy surprises are measured as movements in the Federal Funds Rate in a 30-minute window around Federal Open Market Committee announcements. The first panel includes year fixed effects, while the second panel omits them. Standard errors are shown in parentheses and clustered at the firm level.

Table 7: Returns in Frequency Bins

Equal Weighted	Low	2	High	High-Low
Excess Return	7.463	7.227	7.414	-0.049
	(4.561)	(4.490)	(5.838)	(2.450)
CAPM alpha	-0.796	-0.530	-2.208	-1.412
	(2.242)	(2.012)	(3.078)	(2.263)
FF3 alpha	0.272	0.130	-0.827	-1.099
	(1.918)	(1.869)	(2.876)	(2.288)
FF4 alpha	0.429	0.212	-0.615	-1.044
	(1.695)	(1.842)	(2.799)	(2.325)
FF5 alpha	-0.624	-0.951	-1.792	-1.169
	(1.826)	(1.880)	(2.846)	(2.278)

Value-Weighted	Low	2	High	High-Low
Excess Return	8.545***	7.781**	13.253***	4.708
	(3.010)	(3.116)	(4.538)	(3.815)
CAPM alpha	2.950**	1.681	5.775*	2.825
	(1.301)	(1.446)	(3.148)	(3.787)
FF3 alpha	2.618*	1.141	4.570	1.952
	(1.328)	(1.462)	(2.995)	(3.603)
FF4 alpha	2.619*	1.121	4.543	1.924
	(1.327)	(1.485)	(3.005)	(3.608)
FF5 alpha	1.768	-0.952	2.251	0.483
	(1.248)	(1.344)	(2.607)	(3.269)

*** p<0.01, ** p<0.05, * p<0.1

Average equity returns among firms grouped into terciles based on frequency of price changes from 2006 to 2019. Newey-West standard errors with 12 lags are computed for average returns. The spread between the high and low frequency terciles is shown in the rightmost column. Equal-weighted returns are shown in the top panel, and value-weighted returns in the bottom panel.

Table 8: Returns in Kurtosis Bins

Equal Weighted	Low	2	High	High-Low
Excess Return	3.802	8.143*	10.226**	6.424**
	(5.921)	(4.531)	(4.397)	(2.750)
CAPM alpha	-6.200**	0.018	2.746	8.946***
	(2.443)	(2.313)	(2.492)	(2.158)
FF3 alpha	-4.907**	0.878	3.691	8.598***
	(2.181)	(2.028)	(2.381)	(2.179)
FF4 alpha	-4.622**	0.963	3.770	8.392***
	(2.127)	(1.897)	(2.355)	(2.213)
FF5 alpha	-5.169**	-0.267	2.150	7.319***
	(2.156)	(1.937)	(2.332)	(2.094)

Value-Weighted	Low	2	High	High-Low
Excess Return	5.374	8.344***	12.040***	6.666*
	(5.059)	(2.737)	(3.798)	(3.666)
CAPM alpha	-3.437	2.720**	5.670**	9.107***
	(2.500)	(1.249)	(2.457)	(3.361)
FF3 alpha	-3.471	2.171	4.645*	8.116**
	(2.481)	(1.381)	(2.371)	(3.406)
FF4 alpha	-3.441	2.140	4.639*	8.080**
	(2.505)	(1.400)	(2.378)	(3.453)
FF5 alpha	-4.287*	0.513	2.607	6.895**
	(2.347)	(1.356)	(2.069)	(3.092)

*** p<0.01, ** p<0.05, * p<0.1

Average equity returns among firms grouped into terciles based on kurtosis of price changes from 2006 to 2019. Newey-West standard errors with 12 lags are computed for average returns. The spread between the high and low frequency terciles is shown in the rightmost column. Equal-weighted returns are shown in the top panel, and value-weighted returns in the bottom panel.

Table 9: Double Sorts–Kurtosis within Frequency

Freq	Kurtosis			
	Low	2	High	High-Low
Low	4.825	5.849	11.855***	7.030**
	(5.986)	(5.118)	(3.302)	(3.490)
2	5.206	8.999*	7.545*	2.339
	(5.631)	(4.808)	(4.387)	(4.191)
High	4.096	10.206	8.094	3.998
	(6.507)	(6.646)	(5.459)	(3.352)
HML	-0.729	4.357	-3.761	
	(2.901)	(3.870)	(3.118)	

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Firms are sorted into terciles based on their average frequency of price changes. Within each of these frequency terciles, I then sorts firms into conditional terciles based on kurtosis of price changes. Mean returns over the 2006-2019 sample for each kurtosis bin conditional on frequency bins are shown. The spreads between high and low kurtosis firms within each frequency bin are shown in the right column. The spreads between high and low frequency bins given each conditional kurtosis bin are shown in the bottom row. Standard errors are computed using the Newey-West procedure with 12 lags.

Table 10: Double Sorts–Kurtosis

	Low	2	High	High-Low
Market Cap	3.993	8.903**	9.520*	5.528**
	(5.400)	(4.484)	(4.908)	(2.141)
BM	4.072	8.483*	10.583**	6.511***
	(5.726)	(4.556)	(4.258)	(2.427)
Beta	4.470	7.847	10.069**	5.599**
	(5.424)	(4.848)	(4.595)	(2.470)
Leverage	4.810	7.900*	10.346**	5.536**
	(5.813)	(4.297)	(4.424)	(2.631)
Cashflows	4.284	7.932*	10.286**	6.002***
	(5.456)	(4.723)	(4.628)	(2.224)
Turnover	5.460	8.192*	11.697***	6.237**
	(5.312)	(4.404)	(4.489)	(2.444)
Bid-Ask Spread	3.293	9.278**	9.877**	6.584**
	(6.014)	(4.490)	(4.298)	(2.771)
Price-Cost Margin	3.589	8.984*	10.055**	6.466**
	(5.757)	(4.732)	(4.221)	(2.635)
HH Index	4.546	7.459	10.531**	5.985**
	(5.724)	(4.626)	(4.459)	(2.505)

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Average equity returns for firms based on kurtosis terciles conditional on several accounting and financial control variables. Firms are firms sorted into terciles based on a control variable, then into terciles again based on kurtosis of price changes within the control variable tercile. Equity returns are then averaged across firms in the same control variable tercile, within each conditional kurtosis tercile.

Table 11: Panel Regressions: Frequency and Kurtosis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Frequency	-2.952	-2.905	-1.403	-2.088	-1.658	-2.823	-0.731	-2.004	-2.192	-0.826	-0.691	-5.269
	(4.062)	(3.962)	(3.780)	(4.432)	(4.044)	(3.520)	(3.750)	(3.950)	(3.982)	(3.820)	(3.946)	(3.777)
Kurtosis	1.096**	1.051**	0.870*	0.945*	0.968**	1.058**	0.835*	1.020**	0.998**	0.961**	0.992**	0.894*
	(0.442)	(0.433)	(0.452)	(0.507)	(0.454)	(0.408)	(0.452)	(0.436)	(0.448)	(0.436)	(0.441)	(0.472)
log_mcap_june			0.640*									0.407
			(0.355)									(0.422)
BM_june				3.119								7.429**
				(2.926)								(3.154)
beta_june					-0.131							0.194
					(1.370)							(1.730)
leverage_june						-0.914						4.375
						(3.076)						(4.256)
cashflows_june							17.54					11.81
							(10.88)					(14.71)
turnover_june								0.0360				0.0152
								(0.0626)				(0.0724)
spread_monthly_june									-0.130			-0.165
									(0.149)			(0.252)
pcm_june										2.628		5.027
										(3.895)		(4.271)
HH_index_june											-4.848	-4.289
											(13.61)	(14.18)
Observations	24,590	24,590	24,188	22,404	24,110	21,979	23,828	24,188	24,188	23,714	23,912	20,546
Firms	211	211	211	207	211	202	209	211	211	209	209	200
R-squared	0.000	0.025	0.025	0.024	0.025	0.026	0.026	0.025	0.025	0.026	0.025	0.025
Year FE	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Panel regressions of monthly excess returns on frequency and kurtosis of price changes. Control variables are included one at a time until the final column, when they are all included in the regression. Year fixed effects are included.

A Model Details

A.1 Consumer Demand

In this subsection I derive the consumer's demand for product i and the expression for the economy-wide price level P_t as an aggregation of indiviudal prices $P_{i,k,t}$. Given a consumption basket C_t, the consumer chooses quantity demanded of each good $C_{i,k,t}$ to minimize costs:

$$\min_{\{C_{i,k,t}\}} \int_i \frac{P_{i,k,t}}{P_t} C_{i,t} di$$

such that

$$C_t \leq \left(\int_i C_{i,k,t}^{\frac{\eta-1}{\eta}} di \right)^{\frac{\eta}{\eta-1}}$$

The first order condition for this problem is

$$\frac{P_{i,k,t}}{P_t} = \mu_t \left(\int_i C_{i,k,t}^{\frac{\eta-1}{\eta}} di \right)^{\frac{1}{\eta-1}} C_{i,k,t}^{\frac{-1}{\eta}}$$

Where μ_t is the multiplier on the consumption aggregation constraint. I can rewrite this is

$$\frac{P_{i,k,t}}{P_t} = \mu_t C_t^{\frac{1}{\eta}} C_{i,k,t}^{\frac{-1}{\eta}}$$

Note that the multiplier μ_t is the same regardless of the good i the first order condition is taken for. Therefore, I substitute it out with the FOC for another good j:

$$\frac{P_{i,k,t}}{P_t} = \frac{P_{j,k,t}}{P_t} C_t^{\frac{-1}{\eta}} C_{j,k,t}^{\frac{1}{\eta}} C_t^{\frac{1}{\eta}} C_{i,k,t}^{\frac{-1}{\eta}}$$

Simplifying,

$$C_{j,k,t} = P_{j,k,t}^{-\eta} P_{i,k,t} C_{i,k,t}$$

I now aggregate over all goods $C_{j,k,t}$ to rewrite $C_{i,k,t}$ as a function of the aggregate price level P_t and aggregate consumption C_t. Aggregating $C_{j,k,t}$,

$$\underbrace{\left(\int_j C_{j,k,t}^{\frac{\eta-1}{\eta}} dj\right)^{\frac{\eta}{\eta-1}}}_{C_t} = \left(P_{j,k,t}^{\frac{1}{1-\eta}} dj\right)^{\frac{-\eta}{1-\eta}} P_{i,k,t}^{\eta} C_{i,k,t}$$

The aggregate price index is $P_t = \left(P_{j,k,t}^{\frac{1}{1-\eta}} dj\right)^{\frac{1}{1-\eta}}$. Therefore,

$$C_t = P_t^{-\eta} P_{i,k,t}^{\eta} C_{i,k,t}$$

Finally,

$$C_{i,k,t} = \left(\frac{P_{i,k,t}}{P_t}\right)^{-\eta} C_t$$

A.2 Steady State and Price Grid

Here I derive the the flexble price steady state value of consumption as well as the maximum and minimum real profit-maximizing prices for a firm as a function of idiosyncratic technology and the aggregate states. I repeat the firm's profits:

$$Profits(\hat{P}, Z, A, C) = \hat{P}^{1-\eta} C - \chi C^{\gamma-1} \hat{P}^{-\eta} \frac{1}{ZA}$$

Taking the first order condition,

$$\hat{P}^* = \frac{\eta\chi}{\eta - 1} C^{\gamma} \frac{1}{ZA} \tag{3}$$

In a flexible price steady state, it must be the case that a firm's relative price at its deterministic steady state (that is, when $Z = Z^{SS}$ and $A = A^{SS}$) is equal to 1. Therefore,

$$C^{SS} = \left(Z^{SS} A^{SS} \frac{\eta - 1}{\eta\chi}\right)^{-\gamma}$$

The minimum and maximum optimal relative prices $\hat{P}$ are simply the optimal prices given by Equation 3 when Z, A, and C are at their minimum or maximum gridpoints after discretization. My price grid therefore ranges from $\frac{\eta\chi}{\eta-1}C_{min}^{\gamma}\frac{1}{Z_{max}A_{max}}$ to $\frac{\eta\chi}{\eta-1}C_{max}^{\gamma}\frac{1}{Z_{min}A_{min}}$.

A.3 Computationally Solving the Model

In this subsection, I describe in detail the procedure for calculating the value function $V^k(\hat{P}_{-1}, Z, A, C)$. At the beginning of each period, the firm carries over its nominal price from the previous period $P_{i,t-1}$. Shocks to nominal GDP ϵ_t^{NGDP}, aggregate productivity ϵ_t^a, and idiosyncratic prodcutivity ϵ_t^z are realized. The firm predicts inflation $\hat{\Pi}$ based on the Krusell-Smith approximation given in Equation 2. The firm starts the period with a real price $\hat{P}_{-1}$ that is last period's end -of-period real price minus predicted inflation: $log(\hat{P}_{-1}) = log(\hat{P}_{t-1}) - log(\hat{\Pi})$. The firm then either receives a free price change, or does not receive a free price change and chooses whether or not to pay the menu cost. The value function is shown below again for convenience:

$$\begin{aligned} V^k(\hat{P}_{-1}, Z, A, C) = \alpha_k & \underbrace{\Big[\Pi^R(\hat{P}^*(Z,A,C), Z, A, C) + EM'V^k(\hat{P'}_{-1}, Z', A', C')\Big]}_{\text{Free price change}} \\ + (1-\alpha_k)\max & \Big[\underbrace{\Pi^R(\hat{P}_{-1}, Z, A, C) + EM'V^k(\hat{P'}_{-1}, Z', A', C')}_{\text{No free price change, does not pay } \kappa_k}, \\ & \underbrace{\Pi^R(\hat{P}^*(Z,A,C), Z, A, C) - \kappa_k + EM'V^k(\hat{P'}_{-1}, Z', A', C')}_{\text{No free price change, pays } \kappa_k}\Big] \end{aligned} \tag{4}$$

I use value function iteration to calculate $V^k(\hat{P}_{-1}, Z, A, C)$. Let Ω denote the state of the firm at the beginning of the period, $(\hat{P}_{-1}, Z, A, C)$. Within each iteration, I first calculate the continuation value of each possible state , which is given by

$$EM'V^k(\Omega') = \sum_{\Omega'} M'V^k(\Omega')P(\Omega'|\Omega)$$

The probability of starting in state Ω' in the next period is given by

$$P(\Omega'|\Omega) = P(\hat{p}'_{-1} = \hat{P}'_{-1}|\hat{P}_{-1}, A, C) \times P(z' = Z'|Z) \times P(a' = A'|A) \times P(c' = C'|C, A)$$

Transition probabilities for the state variables are discretized using the procedure from Tauchen 1986. Lower case variables denote random realizations of the the states at the beginning of the next period. Following Midrigan 2011, I drop future states Ω' whose probability of occurence $P(\Omega'|\Omega)$ is less than 0.001%. The continuation value $EM'V^k(\Omega')$ is then the weighted sum of future possible states $M'V^k(\Omega')$.

With the continuation value in hand, I update the value function by calculating Equation 1. I then begin the next iteration and compute continuation values based on the updated value function. This iteration continues until the difference between the previous and updated value functions are within a tolerance bound at every state. Following the recommendation of Aruoba and Fernández-Villaverde 2015, I use **C++** to solve the firm's problem. I use **Matlab** to simulate the economy.

B More Tables and Figures

Table A1: Frequency of Price Changes after Monetary Policy Shocks with Firm Fixed Effects

Panel A: Year Fixed Effects

$Freq_{i,t+h}$	$h=0$	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$	$h=6$
$\|MP_w\|$	0.546**	0.373	0.616**	0.613**	0.595**	0.376	0.395
	(0.248)	(0.229)	(0.237)	(0.238)	(0.246)	(0.231)	(0.241)
$\|MP_w\| \times Kurt_i$	-0.0924**	-0.0888**	-0.105**	-0.0881*	-0.101**	-0.0841*	-0.0737
	(0.0465)	(0.0449)	(0.0462)	(0.0483)	(0.0470)	(0.0449)	(0.0473)
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	14,080	14,080	14,080	14,080	14,080	14,080	14,080
R-squared	0.418	0.424	0.421	0.422	0.420	0.420	0.420

Panel B: No Year Fixed Effects

$Freq_{i,t+h}$	$h=0$	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$	$h=6$
$\|MP_w\|$	0.216	0.124	0.272	0.235	0.246	0.138	0.112
	(0.247)	(0.240)	(0.240)	(0.243)	(0.242)	(0.232)	(0.241)
$\|MP_w\| \times Kurt_i$	-0.0981**	-0.0934**	-0.110**	-0.0951*	-0.108**	-0.0874*	-0.0775
	(0.0471)	(0.0456)	(0.0463)	(0.0486)	(0.0480)	(0.0458)	(0.0484)
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	N	N	N	N	N	N	N
Observations	14,080	14,080	14,080	14,080	14,080	14,080	14,080
R-squared	0.372	0.374	0.373	0.368	0.371	0.373	0.371

*** p<0.01, ** p<0.05, * p<0.1

The fraction of goods whose price changed in week $w+h$ for each firm regressed on the absolute value of monetary policy surprises, denoted by $|MP_w|$, and the interaction between the monetary policy surprise and firm kurtosis, $|MP_w| \times Kurt_i$. Monetary policy surprises are measured as movements in the Federal Funds Rate in a 30-minute window around Federal Open Market Committee announcements. The first panel includes year fixed effects, while the second panel omits them. Standard errors are shown in parentheses and clustered at the firm level.

Table A2: Returns by Kurtosis Bin: 1963-2019

Equal Weighted	Low	2	High	High-Low
Excess Return	8.264***	9.362***	11.085***	2.821**
	(2.677)	(2.025)	(2.192)	(1.319)
CAPM alpha	1.573	3.669***	5.647***	4.074***
	(1.699)	(1.299)	(1.395)	(1.264)
FF3 alpha	-0.195	2.604**	4.790***	4.985***
	(1.197)	(1.119)	(1.271)	(1.097)
FF4 alpha	1.299	3.103***	5.677***	4.378***
	(1.156)	(1.110)	(1.256)	(1.090)
FF5 alpha	-1.687	0.675	2.855***	4.542***
	(1.139)	(0.959)	(1.087)	(1.072)

Value-Weighted	Low	2	High	High-Low
Excess Return	5.244**	7.175***	9.292***	4.048**
	(2.448)	(1.943)	(2.015)	(1.916)
CAPM alpha	-1.469	1.978	4.139***	5.608***
	(1.625)	(1.320)	(1.308)	(1.898)
FF3 alpha	-2.204	2.893**	4.960***	7.164***
	(1.544)	(1.285)	(1.285)	(1.769)
FF4 alpha	-1.307	2.646**	4.833***	6.139***
	(1.548)	(1.285)	(1.285)	(1.776)
FF5 alpha	-3.287**	0.636	2.239**	5.526***
	(1.407)	(1.181)	(1.037)	(1.740)

*** p<0.01, ** p<0.05, * p<0.1

Average equity returns among firms grouped into terciles based on kurtosis of price changes from 1963 to 2019. Newey-West standard errors with 12 lags are computed for average returns. The spread between the high and low kurtosis terciles is shown in the rightmost column. Equal-weighted returns are shown in the top panel, and value-weighted returns in the bottom panel.

Table A3: Returns in $Kurt_{Moors}$ Bins

Equal Weighted				
	Low	2	High	High-Low
Excess Return	4.652	8.737**	8.780*	4.128*
	(5.319)	(4.418)	(5.081)	(2.216)
CAPM alpha	-4.711**	0.794	0.466	5.177**
	(2.328)	(2.071)	(2.779)	(2.152)
FF3 alpha	-3.459*	1.559	1.545	5.004**
	(2.089)	(1.876)	(2.510)	(2.173)
FF4 alpha	-3.248	1.664	1.679	4.928**
	(2.178)	(1.768)	(2.327)	(2.315)
FF5 alpha	-3.772*	0.005	0.458	4.230**
	(2.068)	(1.853)	(2.414)	(2.121)

Value-Weighted				
	Low	2	High	High-Low
Excess Return	6.909**	12.932***	8.846***	1.937
	(2.971)	(4.775)	(2.868)	(1.926)
CAPM alpha	0.729	4.718*	3.841**	3.112
	(1.720)	(2.816)	(1.530)	(1.994)
FF3 alpha	0.607	3.385	3.412**	2.805
	(1.743)	(2.665)	(1.485)	(1.978)
FF4 alpha	0.585	3.394	3.382**	2.797
	(1.733)	(2.655)	(1.495)	(1.983)
FF5 alpha	-1.488	1.309	2.019	3.507*
	(1.728)	(2.356)	(1.360)	(2.005)

*** p<0.01, ** p<0.05, * p<0.1

Average equity returns among firms grouped into terciles based on robust kurtosis of Moors 1988. Newey-West standard errors with 12 lags are computed for average returns. The spread between the high and low robust kurtosis terciles is shown in the rightmost column. Equal-weighted returns are shown in the top panel, and value-weighted returns in the bottom panel.

Table A4: Panel Regressions: No Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Frequency	-2.952	-2.952	-1.419	-2.035	-2.246	-2.966	-0.535	-1.759	-2.455	-0.676	-0.922	-7.044*
	(4.062)	(4.062)	(3.879)	(4.576)	(4.140)	(3.640)	(3.852)	(4.015)	(4.041)	(3.878)	(3.996)	(4.123)
Kurtosis	1.096**	1.096**	0.986**	1.073**	1.116**	1.068***	0.982**	1.082**	1.067**	1.041**	1.069**	1.008**
	(0.442)	(0.442)	(0.451)	(0.527)	(0.455)	(0.410)	(0.458)	(0.435)	(0.454)	(0.436)	(0.437)	(0.507)
log_mcap_june			0.418									0.293
			(0.360)									(0.467)
BM_june				7.192**								12.14***
				(3.059)								(3.383)
beta_june					0.929							1.197
					(1.532)							(1.782)
leverage_june						-0.619						6.350
						(3.344)						(4.553)
cashflows_june							9.986					10.05
							(11.52)					(15.17)
turnover_june								0.0173				-0.0271
								(0.0643)				(0.0762)
spread_monthly_june									-0.204			-0.370
									(0.185)			(0.291)
pcm_june										1.487		6.770
										(4.050)		(4.547)
HH_index_june											7.999	2.570
											(13.01)	(14.80)
Constant	3.699*	3.699*	-2.420	0.410	2.518	4.299**	2.744	3.023	4.483**	2.786	2.553	-9.739
	(2.024)	(2.024)	(5.492)	(3.066)	(2.471)	(1.927)	(2.032)	(2.197)	(2.209)	(2.580)	(2.151)	(9.145)
Observations	24,590	24,590	24,188	22,404	24,110	21,979	23,828	24,188	24,188	23,714	23,912	20,546
R-squared	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Panel regressions of monthly excess returns on frequency and kurtosis of price changes. Control variables are included one at a time until the final column, when they are all included in the regression. No fixed effects are included.

Table A5: Panel Regressions: Industry Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Frequency	-2.952	-1.631	0.0943	-1.104	-1.298	-0.846	1.248	-0.444	-1.170	1.251	1.656	-3.258
	(4.062)	(4.532)	(4.473)	(5.179)	(4.654)	(4.432)	(4.425)	(4.556)	(4.552)	(4.416)	(4.610)	(5.501)
Kurtosis	1.096**	0.852*	0.757*	0.963**	0.936**	0.715	0.768*	0.836*	0.826*	0.840**	0.813*	0.727
	(0.442)	(0.433)	(0.429)	(0.483)	(0.424)	(0.456)	(0.429)	(0.428)	(0.444)	(0.425)	(0.427)	(0.521)
log_mcap_june			0.327									0.391
			(0.380)									(0.508)
BM_june				9.786***								15.16***
				(2.864)								(3.607)
beta_june					2.131							2.522
					(1.611)							(1.941)
leverage_june						0.00858						8.044*
						(3.459)						(4.701)
cashflows_june							6.239					5.210
							(10.67)					(13.53)
turnover_june								0.0195				-0.0456
								(0.0667)				(0.0776)
spread_monthly_june									-0.218			-0.365
									(0.181)			(0.285)
pcm_june										0.640		15.70***
										(5.075)		(5.808)
HH_index_june											-13.27	-22.70
											(18.01)	(20.84)
Observations	24,590	24,590	24,188	22,404	24,110	21,979	23,828	24,188	24,188	23,714	23,912	20,546
R-squared	0.000	0.001	0.001	0.002	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.003
Industry FE	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

*** p<0.01, ** p<0.05, * p<0.1

Panel regressions of monthly excess returns on frequency and kurtosis of price changes. Control variables are included one at a time until the final column, when they are all included in the regression. Industry fixed effects are included.

Table A6: Panel Regressions: Industry Fixed Effects and Year Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Frequency	-2.952	-1.587	0.343	-0.790	-0.739	-0.490	1.278	-0.623	-0.873	1.173	2.500	-0.527
	(4.062)	(4.352)	(4.297)	(4.960)	(4.487)	(4.214)	(4.218)	(4.414)	(4.424)	(4.282)	(4.445)	(4.901)
Kurtosis	1.096**	0.807*	0.635	0.823*	0.791*	0.724	0.622	0.774*	0.756*	0.770*	0.727*	0.614
	(0.442)	(0.426)	(0.435)	(0.474)	(0.434)	(0.462)	(0.430)	(0.436)	(0.447)	(0.429)	(0.434)	(0.491)
log_mcap_june			0.576									0.525
			(0.375)									(0.463)
BM_june				5.399**								9.929***
				(2.564)								(3.337)
beta_june					0.845							1.406
					(1.471)							(1.888)
leverage_june						-0.235						5.972
						(3.159)						(4.389)
cashflows_june							14.79					7.651
							(9.808)					(13.04)
turnover_june								0.0366				0.00243
								(0.0641)				(0.0738)
spread_monthly_june									-0.143			-0.158
									(0.143)			(0.240)
pcm_june										1.997		12.57**
										(4.628)		(5.465)
HH_index_june											-34.65*	-36.17*
											(17.90)	(18.97)
Observations	24,590	24,590	24,188	22,404	24,110	21,979	23,828	24,188	24,188	23,714	23,912	20,546
R-squared	0.000	0.026	0.026	0.025	0.026	0.027	0.026	0.026	0.026	0.026	0.026	0.027
Year FE	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

*** p<0.01, ** p<0.05, * p<0.1

Panel regressions of monthly excess returns on frequency and kurtosis of price changes. Control variables are included one at a time until the final column, when they are all included in the regression. Year and industry fixed effects are included.

Table A7: Panel Regressions: Industry by Year Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Frequency	-2.952	-1.914	0.121	-0.383	-0.873	-0.304	0.748	-0.840	-1.002	0.637	2.330	0.512
	(4.062)	(4.367)	(4.281)	(4.968)	(4.446)	(4.066)	(4.199)	(4.392)	(4.410)	(4.277)	(4.403)	(4.754)
Kurtosis	1.096**	0.784*	0.593	0.771*	0.744*	0.713*	0.584	0.733*	0.715*	0.755*	0.682*	0.676
	(0.442)	(0.412)	(0.413)	(0.454)	(0.413)	(0.423)	(0.404)	(0.417)	(0.426)	(0.405)	(0.410)	(0.456)
log_mcap_june			0.585									0.589
			(0.364)									(0.468)
BM_june				3.881								7.703**
				(2.518)								(3.332)
beta_june					0.681							1.238
					(1.383)							(1.753)
leverage_june						-0.462						3.843
						(2.943)						(4.216)
cashflows_june							14.57					-0.227
							(9.927)					(13.42)
turnover_june								0.0344				-0.00959
								(0.0673)				(0.0793)
spread_monthly_june									-0.117			-0.144
									(0.139)			(0.243)
pcm_june										0.741		9.549*
										(4.540)		(5.150)
HH_index_june											-35.32**	-34.89*
											(17.81)	(18.57)
Observations	24,590	24,590	24,188	22,404	24,110	21,979	23,828	24,188	24,188	23,714	23,912	20,546
R-squared	0.000	0.036	0.036	0.037	0.036	0.036	0.036	0.036	0.036	0.037	0.036	0.038
Industry X Year FE	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Panel regressions of monthly excess returns on frequency and kurtosis of price changes. Control variables are included one at a time until the final column, when they are all included in the regression. Industry by year fixed effects are included.

Table A8: Pricing Statistics and Idiosyncratic Return Volatility Correlation

	Frequency	Kurt	CAPM Vol	FF3 Vol	FF4 Vol	FF5 Vol
Freq	1.00					
Kurtosis	0.32	1.00				
CAPM Idiosyncratic Vol	0.14	-0.13	1.00			
FF3 Idiosyncratic Vol	0.14	-0.13	1.00	1.00		
FF4 Idiosyncratic Vol	0.14	-0.13	1.00	1.00	1.00	
FF5 Idiosyncratic Vol	0.15	-0.12	1.00	1.00	1.00	1.00

Correlations between firm-level pricing statistics and idiosyncratic volatility at the firm level. Idiosyncratic shocks are identified as the residuals of regressions of firms' equity returns on systematic factors, which range from the CAPM to the Fama French 5 models.

Table A9: Pricing Statistics and Idiosyncratic Return Kurtosis Correlation

	Frequency	Kurt	CAPM Kurt	FF3 Kurt	FF4 Kurt	FF5 Kurt
Freq	1.00					
Kurtosis	0.32	1.00				
CAPM Idiosyncratic Kurt	0.02	0.03	1.00			
FF3 Idiosyncratic Kurt	0.02	0.03	1.00	1.00		
FF4 Idiosyncratic Kurt	0.02	0.03	1.00	1.00	1.00	
FF5 Idiosyncratic Kurt	0.02	0.03	1.00	1.00	1.00	1.00

Correlations between firm-level pricing statistics and idiosyncratic volatility at the firm level. Idiosyncratic shocks are identified as the residuals of regressions of firms' equity returns on systematic factors, which range from the CAPM to the Fama French 5 models.

Table A10: Pricing Statistics and Idiosyncratic Return Volatility Rank Correlation

	Frequency	Kurt	CAPM Vol	FF3 Vol	FF4 Vol	FF5 Vol
Freq	1.0000					
Kurtosis	0.3646	1.0000				
CAPM Idiosyncratic Vol	0.1307	-0.2539	1.0000			
FF3 Idiosyncratic Vol	0.1309	-0.2538	0.9986	1.0000		
FF4 Idiosyncratic Vol	0.1306	-0.2520	0.9969	0.9987	1.0000	
FF5 Idiosyncratic Vol	0.1348	-0.2502	0.9980	0.9995	0.9985	1.0000

Correlations between firm-level pricing statistics and idiosyncratic volatility at the firm level. Idiosyncratic shocks are identified as the residuals of regressions of firms' equity returns on systematic factors, which range from the CAPM to the Fama French 5 models.

Table A11: Pricing Statistics and Idiosyncratic Return Kurtosis Rank Correlation

	Frequency	Kurt	CAPM Kurt	FF3 Kurt	FF4 Kurt	FF5 Kurt
Freq	1.0000					
Kurtosis	0.3646	1.0000				
CAPM Idiosyncratic Kurt	-0.0358	0.0088	1.0000			
FF3 Idiosyncratic Kurt	-0.0358	0.0088	1.0000	1.0000		
FF4 Idiosyncratic Kurt	-0.0358	0.0088	1.0000	1.0000	1.0000	
FF5 Idiosyncratic Kurt	-0.0358	0.0088	1.0000	1.0000	1.0000	1.0000

Correlations between firm-level pricing statistics and idiosyncratic volatility at the firm level. Idiosyncratic shocks are identified as the residuals of regressions of firms' equity returns on systematic factors, which range from the CAPM to the Fama French 5 models.

C Statistics Aggregated at UPC Level

In this section, I compute frequency and kurtosis at the UPC level, treating all price changes within a UPC across stores as occuring to a single good. I use only UPCs with at least 5 price changes. My sample consists of 213 firms, only slightly more than the 211 in the main sample based on UPC-store level statistics.

Table A12: Summary Statistics: 2006-2019

	Price Change Statistics					
	Median	Mean	SD	Min	Max	Firms
Frequency	0.267	0.317	0.216	0.016	0.851	213
Kurtosis	5.523	6.404	4.398	1.356	25.596	213
	Financial Variables					
Market Cap	13.897	13.884	2.348	9.119	19.167	212
BM	0.466	0.505	0.365	-0.395	1.972	209
Beta	0.858	0.996	0.653	-0.416	3.384	212
Leverage	0.393	0.437	0.289	0.002	1.822	204
Cashflows	0.077	0.059	0.101	-0.445	0.264	211
Turnover	15.971	18.404	12.251	0.623	72.056	212
Bid-Ask Spread	2.511	4.419	5.728	1.000	43.402	212
Price-Cost Margin	0.352	0.361	0.173	0.044	0.844	211
HH Index	0.071	0.084	0.053	0.025	0.280	211
Annualized Returns	9.857	5.677	25.053	-183.282	79.847	213

Summary statistics for firms when price change statistics are computed at the UPC level. Frequency and kurtosis of price changes are computed for price changes within a UPC, averaging across stores, and aggregated using a weighted average to the firm level. Financial variables are computed annually (if their source is Compustat) or monthly (if from CRSP); see Section 5 for descriptions of how variables are constructed. Summary statistics are shown as unconditional firm averages.

Table A13: Correlations

	Pricing Statistics		Financial Variables									
	Freq	Kurt	Market Cap	BM	Beta	Lev	CF	Turnover	Spread	PCM	HH	Ret
Freq	1.00											
Kurtosis	0.21	1.00										
Market Cap	0.04	0.05	1.00									
BM	0.02	-0.02	-0.28	1.00								
Beta	0.05	-0.08	-0.19	0.04	1.00							
Leverage	0.10	0.15	0.04	-0.38	-0.04	1.00						
Cashflows	0.11	-0.07	0.50	-0.21	-0.19	-0.08	1.00					
Turnover	0.13	-0.03	0.22	0.02	0.28	-0.02	0.09	1.00				
Bid-Ask Spread	-0.11	0.03	-0.47	0.08	-0.17	-0.04	-0.06	-0.40	1.00			
Price-Cost Margin	0.05	-0.02	0.29	-0.19	-0.14	-0.02	0.27	-0.08	-0.05	1.00		
HH Index	0.13	-0.03	0.00	0.08	-0.03	-0.08	-0.09	-0.03	-0.06	0.10	1.00	
Annualized Returns	0.01	-0.06	0.32	-0.10	-0.14	0.03	0.29	0.15	-0.08	0.07	0.01	1.00

Correlations between price change statistics and financial variables. Pricing statistics are calculated across the entire life of a UPC. Each firm's value for each pricing statistic is the average of its UPCs weighted by the total sales value of each UPC. Correlations are calculated at the firm-month level.

Table A14: Returns in Frequency Bins

Equal Weighted	Low	2	High	High-Low
Excess Return	6.791	7.198	8.018	1.228
	(4.757)	(4.399)	(5.571)	(2.076)
CAPM alpha	-1.772	-0.446	-1.288	0.484
	(2.253)	(2.074)	(2.803)	(1.995)
FF3 alpha	-0.608	0.327	-0.140	0.468
	(1.804)	(1.948)	(2.623)	(1.982)
FF4 alpha	-0.438	0.394	0.067	0.505
	(1.516)	(1.931)	(2.552)	(2.017)
FF5 alpha	-1.943	-0.446	-1.068	0.875
	(1.698)	(1.936)	(2.594)	(1.982)

Value-Weighted	Low	2	High	High-Low
Excess Return	8.116***	8.124***	13.331***	5.215
	(3.011)	(3.078)	(4.533)	(3.793)
CAPM alpha	2.494*	2.147*	5.875*	3.382
	(1.445)	(1.260)	(3.129)	(3.744)
FF3 alpha	2.089	1.713	4.636	2.547
	(1.470)	(1.254)	(2.966)	(3.544)
FF4 alpha	2.093	1.700	4.610	2.517
	(1.469)	(1.269)	(2.977)	(3.551)
FF5 alpha	0.772	0.075	2.340	1.568
	(1.363)	(1.160)	(2.583)	(3.268)

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Average equity returns among firms grouped into terciles based on frequency of price changes from 2006 to 2019. Newey-West standard errors with 12 lags are computed for average returns. The spread between the high and low frequency terciles is shown in the rightmost column. Equal-weighted returns are shown in the top panel, and value-weighted returns in the bottom panel.

Table A15: Returns in Kurtosis Bins

Equal Weighted	Low	2	High	High-Low
Excess Return	5.147	8.248**	8.644*	3.496
	(6.199)	(4.167)	(4.447)	(3.023)
CAPM alpha	-5.014*	0.719	0.841	5.854**
	(2.858)	(2.159)	(2.335)	(2.539)
FF3 alpha	-3.644	1.533	1.741	5.385**
	(2.499)	(1.885)	(2.258)	(2.412)
FF4 alpha	-3.349	1.576	1.846	5.196**
	(2.232)	(1.850)	(2.234)	(2.281)
FF5 alpha	-4.203*	0.472	0.319	4.522*
	(2.444)	(1.840)	(2.261)	(2.446)

Value-Weighted	Low	2	High	High-Low
Excess Return	5.539	7.981***	12.926***	7.387**
	(5.052)	(2.817)	(3.634)	(3.574)
CAPM alpha	-3.878*	2.310*	6.744***	10.622***
	(2.010)	(1.265)	(2.429)	(3.036)
FF3 alpha	-3.548*	2.011	5.420**	8.968***
	(2.037)	(1.299)	(2.337)	(3.019)
FF4 alpha	-3.506*	2.003	5.392**	8.898***
	(2.082)	(1.306)	(2.365)	(3.123)
FF5 alpha	-4.027**	0.168	3.572*	7.599***
	(1.946)	(1.188)	(2.025)	(2.690)

*** p<0.01, ** p<0.05, * p<0.1

Average equity returns among firms grouped into terciles based on kurtosis of price changes from 2006 to 2019. Newey-West standard errors with 12 lags are computed for average returns. The spread between the high and low kurtosis terciles is shown in the rightmost column. Equal-weighted returns are shown in the top panel, and value-weighted returns in the bottom panel.

Table A16: Returns in $Kurt_{Moors}$ Bins

Equal Weighted				
	Low	2	High	High-Low
Excess Return	5.183	7.688	9.131*	3.948**
	(5.067)	(4.664)	(4.881)	(1.722)
CAPM alpha	-3.984*	-0.338	0.824	4.808***
	(2.155)	(2.352)	(2.372)	(1.696)
FF3 alpha	-2.705	0.715	1.578	4.283**
	(1.792)	(2.082)	(2.233)	(1.667)
FF4 alpha	-2.469	0.805	1.694	4.163**
	(1.781)	(2.023)	(2.084)	(1.852)
FF5 alpha	-2.832	-1.412	0.796	3.628**
	(1.798)	(2.100)	(2.123)	(1.624)

Value-Weighted				
	Low	2	High	High-Low
Excess Return	5.174	12.764***	8.906***	3.732
	(4.666)	(3.857)	(2.921)	(3.002)
CAPM alpha	-3.919*	6.018**	3.744**	7.663***
	(1.989)	(2.642)	(1.546)	(2.447)
FF3 alpha	-3.643*	4.687*	3.378**	7.021***
	(1.998)	(2.558)	(1.497)	(2.390)
FF4 alpha	-3.620*	4.663*	3.365**	6.985***
	(2.018)	(2.585)	(1.501)	(2.424)
FF5 alpha	-4.930**	2.325	1.996	6.925***
	(1.946)	(2.148)	(1.364)	(2.386)

*** p<0.01, ** p<0.05, * p<0.1

Average equity returns among firms grouped into terciles based on robust kurtosis from Moors 1988. Newey-West standard errors with 12 lags are computed for average returns. The spread between the high and low robust kurtosis terciles is shown in the rightmost column. Equal-weighted returns are shown in the top panel, and value-weighted returns in the bottom panel.

Table A17: Double Sorts–Kurtosis within Frequency

Freq	Kurtosis			
	Low	2	High	High-Low
Low	4.577	7.379*	8.416**	3.839
	(7.196)	(4.196)	(3.982)	(5.337)
2	4.757	8.195**	8.734**	3.977
	(5.980)	(4.000)	(4.303)	(3.926)
High	5.315	9.657*	9.206	3.891
	(6.465)	(5.367)	(5.644)	(3.375)
HML	0.738	2.278	0.789	
	(3.413)	(2.896)	(3.815)	

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Firms are sorted into terciles based on their average frequency of price changes. Within each of these frequency terciles, I then sorts firms into conditional terciles based on kurtosis of price changes. Mean returns over the 2006-2019 sample for each kurtosis bin conditional on frequency bins are shown. The spreads between high and low kurtosis firms within each frequency bin are shown in the right column. The spreads between high and low frequency bins given each conditional kurtosis bin are shown in the bottom row. Standard errors are computed using the Newey-West procedure with 12 lags.

D Regular Prices

In this section, I perform portfolio sorts using regular prices identified by the Kehoe and Midrigan 2015 algorithm. This algorithm filters out sales and temporary price increases by calculating the modal price for a good within a 13-week window. For the details of the algorithm, see Midrigan 2011 and Kehoe and Midrigan 2015.

Table A18: Summary Statistics: 2006-2019

	Price Change Statistics					
	Median	Mean	SD	Min	Max	Firm-Months
Regular Frequency	0.033	0.037	0.017	0.010	0.104	145
Regular Kurtosis	1.621	1.657	0.483	1.000	3.064	145
	Financial Variables					
Market Cap	13.978	14.074	2.312	9.197	19.046	144
BM	0.472	0.496	0.340	-0.312	1.938	142
Beta	0.740	0.903	0.569	-0.445	3.034	144
Leverage	0.447	0.468	0.300	0.002	1.901	139
Cashflows	0.079	0.071	0.074	-0.296	0.217	144
Turnover	15.943	17.234	10.081	0.623	44.321	144
Bid-Ask Spread	2.504	4.270	5.764	1.012	44.252	144
Price-Cost Margin	0.357	0.368	0.180	0.065	0.851	144
HH Index	0.071	0.089	0.053	0.030	0.271	144
Annualized Returns	11.616	8.712	24.005	-177.860	78.003	145

Summary statistics for firms in the regular price change sample. Frequency and kurtosis of regular price changes are computed for price changes within a UPC-store and aggregated using a weighted average to the firm level. Financial variables are computed annually (if their source is Compustat) or monthly (if from CRSP); see Section 5 for descriptions of how variables are constructed. Summary statistics are shown as unconditional firm averages.

Table A19: Correlations

	Pricing Statistics		Financial Variables									
	Freq	Kurt	Market Cap	BM	Beta	Lev	CF	Turnover	Spread	PCM	HH	Ret
Reg Freq	1.00											
Reg Kurtosis	-0.32	1.00										
Market Cap	-0.19	0.27	1.00									
BM	0.16	-0.11	-0.37	1.00								
Beta	0.12	-0.29	-0.19	0.06	1.00							
Leverage	0.03	0.10	0.04	-0.39	0.05	1.00						
Cashflows	-0.22	0.22	0.52	-0.24	-0.21	-0.11	1.00					
Turnover	-0.06	0.01	0.19	0.07	0.21	0.03	0.01	1.00				
Bid-Ask Spread	0.24	-0.14	-0.47	0.17	-0.10	-0.13	-0.10	-0.38	1.00			
Price-Cost Margin	-0.16	0.06	0.38	-0.24	-0.14	-0.00	0.28	-0.14	-0.09	1.00		
HH Index	-0.06	-0.07	0.01	0.08	-0.02	-0.09	-0.08	-0.04	-0.09	0.08	1.00	
Annualized Returns	0.01	0.07	0.27	-0.09	-0.01	-0.08	0.25	0.22	-0.11	0.02	-0.05	1.00

Correlations between regular price change statistics and financial variables. Pricing statistics are calculated across the entire life of a UPC-store. Each firm's value for each regular pricing statistic is the average of its UPC-stores weighted by the total sales value of each UPC-store. Correlations are calculated at the firm-month level.

Table A20: Returns in Frequency Bins

Equal Weighted	Low	2	High	High-Low
Excess Return	8.998**	8.947*	8.536*	-0.462
	(4.321)	(4.722)	(4.657)	(1.906)
CAPM alpha	2.069	0.791	0.091	-1.978
	(2.630)	(2.395)	(2.593)	(1.875)
FF3 alpha	2.534	1.610	1.504	-1.030
	(2.545)	(2.290)	(2.016)	(1.624)
FF4 alpha	2.657	1.713	1.678	-0.978
	(2.464)	(2.155)	(1.858)	(1.620)
FF5 alpha	1.317	0.889	0.415	-0.901
	(2.545)	(2.202)	(1.943)	(1.640)

Value-Weighted	Low	2	High	High-Low
Excess Return	9.637***	7.826**	5.648	-3.989**
	(2.801)	(3.131)	(3.774)	(1.992)
CAPM alpha	4.337***	2.831	-1.707	-6.045***
	(1.431)	(1.853)	(2.008)	(1.834)
FF3 alpha	3.741**	2.364	-1.776	-5.516***
	(1.473)	(1.755)	(2.024)	(1.728)
FF4 alpha	3.691**	2.368	-1.771	-5.462***
	(1.497)	(1.752)	(2.022)	(1.723)
FF5 alpha	2.094	0.752	-2.360	-4.454**
	(1.417)	(1.554)	(2.067)	(1.751)

*** p<0.01, ** p<0.05, * p<0.1

Average equity returns among firms grouped into terciles based on frequency of price changes from 2006 to 2019. Newey-West standard errors with 12 lags are computed for average returns. The spread between the high and low frequency terciles is shown in the rightmost column. Equal-weighted returns are shown in the top panel, and value-weighted returns in the bottom panel.

Table A21: Returns in Kurtosis Bins

Equal Weighted				
	Low	2	High	High-Low
Excess Return	8.413	8.007*	10.060**	1.647
	(5.511)	(4.148)	(3.960)	(2.570)
CAPM alpha	-1.456	0.734	3.717	5.173***
	(2.650)	(2.306)	(2.488)	(1.882)
FF3 alpha	-0.115	1.250	4.549*	4.664***
	(2.240)	(2.194)	(2.346)	(1.781)
FF4 alpha	0.125	1.375	4.580**	4.455**
	(2.117)	(2.050)	(2.309)	(1.964)
FF5 alpha	-0.476	0.076	3.032	3.508**
	(2.259)	(2.080)	(2.213)	(1.636)

Value-Weighted				
	Low	2	High	High-Low
Excess Return	6.113	8.103***	9.023***	2.910
	(5.159)	(3.030)	(2.983)	(3.818)
CAPM alpha	-2.581	2.175	4.051**	6.631*
	(3.436)	(1.542)	(1.705)	(3.567)
FF3 alpha	-2.856	1.820	3.481**	6.337*
	(3.432)	(1.565)	(1.704)	(3.646)
FF4 alpha	-2.819	1.829	3.416*	6.234*
	(3.462)	(1.558)	(1.748)	(3.755)
FF5 alpha	-1.749	-0.085	2.098	3.847
	(3.438)	(1.562)	(1.537)	(3.564)

*** p<0.01, ** p<0.05, * p<0.1

Average equity returns among firms grouped into terciles based on kurtosis of price changes from 2006 to 2019. Newey-West standard errors with 12 lags are computed for average returns. The spread between the high and low kurtosis terciles is shown in the rightmost column. Equal-weighted returns are shown in the top panel, and value-weighted returns in the bottom panel.

Table A22: Double Sorts–Kurtosis within Frequency

Freq	Kurtosis			
	Low	2	High	High-Low
Low	5.914	9.572**	11.535***	5.621*
	(5.759)	(4.121)	(3.773)	(3.268)
2	10.719*	7.104	9.132*	-1.587
	(5.571)	(4.669)	(5.123)	(3.333)
High	6.603	9.924*	9.253**	2.650
	(5.647)	(5.630)	(4.082)	(4.007)
HML	0.689	0.352	-2.282	
	(3.767)	(3.378)	(2.986)	

*** p<0.01, ** p<0.05, * p<0.1

Firms are sorted into terciles based on their average frequency of regular price changes. Within each of these frequency terciles, I then sorts firms into conditional terciles based on kurtosis of regular price changes. Mean returns over the 2006-2019 sample for each kurtosis bin conditional on frequency bins are shown. The spreads between high and low kurtosis firms within each frequency bin are shown in the right column. The spreads between high and low frequency bins given each conditional kurtosis bin are shown in the bottom row. Standard errors are computed using the Newey-West procedure with 12 lags.