Are Sticky Prices Costly? Evidence From The Stock Market*

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Abstract

We show that after monetary policy announcements, the conditional volatility of stock market returns rises more for firms with stickier prices than for firms with more flexible prices. This differential reaction is economically large as well as strikingly robust to a broad array of checks. These results suggest that menu costs—broadly defined to include physical costs of price adjustment, informational frictions, etc.—are an important factor for nominal price rigidity. We also show that our empirical results are qualitatively and, under plausible calibrations, quantitatively consistent with New Keynesian macroeconomic models where firms have heterogeneous price stickiness. Since our framework is valid for a wide variety of theoretical models and frictions preventing firms from price adjustment, we provide "model-free" evidence that sticky prices are indeed costly.

JEL classification: E12, E31, E44, G12, G14

Keywords: menu costs, sticky prices, asset prices, high frequency identification

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I Introduction

In principle, fixed costs of changing prices can be observed and measured. In practice, such costs take disparate forms in different firms, and we have no data on their magnitude. So the theory can be tested at best indirectly, at worst not at all. Alan Blinder (1991)

Are sticky prices costly? This simple question stirs an unusually heated debate in macroeconomics. While there seems to be a growing consensus that prices at the micro-level are fixed in the short run,[1] it is still unclear why firms have rigid prices. A central tenet of New Keynesian macroeconomics is that firms face fixed "menu" costs of nominal price adjustment which can rationalize why firms may forgo an increase in profits by keeping existing prices unchanged after real or nominal shocks. However, the observed price rigidity does not necessarily entail that nominal shocks have real effects or that the inability of firms to adjust prices burdens firms. For example, Head et al. (2012) present a theoretical model where sticky prices arise endogenously even if firms are free to change prices at any time without any cost. This alternative theory has vastly different implications for business cycles and policy. How can one distinguish between these opposing motives for price stickiness? The key insight of this paper is that in New Keynesian models, sticky prices are costly to firms, whereas in other models they are not. While the sources and types of "menu" costs are likely to vary tremendously across firms thus making the construction of an integral measure of the cost of sticky prices extremely challenging, looking at market valuations of firms can provide a natural metric to determine whether price stickiness is indeed costly. In this paper, we exploit stock market information to explore these costs and— to the extent that firms equalize costs and benefits of nominal price adjustment—quantify "menu" costs. The evidence we document is consistent with the New Keynesian interpretation of price stickiness.

Specifically, we merge confidential micro-level data underlying the producer price index (PPI) from the Bureau of Labor Statistics (BLS) with stock price data for individual firms from NYSE Trade and Quote (taq) and study how stock returns of firms with different frequencies of price adjustment respond to monetary shocks (identified as changes in futures on the fed funds rates, the main policy instrument of the Fed) in narrow time windows around press releases of the Federal Open Market Committee (FOMC). To guide

[1] Bils and Klenow (2004), Nakamura and Steinsson (2008).

our empirical analyses, we show in a basic New Keynesian model that firms with stickier prices should experience a greater increase in the volatility of returns than firms with more flexible prices after a nominal shock. Intuitively, firms with larger costs of price adjustment tolerate larger departures from the optimal reset price. Thus, the range in which the discounted present value of cash flows can fluctuate is wider. The menu cost in this theoretical exercise is generic and, hence, our framework covers a broad range of models with inflexible prices.

Consistent with this logic, we find that returns for firms with stickier prices exhibit greater volatility after monetary shocks than returns of firms with more flexible prices, with the magnitudes being broadly in line with the estimates one can obtain from a calibrated New Keynesian model with heterogeneous firms: a hypothetical monetary policy surprise of 25 basis points (bps) leads to an increase in squared returns of $8\%^2$ for the firms with stickiest prices. This sensitivity is reduced by a factor of three for firms with the most flexible prices in our sample. Our results are robust to a large battery of specification checks, subsample analyses, placebo tests, and alternative estimation methods.[2]

Our work contributes to a large literature aimed at quantifying the costs of price adjustment. Zbaracki et al. (2004) and others measure menu costs directly by keeping records of costs associated with every stage of price adjustments at the firm level (data collection, information processing, meetings, physical costs). Anderson et al. (2012) have access to wholesale costs and retail price changes of a large retailer. Exploiting the uniform pricing rule employed by this retailer for identification, they show that the absence of menu costs would lead to 18% more price changes. This approach sheds light on the process of adjusting prices, but it is difficult to generalize these findings given the heterogeneity of adjustment costs across firms and industries. Our approach is readily applicable to any firm with publicly traded equity, independent of industry, country or location. A second strand (e.g., Blinder (1991)) elicits information about costs and mechanisms of price adjustment from survey responses of managers. This approach is remarkably useful in documenting reasons for rigid prices but, given the qualitative nature of survey answers, it cannot provide a magnitude of the costs associated with

[2]Uncertainty shocks proxied by stock market volatility have recently gained attention as a potential driver of business cycles (see among others Bloom (2009)). Our results suggest that one should be cautious with using stock market volatility as a measure of uncertainty shocks because conditional heteroskedasticity could be an *outcome* of an interaction between differential menu costs and nominal or real shocks.

price adjustment. In contrast, our approach can provide a quantitative estimate of these costs. A third group of papers (e.g. Klenow and Willis (2007), Nakamura and Steinsson (2008)) integrates menu costs into fully fledged dynamic stochastic general equilibrium (DSGE) models. Menu costs are estimated or calibrated at values that match moments of aggregate (e.g. persistence of inflation) or micro-level (e.g. frequency of price changes) data. This approach is obviously most informative if the underlying model is correctly specified. Given the striking variety of macroeconomic models in the literature and limited ability to discriminate between models with available data, one may be concerned that the detailed structure of a given DSGE model can produce estimates that are sensitive to auxiliary assumptions necessary to make the model tractable or computable. In contrast, our approach does not have to specify a macroeconomic model and thus our estimates are robust to alternative assumptions about the structure of the economy.[3]

Our paper is also related to the literature investigating the effect of monetary shocks on asset prices. In a seminal study, Cook and Hahn (1989) use an event study framework to examine the effects of changes in the federal funds rate on bond rates using a daily event window. They show that changes in the federal funds target rate are associated with changes in interest rates in the same direction with larger effects at the short end of the yield curve. Bernanke and Kuttner (2005)—also using a daily event window—focus on unexpected changes in the federal funds target rate. They find that an unexpected interest rate cut of 25 basis points leads to an increase in the CRSP value weighted market index of about 1 percentage point. Gürkaynak et al. (2005) focus on intraday event windows and find effects of similar magnitudes for the S&P500. Weber (2013) uses non-parametric portfolio sorts and panel regressions to show that sticky price firms command a cross sectional return premium of up to 4% compared to flexible price firms. In addition, besides the impact on the level of returns, monetary policy surprises also lead to greater stock market volatility. For example, consistent with theoretical models predicting increased trading and volatility after important news announcements (e.g. Harris and Raviv (1993) and Varian (1989)), Bomfim (2003) finds that the conditional volatility of the S&P500 spikes after unexpected FOMC policy movements. Given that monetary

[3]Other recent contributions to this literature are Goldberg and Hellerstein (2011), Eichenbaum et al. (2011) Midrigan (2011), Eichenbaum et al. (2012), Bhattarai and Schoenle (2012), Vavra (2013), Berger and Vavra (2013). See Klenow and Malin (2010) and Nakamura and Steinsson (2013) for recent reviews of this literature.

policy announcements also appear to move many macroeconomic variables (see e.g. Faust et al. (2004b)), these shocks are, thus, a powerful source of variation in the data.

There are several limitations to our approach. First, we require information on returns with frequent trades to ensure that returns can be precisely calculated in narrow event windows. This constraint excludes illiquid stocks with infrequent trading. We focus on the constituents of the S&P500 which are all major US companies with high stock market capitalization.[4] Second, our methodology relies on unanticipated, presumably exogenous shocks that influence the stock market valuation of firms. A simple metric of this influence could be whether a given shock moves the aggregate stock market. While this may appear an innocuous constraint, most macroeconomic announcements other than the Fed's (e.g. the surprise component of announcements of GDP or unemployment figures by the Bureau of Economic Analysis (BEA) and BLS) fail to consistently move the stock market in the U.S. Third, our approach is built on "event" analysis and therefore excludes shocks that hit the economy continuously. Finally, we rely on the efficiency of financial markets.[5]

The rest of the paper is structured as follows. The next section describes how our measure of price stickiness at the firm level is constructed. Section III lays out a static version of a New Keynesian model with sticky prices and provides guidance for our empirical specification. This section also discusses our high frequency identification strategy employing nominal shocks from fed funds futures and the construction of our variables and controls. Section IV presents the estimates of the sensitivity of squared returns to nominal shocks as a function of price stickiness. Section V calibrates a

[4] The intraday event window restricts our universe of companies to large firms as small stocks in the early part of our sample often experienced no trading activity for several hours even around macroeconomic news announcements contrary to the constituents of the S&P500. Given the high volume of trades for the latter firms, news are quickly incorporated into stock prices. For example, Zebedee et al. (2008) among others show that the effect of monetary policy surprises is impounded into prices of the S&P500 within minutes.

[5] Even though the information set required by stock market participants may appear large (frequencies of price adjustments, relative prices etc.), we document in Subsection *E.* of Section IV that the effects for conditional stock return volatility also hold for firm profits. Therefore, sophisticated investors can reasonably identify firms with increased volatility after monetary policy shocks and trade on this information using option strategies such as straddles. A straddle consists of simultaneously buying a call and a put option on the same stock with the same strike price and time to maturity and profits from increases in volatility. It is an interesting question to analyze the identity of traders around macroeconomic news announcements: private investors or rational arbitrageurs and institutional investors. Results of Erenburg et al. (2006) and Green (2004) and the fact that news are incorporated into prices within minutes indicate the important role of sophisticated traders around macroeconomic news announcements.

dynamic version of a New Keynesian model to test whether our empirical estimates can be rationalized by a reasonably calibrated model. Section VI concludes and discusses further applications of our novel methodology.

II Measuring Price Stickiness

A key ingredient of our analysis is a measure of price stickiness at the firm level. We use the confidential microdata underlying the PPI of the BLS to calculate the frequency of price adjustment for *each* firm in our sample. The PPI measures changes in selling prices from the perspective of producers, as compared to the Consumer Price Index (CPI) which looks at price changes from the consumers' perspective. The PPI tracks prices of all goods producing industries such as mining, manufacturing, gas and electricity, as well as the service sector. The PPI covers about three quarters of the service sector output.

The BLS applies a three stage procedure to determine the individual goods included in the PPI. In the first step, the BLS compiles a list of all firms filing with the Unemployment Insurance system. This information is then supplemented with additional publicly available data which is of particular importance for the service sector to refine the universe of establishments.

In the second step, individual establishments within the same industry are combined into clusters. This step ensures that prices are collected at the price forming unit as several establishments owned by the same company might constitute a profit maximizing center. Price forming units are selected for the sample based on the total value of shipments or the number of employees.

After an establishment is chosen and agrees to participate, a probability sampling technique called *disaggregation* is applied. In this final step, the individual goods and services to be included in the PPI are selected. BLS field economists combine individual items and services of a price forming unit into categories, and assign sampling probabilities proportional to the value of shipments. These categories are then further broken down based on price determining characteristics until unique items are identified. If identical goods are sold at different prices due to e.g. size and units of shipments, freight type, type of buyer or color then these characteristics are also selected based on probabilistic sampling.

The BLS collects prices from about 25,000 establishments for approximately 100,000 individual items on a monthly basis. The BLS defines PPI prices as "net revenue accruing to a specified producing establishment from a specified kind of buyer for a specified product shipped under specified transaction terms on a specified day of the month".[6] Taxes and fees collected on behalf of federal, state or local governments are not included. Discounts, promotions or other forms of rebates and allowances are reflected in PPI prices insofar as they reduce the revenues received by the producer. The same item is priced month after month. The BLS undertakes great efforts to adjust for quality changes and product substitutions so that only true price changes are measured.

Prices are collected via a survey which is emailed or faxed to participating establishments.[7] The survey asks whether the price has changed compared to the previous month and if yes, the new price is asked.[8] Individual establishments remain in the sample for an average of seven years until a new sample is selected in the industry. This resampling occurs to account for changes in the industry structure and changing product market conditions within the industry.[9]

We calculate the frequency of price adjustment as the mean fraction of months with price changes during the sample period of an item. For example, if an observed price path is $4 for two months and then $5 for another three months, there is one price change during five months and hence the frequency is 1/5.[10] When calculating the frequency of price adjustment, we exclude price changes due to sales. We identify sales using the filter employed by Nakamura and Steinsson (2008). Including sales does not affect our results in any material way because, as documented in Nakamura and Steinsson (2008), sales are rare in producer prices.

We aggregate frequencies of price adjustments at the establishment level and further

[6]See Chapter 14, BLS Handbook of Methods, available under http://www.bls.gov/opub/hom/.

[7]The online appendix contains a sample survey.

[8]This two stage procedure might lead to a downward bias in the frequency of price adjustment. Using the anthrax scare of 2001 as a natural experiment, Nakamura and Steinsson (2008) show, however, that the behavior of prices is insensitive to the collection method: during October and November 2001 all government mail was redirected and the BLS was forced to collect price information via phone calls. Controlling for inflation and seasonality in prices, they do not find a significant difference in the frequency of price adjustment across the two collection methods.

[9]Goldberg and Hellerstein (2011) show that forced product substitutions and sales are negligible in the microdata underlying the PPI.

[10]We do not consider the first observation as a price change and do not account for left censoring of price spells. Bhattarai and Schoenle (2012) verify that explicitly accounting for censoring does not change the resulting distribution of probabilities of price adjustments. Our baseline measure treats missing price values as interrupting price spells. The appendix contains results for alternative measures of the frequency of price adjustment; results are quantitatively and statistically very similar.

aggregate the resulting frequencies at the company level. The first aggregation is performed via internal establishment identifiers of the BLS. To perform the firm level aggregation, we *manually* check whether establishments with the same or similar names are part of the same company. In addition, we search for names of subsidiaries and name changes e.g. due to mergers, acquisitions or restructurings occurring during our sample period for all firms in our financial dataset.

We discuss the fictitious case of a company Milkwell Inc. to illustrate aggregation to the firm level. Assume we observe product prices of items for the establishments Milkwell Advanced Circuit, Milkwell Aerospace, Milkwell Automation and Control, Milkwell Mint, and Generali Enel. In the first step, we calculate the frequency of product price adjustment at the item level and aggregate this measure at the establishment level for all of the above mentioned establishments.[11] We calculate both equally weighted frequencies (baseline) and frequencies weighted by values of shipments associated with items/establishments (see appendix) say for establishment Milkwell Aerospace. We then use publicly available information to check whether the individual establishments are part of the same company. Assume that we find that all of the above mentioned establishments with Milkwell in the establishment name but Milkwell Mint are part of Milkwell Inc. Looking at the company structure, we also find that Milkwell has several subsidiaries, Honeymoon, Pears and Generali Enel. Using this information, we then aggregate the establishment level frequencies of Milkwell Advanced Circuit, Milkwell Aerospace, Milkwell Automation and Control and Generali Enel at the company level, again calculating equally weighted and value of shipments weighted frequencies. Our measure of price stickiness is constant at the firm level. Allowing for time series variation has little impact on our findings as there is little time variation in the frequency of price adjustment at the firm level.

Table 1 reports mean probabilities, standard deviations and the number of firm-event observations for our measures of the frequency of price adjustment, both for the total sample and for each industry separately.[12] The overall mean frequency of price adjustment (FPA) is 14.66%/month implying an average duration, $-1/ln(1-FPA)$, of 6.03 months. There is a substantial amount of heterogeneity in the frequency across sectors, ranging

[11]Items in our dataset are alpha-numeric codes in a SAS dataset and we cannot identify their specific nature.

[12]The coarse definition of industries is due to confidentiality reasons and also partially explains the substantial variation of our measures of price stickiness within industry.

from as low as 8.07%/month for the service sector (implying a duration of almost one year) to 25.35%/month for agriculture (implying a duration of 3.42 months). Finally, the high standard deviations highlight dramatic heterogeneity in measured price stickiness across firms even within industries. Different degrees of price stickiness of similar firms operating in the same industry can arise due to a different customer and supplier structure, heterogeneous organizational structure or varying operational efficiencies and management philosophies.[13]

III Framework

In this section, we outline the basic intuition for how returns and price stickiness are related in the context of a New Keynesian macroeconomic model. We will focus on one shock—monetary policy surprises—which has a number of desirable properties.[14] While restricting the universe of shocks to only monetary policy shocks limits our analysis in terms of providing an integral measure of costs of sticky prices, it is likely to greatly improve identification and generate a better understanding of how sticky prices and stock returns are linked. This section also guides us in choosing regression specifications for the empirical part of the paper and describes how variables are constructed.

A. Static model

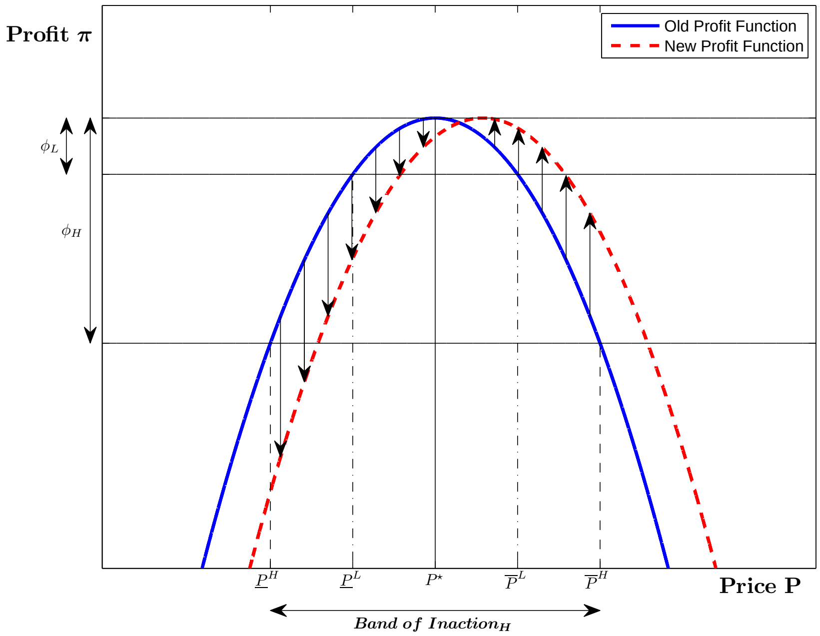
We start with a simple, static model to highlight intuition for our subsequent theoretical and empirical analyses. Suppose that a second-order approximation to a firm's profit function is valid so that the payoff of firm i can be expressed as $\pi_i \equiv \pi(P_i, P^*) = \pi_{max} - \psi(P_i - P^*)^2$ where P^* is the optimal price given economic conditions, P_i is the current price of firm i, π_{max} is the maximum profit a firm can achieve and ψ captures the curvature of the profit function.[15] The blue, solid line in Figure 1 shows the resulting approximation. Furthermore assume that a firm has to pay a menu cost ϕ if it wants to reset its price. This cost should be interpreted broadly as not only the cost of re-printing

[13]Nakamura and Steinsson (2008) report a median frequency of price changes for producer prices between 1998 and 2005 of 10.8%, 13.3% and 98.9% for finished producer goods, intermediate goods and crude materials, respectively corresponding to median implied durations of 8.7, 7 and 0.2 months.

[14]Bernanke and Kuttner (2005) emphasize the importance of financial markets for the conduct of monetary policy: "The most direct and immediate effects of monetary policy actions, such as changes in the Federal funds rate, are on financial markets; by affecting asset prices and returns, policymakers try to modify economic behavior in ways that will help to achieve their ultimate objectives."

[15]This expansion does not have a first-order term in $(P_i - P^*)$ because firm optimization implies that the first derivative is zero in the neighborhood of P^*.

Figure 1: Impact of a Nominal Shock on Stock Returns via a Shift in Firm's Profit Function



This figure plots profit at the firm level as a function of price. Low and high menu costs (ϕ_L and ϕ_H) translate into small and large bands of inaction within which it is optimal for a firm not to adjust prices following nominal shocks. The blue, solid line indicates the initial profit function and P^* is the initial optimal price. For example an expansionary monetary policy shock shifts the profit function to the right, indicated by the dashed, red line. Depending on the initial position, this shift can either lead to an increase or a decrease in profits as exemplified by the arrows.

a menu with new prices but also includes costs associated with collecting and processing information, bargaining with suppliers and customers, etc. A firm resets its price from P_i to P^* only if the gains from doing so exceed the menu cost, that is, $\psi(P_i - P^*)^2 > \phi$. If the menu cost is low ($\phi = \phi_L$), then the range of prices consistent with inaction (non-adjustment of prices) is $(\underline{P}_L, \overline{P}_L)$. If the menu cost is high ($\phi = \phi_H$), then the range of price deviations from P^* is wider $(\underline{P}_H, \overline{P}_H)$. As a result, the frequency of price adjustment is ceteris paribus lower for firms with larger menu costs. Denote the frequency of price adjustment with $\lambda \equiv \lambda(\phi)$ with $\partial\lambda/\partial\phi < 0$. We can interpret $1 - \lambda$ as degree of price stickiness.

Without loss of generality, we can assume that prices of low-menu-cost and high-menu-cost firms are spread in $(\underline{P}_L, \overline{P}_L)$ and $(\underline{P}_H, \overline{P}_H)$ intervals, respectively, because firms are hit with idiosyncratic shocks (e.g. different timing of price adjustments as in Calvo (1983), firm-specific productivity, cost and demand shocks) or aggregate shocks we are not controlling for in our empirical exercise. Suppose there is a nominal shock which moves P^* to the right (denote this new optimal price with P^*_{new}) so that the payoff function is now described by the red, dashed line. This shift can push some firms outside their inaction bands and they will reset their prices to P^*_{new} and thus weakly increase their payoffs, (i.e. $\pi(P^*_{new}, P^*_{new}) - \pi(P_i, P^*_{new}) \geqslant \phi$). If the shock is not too large, many firms will continue to stay inside their inaction bands.

Obviously, this non-adjustment does not mean that firms have the same payoffs after the shock. Firms with negative $(P_i - P^*)$ will clearly lose (i.e. $\pi(P_i, P^*_{new}) - \pi(P_i, P^*) < 0$) as their prices become even more suboptimal. Firms with positive $(P_i - P^*_{new})$ will clearly gain (i.e. $\pi(P_i, P^*_{new}) - \pi(P_i, P^*) > 0$) as their suboptimal prices become closer to optimal. Firms with positive $(P_i - P^*)$ and negative $(P_i - P^*_{new})$ may lose or gain. In short, a nominal shock to P^* redistributes payoffs.

Note that there are losers and winners for both low-menu-cost and high-menu-cost firms. In other words, if we observe an increased payoff, we cannot infer that this increased payoff identifies a low-menu-cost firm. If we had information about $(P_i - P^*_{new})$ and/or $(P_i - P^*)$, that is, *relative* prices of firms, then we could infer the size of menu costs directly from price resets. It is unlikely that this information is available in a plausible empirical setting as P^* is hardly observable.

Fortunately, there is an unambiguous prediction with respect to the variance of changes in payoffs in response to shocks. Specifically, firms with high menu costs have larger variability in payoffs than firms with low menu costs. Indeed, high-menu-cost firms can tolerate a loss of up to ϕ_H in profits while low-menu-cost firms take at most a loss of ϕ_L. This observation motivates the following empirical specification:

$$(\Delta\pi_i)^2 = b_1 \times v^2 + b_2 \times v^2 \times \lambda(\phi_i) + b_3 \times \lambda(\phi_i) + error. \tag{1}$$

where $\Delta\pi_i$ is a change in payoffs (return) for firm i, v is a shock to the optimal price P^*, $error$ absorbs movements due to other shocks. In this specification, we expect $b_1 > 0$ because a shock v results in increased volatility of payoffs. We also expect $b_2 < 0$ because the volatility increases less for firms with smaller bands of inaction and hence with more flexible prices. Furthermore, the volatility of profits should be lower for low-menu-cost firms unconditionally so that $b_3 < 0$. In the polar case of no menu costs, there is no volatility in payoffs after a nominal shock as firms always make π_{max}. Therefore, we also expect that $b_1 + b_2 \approx 0$. To simplify the exposition of the static model, we implicitly assumed that nominal shocks do not move the profit function up or down. If this assumption is relaxed, $b_1 + b_2$ can be different from zero. We do *not* make this assumption in either the dynamic version of the model presented in Section V or our empirical analyses. We find in simulations and in the data that $b_1 + b_2 \approx 0$.

While the static model provides intuitive insights about the relationship between payoffs and price stickiness, it is obviously not well suited for quantitative analyses for several reasons. First, when firms decide whether to adjust their product prices they compare the cost of price adjustment with the present value of future increases in profits associated with adjusting prices. Empirically, we measure returns that capture both current dividends/profits and changes in the valuation of firms. Since returns are necessarily forward looking, we have to consider a dynamic model. Second, general equilibrium effects may attenuate or amplify effects of heterogeneity in price stickiness on returns. Indeed, strategic interaction between firms is often emphasized as the key channel of gradual price adjustment in response to aggregate shocks. For example, in the presence of strategic interaction and some firms with sticky prices, even flexible price firms may be reluctant to change their prices by large amounts and thus may appear to have inflexible prices (see e.g. Haltiwanger and Waldman (1991) and Carvalho (2006)). Finally, the sensitivity of returns to macroeconomic shocks is likely to depend on the cross-sectional distribution of relative prices which varies over time and may be difficult to characterize analytically.

To address these concerns and check whether the parameter estimates in our empirical analysis of Section IV are within reasonable ranges, we calibrate the dynamic multi-sector model developed in Carvalho (2006) where firms are heterogeneous in the degree of price stickiness in Section V.

B. Identification

Identification of unanticipated, presumably exogenous shocks to monetary policy is central for our analysis. In standard macroeconomic contexts (e.g. structural vector autoregressions), one may achieve identification by appealing to minimum delay restrictions where monetary policy is assumed to be unable to influence the economy (e.g. real GDP or unemployment rate) within a month or a quarter. However, asset prices are likely to respond to changes in monetary policy within days if not hours or minutes. Balduzzi et al. (2001) show for bonds and Andersen et al. (2003) for exchange rates that announcement surprises are almost immediately incorporated into asset prices. Furthermore, Rigobon and Sack (2003) show that monetary policy is systematically influenced by movements in financial markets within a month. In short, stock prices and monetary policy can both change following major macroeconomic news and can respond to changes in each other even in relatively short time windows.

To address this identification challenge, we employ an event study approach in the tradition of Cook and Hahn (1989) and more recently Kuttner (2001), Bernanke and Kuttner (2005) and Gürkaynak et al. (2005). Specifically, we examine the behavior of returns and changes in the Fed's policy instrument in narrow time windows (30 minutes, 60 minutes, daily) around FOMC press releases. In these narrow time windows, the only relevant shock (if any) is likely due to changes in monetary policy.

However, not every change in policy rates affects stock prices at the time of the change. In informationally efficient markets, anticipated changes in monetary policy are already incorporated into prices and only the surprise components of monetary policy changes should matter for stock returns.[16] To isolate the unanticipated part of the announced changes of the target rate, we use federal funds futures which provide a high-frequency market-based measure of the anticipated path of the fed funds rate. This measure has a number of advantages: i) it allows for a flexible characterization of the policy reaction function; ii) it can accommodate changes in the policy reaction function of decision makers at the FOMC; and iii) it aggregates a vast amount of data processed by the market. Krueger and Kuttner (1996) show that federal funds futures are an efficient predictor of future federal funds rates. Macroeconomic variables such as the change in unemployment rate or industrial production growth have no incremental forecasting power for the federal funds rate once the federal funds futures is included in forecasting regressions. In similar spirit, Gürkaynak et al. (2007) provide evidence that the federal funds futures dominate other market based instruments in forecasting the federal funds rate. In short, fed funds futures provides a powerful and simple summary of market expectations for the path of future fed funds rates. Using this insight, we can calculate

[16] Bernanke and Kuttner (2005) perform a decomposition in expected and unexpected changes in the federal funds target rate and indeed show that only the unanticipated component systematically moves the stock market.

the surprise component of the announced change in the federal funds rate as:

$$v_t = \frac{D}{D-t}(ff^0_{t+\Delta t^+} - ff^0_{t-\Delta t^-}) \tag{2}$$

where t is the time when the FOMC issues an announcement, $ff^0_{t+\Delta t^+}$ is the fed funds futures rate shortly after t, $ff^0_{t-\Delta t^-}$ is the fed funds futures rate just before t, and D is the number of days in the month.[17] The $D/(D-t)$ term adjusts for the fact that the federal funds futures settle on the average effective overnight federal funds rate. We follow Gürkaynak et al. (2005) and use the unscaled change in the next month futures contract if the event day occurs within the last seven days of the month. This ensures that small targeting errors in the federal funds rate by the trading desk at the New York Fed, revisions in expectations of future targeting errors, changes in bid-ask spreads or other noise, which have only a small effect on the current month average, is not amplified through multiplication by a large scaling factor.

Using this shock series, we apply the following empirical specification to assess whether price stickiness leads to differential responses of stock returns:

$$\begin{aligned} R^2_{it} &= b_0 + b_1 \times v^2_t + b_2 \times v^2_t \times \lambda_i + b_3 \times \lambda_i \\ &\quad + FirmControls + FirmControls \times v^2_t + error \end{aligned} \tag{3}$$

where R^2_{it} is the squared return of stock i in the interval $[t-\Delta t^-, t+\Delta t^+]$ around event t, v^2_t is the squared monetary policy shock and λ_i is the frequency of price adjustment of firm i. Below, we provide details on how high frequency shocks and returns are constructed and we briefly discuss properties of the constructed variables. Our identification does not require immediate reaction of inflation to monetary policy shocks but can also operate trough changes in current and future demand and costs which are immediately incorporated in returns through changes in the discounted value of profits.[18]

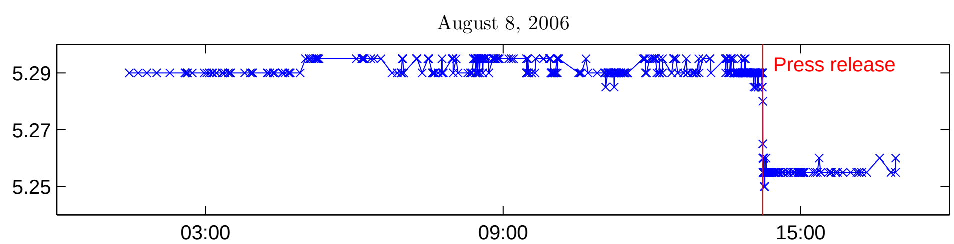
[17] We implicitly assume in these calculations that the average effective rate within the month is equal to the federal funds target rate and that only one rate change occurs within the month. Due to changes in the policy target on unscheduled meetings we have six observations with more than one change in a given month. As these policy moves were not anticipated, they most likely have no major impact on our results. We nevertheless analyze intermeeting policy decisions separately in our empirical analyses. While constructing v_t, we have also implicitly assumed that a potential risk premium does not change in the $[t-\Delta t^-, t+\Delta t^+]$ window, which is consistent with results in Piazzesi and Swanson (2008).

[18] Bernanke and Kuttner (2005) show for a sample period similar to ours that surprises in the federal funds rate on market excess returns operate mainly trough their impact on future dividends highlighting the importance of the cash flow channel in explaining the effects of monetary policy shocks on *aggregate* stock market returns. Vuolteenaho (2002) shows that stock returns at the *firm* level are mainly driven by cash flow news contrary to the findings of Campbell (1991) and Cochrane (1992) for the *aggregate* market.

C. Data

We acquired tick-by-tick data of the federal funds futures trading on the Chicago Mercantile Exchange (CME) Globex electronic trading platform (as opposed to the open outcry market) directly from the CME. Using Globex data has the advantage that trading in these contracts starts on the previous trading day at 6.30 pm ET (compared to 8.20am ET in the open outcry market). We are therefore able to calculate the monetary policy surprises for all event days including the intermeeting policy decisions occurring outside of open outcry trading hours. To provide some insights into the quality of the data and the adequacy of our high frequency identification strategy we plot the futures based expected federal funds rate for one event date in Figure 2.[19] This plot shows two general patterns in the data: high trading activity around FOMC press releases and immediate market reaction following the press release.

Figure 2: Intraday Trading in Globex Federal Funds Futures



This figure plots the tick–by–tick trades in the Globex federal funds futures for the FOMC press release on August 8th 2006 with release time at 2.14pm.

The FOMC has eight scheduled meetings per year and starting with the first meeting in 1995, most press releases are issued around 2.15 pm ET. Table 8 in the appendix reports event dates, times stamps of the press releases, actual target rates changes as well as expected and unexpected changes. We obtained these statistics for the period up to 2004 from Gürkaynak et al. (2005). The time stamps of the press releases in the later part of the sample were provided by the FOMC Freedom of Information Service Act Service Center. The release times are based on the timing of the first FOMC statement related story appearing in the press. We consider "tight" and "wide" time windows around the announcement. The tight (wide) window is 30 (60) minutes and starts $\Delta t^{-} = 10$ (15) minutes before the press releases are issued.

[19]The appendix contains figures for additional event dates. Similar plots for the earlier part of our sample can be found in Gürkaynak et al. (2005).

Panel A of Table 2 reports descriptive statistics for surprises in monetary policy for all 137 event dates between 1994 and 2009 as well as separately for turning points in monetary policy and intermeeting policy decisions. Turning points are target rate changes in the direction opposite to previous changes. Jensen et al. (1996) argue that the Fed is operating under the same fundamental monetary policy regime until the first change in the target rate in the opposite direction. This is in line with the observed level of policy inertia and interest rate smoothing (cf Piazzesi (2005) and Coibion and Gorodnichenko (2012) as well as Figure 2 in the appendix). Monetary policy reversals therefore contain valuable information on the future policy stance.

The average monetary policy shock is approximately zero. The most negative shock is with more than -45 bps about three times larger in absolute value than the most positive shock. Policy surprises on intermeeting event dates and turning points are more volatile than surprises on scheduled meetings. Andersen et al. (2003) point out that financial markets react differently on scheduled versus non-scheduled announcement days. Lastly, the monetary policy shocks are almost perfectly correlated across the two event windows (see Figure 3 in the appendix).[20]

We sample returns for all constituents of the S&P500 for all event dates. We use the CRSP database to obtain the constituent list of the S&P500 for the respective event date and link the CRSP identifier to the ticker of the NYSE taq database via historical CUSIPs (an alphanumeric code identifying North American securities). NYSE taq contains all trades and quotes for all securities traded on NYSE, Amex and the Nasdaq National Market System. We use the last observation before the start of the event window and the first observations after the end of the event window to calculate event returns. We manually checked all event returns which are larger than 5% in absolute value for potential data entry errors in the tick-by-tick data. For the five event dates for which the press releases were issued before start of the trading session (all intermeeting releases in the easing cycle starting in 2007, see Table 8 in the appendix) we calculate event returns using

[20] Only two observations have discernible differences: August 17, 2007 and December 16, 2008 . The first observation is an intermeeting event day on which the FOMC unexpectedly cut the discount rate by 50 bps at 8.15am ET just before the opening of the open-outcry futures market in Chicago. The financial press reports heavy losses for the August futures contract on that day and a very volatile market environment. The second observation, December 16, 2008, is the day on which the FOMC cut the federal funds rate to a target range between zero and 0.25 percent.

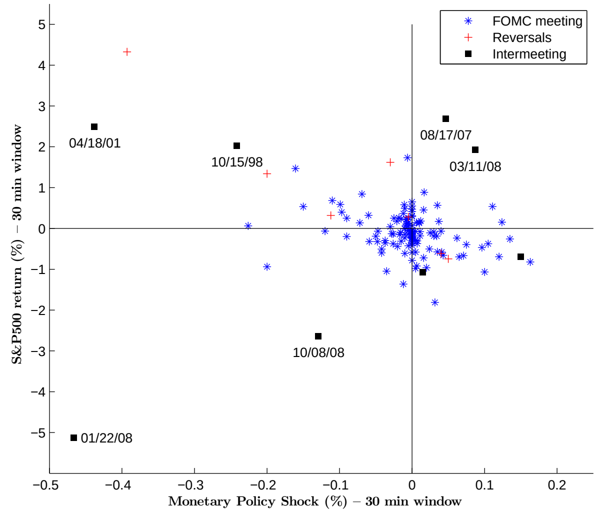
closing prices of the previous trading day and opening prices of the event day.[21]

Our sample period ranges from February 2, 1994, the first FOMC press release in 1994, to December 16, 2009, the last announcement in 2009 for a total of 137 FOMC meetings. We exclude the rate cut of September 17, 2001—the first trading day after the terrorist attacks of September 11, 2001. Our sample starts in 1994 as our tick-by-tick stock price data is not available before 1993 and the FOMC changed the way it communicated its policy decisions. Prior to 1994, the market became aware of changes in the federal funds target rate through the size and the type of open market operations of the New York Fed's trading desk. Moreover, most of the changes in the federal funds target rate took place on non-meeting days. With the first meeting in 1994, the FOMC started to communicate its decision by issuing press releases after every meeting and policy decision. Therefore, the start of our sample eliminates almost all timing ambiguity (besides the nine intermeeting policy decisions). The increased transparency and predictability makes the use of our intraday identification scheme more appealing as our identification assumptions are more likely to hold.

Panel B of Table 2 reports descriptive statistics for the percentage returns of the S&P500 for all 137 event dates between 1994 and 2009, turnings points and intermeeting policy decisions. We use the event returns of the 500 firms comprising the S&P500 to calculate index returns using the market capitalization at the end of the previous trading day as weights. The average return is close to zero with an event standard deviation of about one percent. The large absolute values of the tight (30 minute) and wide (60 minute) event returns are remarkable. Looking at the columns for intermeeting press releases and turning points, we see that the most extreme observations occur on non-regular release dates. Figure 3, a scatterplot of S&P500 event returns versus monetary policy shocks, highlights this point. Specifically, this figure shows a clear negative relation between monetary policy shocks and stock returns on regular FOMC meetings and on policy reversal dates in line with Bernanke and Kuttner (2005) and Gürkaynak et al. (2005). The scatterplot, however, also documents, that anything goes on intermeeting announcement days: negative (positive) monetary policy shocks induce positive and

[21]Intermeeting policy decisions are special in several respects as we discuss later. Markets might therefore need additional time to fully incorporate the information contained in the FOMC press release into prices. In a robustness check, we calculate event returns using the first trade after 10am on the event date. Result do not change materially.

Figure 3: Return of the S&P500 versus Monetary Policy Shocks (tight window)



This figure is a scatterplot of the percentage returns on the S&P500 versus the federal funds futures based measure of monetary policy shocks calculated according to equation 2 for the tight (30min) event window. The full sample ranges from February 1994 through December 2009, excluding the release of September 17th 2001, for a total of 137 observations. We distinguish between regular FOMC meetings, turning points in monetary policy and intermeeting press releases.

negative stock market reactions with about equal probabilities. Faust et al. (2004a) argue that intermeeting policy decisions are likely to reflect new information about the state of the economy and hence the stock market reacts to this new information rather than changes in monetary policy. This logic calls for excluding intermeeting announcements.[22]

Firms are heterogeneous in many dimensions. Ehrmann and Fratzscher (2004) and Ippolito et al. (2013) among others show that firms with low cash flows, small firms, firms with low credit ratings, high price earnings multiples and Tobin's q show a higher sensitivity to monetary policy shocks in line with bank lending, balance sheet and interest rate channels of monetary policy. To rule out that this heterogeneity drives our results,

[22]Romer and Romer (2000) document that the inflation forecasts of the Fed's staff beat commercial forecasts which is consistent with the Fed having an informational advantage over professional forecasters and thus opens a possibility that our measured surprises in the fed funds rate can capture both policy surprises and the Fed's revelation of information about the state of the economy. On the other hand, Coibion and Gorodnichenko (2012) document (see their Table 6) that, at least over the horizons of a few quarters, financial markets are as good in predicting movements in the fed funds rates as the Fed's staff and hence quantitatively the revelation component is probably small. In addition, Faust et al. (2004a) argue that FOMC announcements do not contain superior information about the state of the economy as professional forecasters do not systematically change their forecasts for a wide range of macroeconomic variables following FOMC press releases and these forecasts are efficient given the announcement. Finally, while the revelation component can make the mapping of empirical results to a theoretical model less straightforward, it does not invalidate our empirical analysis as we only need an unanticipated shock that moves optimal reset prices and therefore returns. The nature of this shock is not material.

we control for an extended set of variables at the firm and industry level. For example, we construct measures of firm size, volatility and cyclical properties of demand, market power, cost structure, financial dependence, access to financial markets, etc. We use data from a variety of sources such as the Standard and Poor's Compustat database, publications of the U.S. Census Bureau, and previous studies. The appendix contains detailed information on how these variables are measured.

IV Empirical Results

A. Aggregate Market Volatility

We first document the effects of monetary policy shocks on the return of the aggregate market to ensure that these shocks are a meaningful source of variation. Table 3 reports results from regressing returns of the S&P500 on monetary policy surprises as well as squared index returns on squared policy shocks for our tight event window (30 min).[23] Column (1) shows that a higher than expected federal funds target rate leads to a drop in stocks prices. This effect—contrary to findings in the previous literature—is not statistically significant. Restricting our sample period to 1994-2004 (or 1994-2007), we can replicate the results of Bernanke and Kuttner (2005), Gürkaynak et al. (2005), and others: a 25 bps unexpected cut in interest rates leads to an increase of the S&P500 by more than 1.3%. In column (3), we find a highly statistically significant impact of squared policy shocks on squared index returns. Conditioning on different types of meetings shows that the overall effect is mainly driven by turning points in monetary policy. Widening the event window mainly adds noise, increasing standard errors and lowering R^2s, but does not qualitatively alter the results (see appendix). In summary, monetary policy surprises are valid shocks for our analysis.

B. Baseline

Panel A of Table 4 presents results for the baseline specification (3) where we regress squared event returns at the firm level on the squared policy surprise, the frequencies of price adjustments and their interactions. To account for correlation of error terms across

[23] Table 2 in the online appendix contains results both for the 30 minutes event window in columns (1) to (6) as well as the 60 minutes event window in columns (7) to (12).

time and firms, we report Driscoll and Kraay (1998) standard errors in parentheses.[24]

Column (1) of Panel A. shows that squared surprises have a large positive impact on squared stocks returns. The point estimate is economically large and statistically significant at the 1% level: a hypothetical policy surprise of 25 bps leads to an increase in squared returns of roughly $8\%^2$ ($0.25^2 \times 128.50 = 8.03$). The estimated coefficient on the interaction of the frequency of price adjustment and the squared shock indicates that this effect is lower for firms with more flexible prices. For the firms with the most flexible prices in our sample (which have a probability of price adjustment of roughly 0.5 per month), the impact of squared monetary policy shocks is reduced by a factor of three, that is, $(\beta_1 - 0.5 \times \beta_3)/\beta_1 \approx 1/3$. Importantly, this sensitivity is broadly in line with the estimates we obtain for simulated data from a calibrated New Keynesian model (see Section V.).

The differential response of conditional volatility for sticky and flexible price firms is a very robust result. Controlling for outliers (column (2)),[25] adding firm fixed effects (columns (3) and (4)), firm and event (time) fixed effects (columns (5) and (6)), or looking at a 60 minutes event window (columns (7) and (8)) does not materially change point estimates and statistical significance for the interaction term between squared policy surprises and the frequency of price adjustment. Increasing the observation period to a daily event window (columns (9) and (10)) adds a considerable amount of noise, reducing explanatory power and increasing standard errors. Point estimates are no longer statistically significant but they remain economically large and relative magnitudes are effectively unchanged. This pattern is consistent with Bernanke and Kuttner (2005) and Gürkaynak et al. (2005) who document that for the aggregate market that R^2s are reduced by a factor of 3 and standard errors increase substantially as the event window increases to the daily frequency.[26]

While in the baseline measurement of stock returns we use only two data ticks, we

[24]Note that we have 956 unique firms in sample due to changes in the index composition during our sample period out of which we were able to merge 760 with the BLS pricing data.

[25]We use a standard approach of identifying outliers by jackknife as described in Belsley, Kuh, and Welsch (1980) and Bollen and Jackman (1990).

[26]While the effects for the aggregate market can be explained by additional macro announcements or stock market relevant news, many more stock price relevant news can be observed for individual stocks such as earning announcements, analyst reports, management decisions etc. rationalizing the large increase in standard errors. Rigobon and Sack (2004) and Gürkaynak and Wright (2013) also highlight that intraday event windows are more well suited from an econometric point of view as daily event windows might give rise to biased estimates.

find very similar results (Panel B. columns (1) and (2)) when we weight returns by trade volume in time windows before and after our events. The results also do not change qualitatively when we use absolute returns and policy shocks (columns (3) and (4) of Panel B.) instead of squared returns and squared shocks.

One may be concerned that the heterogeneity in volatility across firms is largely driven by market movements or exposure to movements of other risk factors rather than forces specific to the price stickiness of particular firms. To address this concern, we consider squared market-adjusted returns (i.e. $(R_{it} - R_t^{SP})^2$), squared CAPM-adjusted returns (i.e. $(R_{it} - \beta_i R_t^{SP})^2$), and squared Fama-French-adjusted returns ($(R_{it} - \beta_{iFF} R_t^{FF})^2$) where β_i and β_{iFF} are time series factor loadings of the excess returns of firm i on the market excess returns and the three Fama-French factors. All three adjustments (Panel B.: columns (5) and (6), columns (7) and (8), and columns (9) and (10)) take out a lot of common variation, reducing both explanatory power and point estimates somewhat but leaving statistical significance and relative magnitudes unchanged or even increasing it slightly. Thus, conditional volatility responds differentially across firms even after we adjust for movements of the aggregate market and other risk factors which itself could be influenced by nominal rigidities as no firm in our sample has perfectly flexible prices.

The sensitivity of the conditional volatility to monetary policy shocks may vary across types of events. For example, Gürkaynak et al. (2005) and others show that monetary policy announcements about changes in the path/direction of future policy are more powerful in moving markets. Panel C. of Table 4 contains results for different event types. We restrict our sample in columns (3) and (4) to observations before 2007 to control for the impact of the Great Recession and the zero lower bound. The effect of price flexibility increases both statistically and economically in the restricted sample. In the next two columns, we follow Bernanke and Kuttner (2005) and restrict the sample only to episodes when the FOMC changed the policy interest rate. While this reduces our sample size by more than 50%, it has no impact on estimated coefficients. Some of the monetary policy shocks are relatively small. To ensure that the large effects of price rigidity are not driven by these observations, we restrict our sample to events with shocks larger than 0.05 in absolute value in columns (7) and (8). Both for the full and the no outliers samples, statistical and economic significance remains stable or even slightly increases. The next column conditions on reversals in monetary policy (i.e. turning points in policy). The coefficient on the interaction term between the probability of price adjustment and squared policy shocks increases by a factor of three. The effect of policy shocks is somewhat reduced for intermeeting releases as shown in the last column.

C. Additional controls and subsamples

In Table 5, we add a wide range of controls to disentangle the effect of price stickiness from potentially confounding firm and industry effects. In the first column we repeat the baseline regression excluding outliers. In the first set of controls, we focus on measures of market power and profitability. For example, in column (2) we include the squared shock interacted with the price cost margin (*pcm*) as an additional regressor. While firms with larger *pcm* appear to have volatility more sensitive to monetary policy shocks, the sensitivity of the volatility across firms with different frequencies of price adjustment is barely affected by including *pcm*. Likewise, controlling directly for market power with industry concentration (the share of sales by the four largest firms, $4F - conc\ ratio$, column (3)) does not change our main result. We also find that our results for b_2 in equation (3) do not alter when we control for the book to market ratio (column (4)) or firm size (column (5)).[27]

The differential sensitivity of volatility across sticky and flexible price firms may arise from differences in the volatility of demand for sticky and flexible price firms. For example, all firms could face identical menu costs but firms which are hit more frequently by idiosyncratic shocks have a higher frequency of price adjustment and hence may be closer to their optimal reset prices which in turn entails that they could have a lower sensitivity to nominal shocks. To disentangle this potentially confounding effect, we explicitly control for the volatility of sales (standard deviation of sales growth rates, *std sale*,[28] column (6)) and for durability of output (columns (7) and (8)) using the classifications of Gomes et al. (2009) and Bils et al. (2012), respectively. The latter control is important as demand for durable goods is particularly volatile over the business cycle and consumers can easily shift the timing of their purchases thus making price sensitivity especially high. Even with

[27]Note that the coefficient on the squared policy surprise now turns negative. This coefficient, however, can no longer be as easily interpreted as before in the presence of additional control variables. If we report results evaluating additional controls at their mean level, coefficients are similar in size to our benchmark estimation.

[28]We use the standard deviation of annual sales growth at the quarterly frequency to control for seasonality in sales. Ideally, we would want to have higher frequency data to construct this variable but publicly available sources only contain sales at the quarterly frequency.

these additional regressors, we find that the estimated differential sensitivity of volatility across sticky and flexible price firms is largely unchanged.

Some heterogeneity of stickiness in product prices may reflect differences in the stickiness of input prices. For example, labor costs are often found to be relatively inflexible due to rigid wages. In column (9), we control for input price stickiness proxied by the share of labor expenses in sales and we indeed find that firms with a larger share of labor cost have greater sensitivity to monetary policy shocks. This additional control however does not affect our estimates of how stickiness of product prices influences conditional volatility of returns. In columns (10) to (18), we additionally control for fixed costs to sales ($FC2Y$) as a higher ratio might decrease the flexibility to react to monetary policy shocks, receivables minus payables to sales ratio ($RecPay2Y$) to control for the impact of short term financing, investment to sales ratio ($I2Y$) to control for investment opportunities, depreciation to assets ratio ($D2A$) as a measure of capital intensity, the rate of synchronization in price adjustments within a firm (*sync*), the number of products at the firm level (*#prod*) as well as the S&P long term issuer rating (*Rat*) and the Kaplan - Zingales index (KZ) to investigate the impact of financial constraints. Overall, none of the controls—neither individually nor jointly—attenuates the effect of price stickiness which is highly statistically and economically significant.

In Panel A. of Table 6 we run our baseline regression at the industry level to control for possible unobserved industry heterogeneity. In this exercise, we have typically much fewer firms and thus estimates have higher sampling uncertainty. Despite large reductions in sample sizes, for four out of the six industries we find a statistically significant negative coefficient on the interaction term between the frequency of price adjustment and squared monetary policy surprises. For the finance industry, this coefficient is not statistically significant. For the service sector, the estimate for the full sample is positive and significant but this result is driven by a handful of outliers. Once these outliers are removed, the point estimate becomes much smaller and statistically insignificantly different from zero. This test uses only variation of our measure of price stickiness within industry. We see these results as comforting insofar as they document that our baseline effects are not driven by unobserved industry characteristics.

An alternative possibility which could drive our results is a general return sensitivity to monetary policy surprises independent of price stickiness. To rule out that this alternative explanation, we directly add the return sensitivity to monetary policy shocks.[29] To perform this test we first estimate the sensitivity (β_{v_t}) by regressing firm-level event returns on monetary policy shocks in our narrow event window. Then we add the return sensitivity interacted with the squared monetary policy surprise in various specifications as an additional control variable in our baseline regression. Panel B. of Table 6 shows that a higher squared return sensitivity to monetary policy surprises indeed leads to an increase in event return volatilities but this additional control has a negligible effect on the interaction term of our measure of price stickiness and squared monetary policy shocks.

D. Relative Volatility and Placebo Test

In this subsection, we perform two additional economically motivated robustness checks to further examine potentially confounding unobserved firm heterogeneity: one in which price stickiness should matter and one where we do not expect to find an effect of price stickiness.

Specifically, the first check is built on the idea that if inflexible price firms have unconditionally higher volatility than flexible price firms and this drives the previously documented effects, then we should find no effects of price stickiness once we scale the event volatilities by their unconditional volatilities. To implement this test, we pick a pseudo event window in the middle of two adjacent event dates t and $t-1$ (date $\tau = t - 1/2$) and calculate a pseudo event volatility $(1 + R_{i\tau})^2$ in a 30 minute window bracketing 2.15pm at date τ. We then scale the event volatilities of the following event date with these volatilities, $(1 + R_{it})^2/(1 + R_{i\tau})^2$, and run our baseline regression with $(1 + R_{it})^2/(1 + R_{i\tau})^2$ as the dependent variable.

Column (1) in Panel A. of Table 7 shows that this story cannot explain our result that flexible price firms have lower conditional volatilities than sticky price firms. Monetary policy surprises increase event volatility compared to non-event dates. This conditional increase is completely offset for the most flexible firms with both coefficients being highly statistically significant. Controlling for outliers in column (2), firm fixed effects, event fixed effects or both in columns (3) to (8) does not change this conclusion.

The second check is aimed to address the concern that unobserved heterogeneity can drive our results is to directly run our baseline regression on the pseudo event volatilities. We perform this test in Panel B. of Table 7: all coefficients are economically small,

[29]We thank David Romer for suggesting this test.

none of them is statistically significant and once we exclude outliers, the coefficient on the interaction term between the monetary policy surprise and the frequency of price adjustment changes sign.

E. Profits

The large differential effects of price stickiness on the volatility of returns suggest that firms with inflexible prices should experience an increased volatility of profits relative to firms with flexible prices. This response in fundamentals may be difficult to detect as information on firm profits is only available at quarterly frequency. To match this much lower frequency, we sum shocks v_t in a given quarter and treat this sum as the unanticipated shock. Denote this shock with $\tilde{v}_t$. We also construct the following measure of change in profitability between the previous four quarters and quarters running from $t+H$ to $t+H+3$:

$$\Delta\pi_{it,H} = \frac{\frac{1}{4}\sum_{s=t+H}^{t+H+3} OI_{is} - \frac{1}{4}\sum_{s=t-4}^{t-1} OI_{is}}{TA_{it-1}} \times 100 \tag{4}$$

where OI is quarterly operating income before depreciation, TA is total assets, and H can be interpreted as the horizon of the response. We use four quarters before and after the shock to address seasonality of profits. Using this measure of profitability, we estimate the following modification of our baseline specification:

$$(\Delta\pi_{it,H})^2 = b_0 + b_1 \times \Delta\tilde{v}_t^2 + b_2 \times \tilde{v}_t^2 \times \lambda_i + b_3 \times \lambda_i + error \tag{5}$$

We find (Table 8) that flexible price firms have a statistically lower volatility in operating income than sticky price firms ($b_2 < 0$). This effect is increasing up to $H = 6$ quarters ahead and then this difference becomes statistically insignificant and gradually converges to zero. Firms with more inflexible prices (smaller FPA) tend to have larger volatilities of profits. Interestingly, the estimate of b_1 is statistically positive only at $H = 0$ and turns statistically negative after $H = 5$.

V Dynamic General Equilibrium Model

While the static version of the New Keynesian model in section III was useful in guiding our empirical specifications it is not well suited for a quantitative analysis. To assess whether our empirical findings can be rationalized by a dynamic multi-sector New Keynesian model we calibrate the Carvalho (2006) model and run our baseline specification on simulated data from the model.

In the interest of space, we only verbally discuss the model and focus on key equations.[30] In this model, a representative household lives forever. The instantaneous utility of the household depends on consumption and labor supply. The intertemporal elasticity of substitution for consumption is σ. Labor supply is firm-specific. For each firm, the elasticity of labor supply is η. Household's discount factor is β. Households have a love for variety and have a CES Dixit-Stiglitz aggregator with the elasticity of substitution θ.

Firms set prices as in Calvo (1983). There are k sectors in the economy with each sector populated by a continuum of firms. Each sector is characterized by a fixed λ_k, the probability of any firm in industry k to adjust its price in a given period.[31] The share of firms in industry k in the total number of firms in the economy is given by the density function $f(k)$. Firms are monopolistic competitors and the elasticity of substitution θ is the same for all firms both within and across industries. While this assumption is clearly unrealistic, it greatly simplifies the algebra and keeps the model tractable. The production function for output Y is linear in labor N which is the only input. The optimization problem of firm j in industry k is then to pick a reset price X_{jkt}:

$$\max \mathbb{E}_t \quad \sum_{s=0}^{\infty} Q_{t,t+s}(1-\lambda_k)^s [X_{jkt}Y_{jkt+s} - W_{jkt+s}N_{jkt+s}] \tag{6}$$

subject to its demand function and production technology where variables without subscripts k and j indicate aggregate variables, W is wages (taken as given by firms) and Q is the stochastic discount factor. Wages are determined by the household's intratemporal elasticity between labor and consumption. The central bank follows a Taylor rule.

After substituting in optimal reset prices and firm-specific demand and wages, the value of the firm V with price P_{jkt} is given by:

$$V(P_{jkt}) \;=\; \mathbb{E}_t \left\{ Y_t^{\sigma} P_t \left[\Delta_{kt}^{(1)} \left(\frac{P_{jkt}}{P_t} \right)^{1-\theta} - \Delta_{kt}^{(2)} \left(\frac{P_{jkt}}{P_t} \right)^{-\theta(1+1/\eta)} + \Upsilon_{kt}^{(1)} - \Upsilon_{kt}^{(2)} \right] \right\}, \tag{7}$$

where $\Upsilon_{kt}^{(1)}$, $\Delta_{kt}^{(1)}$, $\Upsilon_{kt}^{(2)}$ and $\Delta_{kt}^{(2)}$ follow simple recursions and are not indexed by j, which allows particularly easy solution and simulation of this non-linear model.

[30] The appendix contains a more detailed description of the model.

[31] The fixed probability of price adjustment should be interpreted as a metaphor that allows particularly fast *non-linear* solutions to multi-sector models with large state spaces as well as easy interpretation of results. However we find similar results in the Dotsey et al. (1999) model with state-dependent price adjustment. Results are available upon request.

We calibrate the model at quarterly frequency using standard parameter values in the literature (Table 9). Ashenfelter et al. (2010) survey the literature on the elasticity of labor supply faced by firms. They document that the short-run elasticity is in the 0.1-1.5 range while the long-run elasticity is between 2 and 4. We take the middle of the range of these elasticities and set $\eta = 2$. The elasticity of demand θ is often calibrated at 10 in macroeconomic studies. However, since firms in our model compete not only with firms in the same sector but also with firms in other sectors we calibrate $\theta = 7$ which captures the notion that the elasticity of substitution across sectors is likely to be low. Other preference parameters are standard: $\sigma = 2$ and $\beta = 0.99$. Parameters of the policy reaction function are taken from Taylor (1993) and Coibion and Gorodnichenko (2012). We follow Carvalho (2006) and calibrate the density function $f(k) = 1/5$ and use the empirical distribution of frequencies of price adjustment reported in Nakamura and Steinsson (2008) to calibrate $\{\lambda_k\}_{k=1}^{5}$. Specifically, we sort industries by the degree of price stickiness and construct five synthetic sectors which correspond to the quintiles of price stickiness observed in the data. Each sector covers a fifth of consumer spending. The Calvo rates of price adjustment range from 0.094 to 0.975 per quarter with the median sector having a Calvo rate of 0.277 (which implies that this sector updates prices approximately once a year).

We solve the model using a third-order approximation as implemented in DYNARE and simulate the model for 100 firms per sector for 2000 periods, but discard the first 1000 periods as burn-in. For each firm and each time period, we calculate the value of the firm $V(P_{jkt})$ and the value of the firm net of dividend $\tilde{V}(P_{jkt}) \equiv V(P_{jkt}) - (P_{jkt}Y_{jkt+s} - W_{jkt+s}N_{jkt+s})$ as well as the implied return $R_{jkt} = V(P_{jkt})/\tilde{V}(P_{jkt-1}) - 1$. As we discussed in the case of the static model, realized returns can increase or decrease in response to a nominal shock. Hence, we consider the specification suggested previously:

$$R_{jkt}^2 = b_0 + b_1 \times v_t^2 + b_2 \times v_t^2 \times \lambda_j + b_3 \times \lambda_j + error \tag{8}$$

We report resulting estimates of b_1, b_2 and b_3 in Table 9 for the baseline calibration as well as for alternative parametrizations. We find that a large, positive $\hat{b}_1$ and a large, negative $\hat{b}_2$ are very robust features of the model with estimates in the ballpark of our empirical findings in Section IV. Magnitudes of the coefficients are such that $\hat{b}_1 + \hat{b}_2 \approx 0$. The estimates of $\hat{b}_3$ are negative, as predicted, but generally close to zero.

We can also use this model to calculate lost profits due to price stickiness: we compute the median profit $\bar{\pi}_k$ for each firm type k and then use $(\bar{\pi}_k - \bar{\pi}_5)/\bar{\pi}_5$ to assess how an increase in the duration of price spells from $(1/\lambda_5)$ (the sector with practically flexible prices) to $(1/\lambda_k)$ influences profits. We find that going from flexible prices to prices fixed for roughly one year (sector 3) reduces profits by about 25%. While in the model the only source of firm heterogeneity is the duration of price spells and thus differences in profits can be attributed to price stickiness, the duration of price spells in the data is affected by heterogeneous costs and benefits of price adjustment so that the mapping of lost profits to the size of menu costs is likely to be complex. However, the magnitudes we observe in our simulations appear broadly in line with those observed in the data. Zbaracki et al. (2004) show that a manufacturing firm with an average duration of price spells of one year spends about 20 percent of its net profit margin on nominal price adjustment.

Obviously, these calculations of menu-cost estimates depend of structural parameters of the model. One may use empirical moments to infer these structural parameters. The answer in this exercise is likely to depend on the details of the model, which can limit the robustness. However, these simulations highlight the relationship between price stickiness and returns and provides a sense of magnitudes one may expect in a reasonably calibrated New Keynesian model with heterogeneous firms.

VI Concluding Remarks

Are sticky prices costly? We propose a simple framework to address this question using the conditional volatility of stock market returns after monetary policy announcements. We document that the conditional volatility rises more for firms with stickier prices than for firms with more flexible prices. This differential reaction is economically and statistically large as well as strikingly robust to a broad spectrum of checks. This result suggests that menu costs—broadly defined to include physical costs of price adjustment, informational frictions, etc.—are an important factor for nominal price rigidity. Our empirical evidence lends support to the New Keynesian interpretation of the observed nominal price rigidity at the microlevel: sticky prices are costly. Our results are qualitatively and, under plausible calibrations, quantitatively consistent with New Keynesian macroeconomic models where firms have heterogeneous price stickiness. Our "model-free" evidence unambiguously suggests that sticky prices are indeed costly for firms, which is consistent with the tenets of New Keynesian macroeconomics.

Our results have a number of policy implications. First, our findings provide foundations for policy-workhorse macroeconomic models such as Christiano et al. (2005) in which nominal frictions play a prominent role. Second, increasing trend inflation—a policy suggested by a number of economists to combat deflationary spirals in the Great Recessions—has possibly non-negligible costs in the light of our results. Third, the presence of sticky prices is likely to generate larger fiscal multipliers (especially in times of a binding zero lower bound on interest rates, see Christiano et al. (2011)) and thus potentially justifies more activist fiscal policy aimed at stabilizing business cycles. Finally, as emphasized by Bernanke and Kuttner (2005), monetary policy can influence the economy via changes in asset prices and our results can provide a new perspective on this channel as well as highlight its distributional aspects.

The high-frequency identification of causal effects of monetary shocks on the volatility of stock returns suggests that connecting stock returns and measures of price stickiness is a fruitful avenue for future research. For example, Weber (2013) studies how firm-level and portfolio returns vary with measured price stickiness which can provide a simple metric of the size of menu costs and shed new light on the sources of the cross-sectional distribution of returns. Alternatively, one may integrate asset prices into fully fledged DSGE models to obtain structural estimates of menu costs. We anticipate that using information on stock returns in conjunction with firm-level measures of price stickiness can help to discriminate between alternative models explaining the large real effect of monetary policy with moderate degrees of price stickiness and the inertial reaction of inflation, improve our understanding of how to price securities, and further bridge finance and macroeconomics.

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

This table reports average frequencies of price adjustments at the industry and aggregate levels with standard deviations in parentheses. Equally weighted frequencies of price adjustments are calculated at the firm level using the microdata underlying the producer price index.

	Total	Agriculture	Manufacturing	Utilities	Trade	Finance	Service
Mean	14.66%	25.35%	11.88%	21.45%	22.19%	13.82%	8.07%
Std	(12.90%)	(17.23%)	(11.12%)	(13.44%)	(13.71%)	(11.41%)	(7.72%)
Nobs	57,541	3,634	27,939	7,397	3,845	9,856	4,870

Table 2: **Descriptive Statistics For High-Frequency Data**

This table reports descriptive statistics for monetary policy shocks (bps) in Panel A and for the returns of the S&P500 in Panel B, separately for all 137 event days between 1994 and 2009, turning points in monetary policy and intermeeting policy decisions. The policy shock is calculated according to equation (2) as the scaled change in the current month federal funds futures in a 30 minutes (tight) window bracketing the FOMC press releases and a 60 minutes (wide) event window around the release times, respectively. The return of the S&P500 is calculated as weighted average of the constituents' returns in the respective event windows, where the market capitalizations at the end of the previous trading days are used to calculate the weights.

	All Event Days		Turning Points		Intermeeting Releases	
	Tight	Wide	Tight	Wide	Tight	Wide
Panel A. Monetary Policy Shocks						
Mean	−1.60	−1.46	−6.09	−5.68	−12.23	−11.09
Median	0.00	0.00	−1.75	−2.75	−5.73	−5.15
Std	8.94	9.11	17.28	16.40	23.84	25.23
Min	−46.67	−46.30	−39.30	−36.50	−46.67	−46.30
Max	16.30	15.20	16.30	15.20	15.00	15.00
Correlation	0.99		0.99		0.99	
Nobs	137		8		8	
Panel B. S&P500 Returns						
Mean	−0.05%	0.05%	0.71%	0.71%	−0.04%	−0.06%
Median	−0.12%	0.02%	0.30%	0.50%	0.64%	0.42%
Std	0.91%	0.97%	1.73%	1.52%	2.83%	2.90%
Min	−5.12%	−5.12%	−0.81%	−0.78%	−5.12%	−5.12%
Max	4.32%	3.61%	4.32%	3.61%	2.69%	2.69%
Correlation	0.90		0.99		0.99	
Nobs	137		8		8	

Table 3: **Response of the S&P500 to Monetary Policy Shocks**

This table reports the results of regressing returns and squared returns in percent of the S&P500 in an event window bracketing the FOMC press releases on the federal funds futures based measure of monetary policy shocks calculated according to equation 2, v_t, and the squared shocks, v_t^2, for different event types in a 30 minutes window bracketing the FOMC press releases. The return of the S&P500 is calculated as a weighted average of the constituents' return in the respective event window, where the market capitilization at the end of the previous trading day is used to calculate the weights. The full sample ranges from February 1994 through December 2009, excluding the release of September 17th 2001, for a total of 137 observations. Robust standard errors are reported in parentheses.

	Returns		Squared Returns			
		pre 2005	All	Regular	Turning Point	Intermeeting
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	−0.08	−0.12*	0.13	0.23***	−0.36	2.68
	(0.06)	(0.05)	(0.13)	(0.05)	(0.77)	(1.64)
v_t	−1.66	−5.31***				
	(2.93)	(1.41)				
v_t^2			84.38***	9.57	116.60***	67.15
			(23.18)	(8.67)	(9.68)	(38.79)
(38.79)						
R^2	0.03	0.44	0.69	0.02	0.92	0.53
Observations	137	92	137	121	8	8

Standard errors in parentheses

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

Table 4: **Response of the Constituents of the S&P500 to Monetary Policy Shocks**

This table reports the results of regressing squared percentage returns of the constituents of the S&P500 in different event windows bracketing the FOMC press releases on the federal funds futures based measure of monetary policy shocks calculated according to equation (2), v_t^2, the frequency of price adjustment, FPA, as well as their interactions. See specification (3). Equally weighted frequencies of price adjustments are calculated at the firm level using the microdata underlying the producer price index. The full sample ranges from February 1994 through December 2009, excluding the release of September 17th 2001, for a total of 137 observations. Driscoll-Kraay standard errors are reported in parentheses.

Panel A. Baseline

	Tight Window		Firm FE		Firm & Event FE		Wide Window		Daily Window	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
v_t^2	128.50***	76.95***	127.50***	76.59***			119.60***	95.38***	245.60 **	158.40 **
	(23.05)	(15.25)	(22.80)	(15.13)			(30.71)	(20.87)	(118.70)	(74.82)
$FPA \times v_t^2$	−169.80 **	−67.26***	−168.00 **	−69.05***	−166.60 **	−41.33***	−130.40*	−78.07***	−340.10	−178.30
	(78.50)	(5.33)	(75.55)	(5.04)	(76.18)	(5.89)	(67.08)	(27.67)	(245.90)	(132.90)
FPA	0.41	0.09					0.55	0.08	0.10	−2.27
	(0.34)	(0.18)					(0.68)	(0.22)	(2.83)	(2.56)
Correction for outliers	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.12	0.12					0.03	0.09	0.01	0.00
Observations	57,541	57,441	57,541	57,440	57,541	57,420	57,541	55,022	57,541	57,506

Panel B. Variations

	Volume Weighted		Absolute Returns & Shocks		Market adj		CAPM adj		Fama & French adj	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
v_t^2/v_t^{abs}	144.50***	86.42***	6.33***	5.37***	47.76***	25.40***	43.80***	27.71***	38.29***	25.80***
	(34.71)	(14.39)	(1.17)	(1.06)	(17.05)	(7.27)	(8.87)	(5.32)	(6.05)	(3.68)
$FPA \times v_t^2/v_t^{abs}$	−205.90*	−64.59***	−4.11*	−2.84***	−71.52 **	−13.20***	−52.96***	−18.35***	−42.57 **	−22.52***
	(110.20)	(24.52)	(2.20)	(0.83)	(30.70)	(1.95)	(15.99)	(5.32)	(18.79)	(3.61)
FPA	0.82	0.45	0.11	0.06	0.05	−0.12	−0.12	−0.23	0.05	−0.12
	(0.68)	(0.58)	(0.07)	(0.04)	(0.23)	(0.19)	(0.22)	(0.21)	(0.23)	(0.19)
Correction for outliers	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.06	0.04	0.21	0.19	0.03	0.03	0.03	0.03	0.02	0.02
Observations	55,065	54,996	57,541	57,426	57,541	57,492	57,541	57,491	57,541	57,497

Panel C. Condition on Event Type

	baseline		pre 2007		change in FFR		shock > 0.05		turning point	intermeeting
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
v_t^2	128.50***	76.95***	123.10***	53.81***	133.50***	83.76***	134.50***	90.13***	235.10***	78.25***
	(23.05)	(15.25)	(38.51)	(4.46)	(26.39)	(16.03)	(22.36)	(16.80)	(10.41)	(22.19)
$FPA \times v_t^2$	−169.80 **	−67.26***	−245.80***	−77.75***	−178.10 **	−64.97***	−185.60 **	−77.20***	−512.20***	−99.31 **
	(78.50)	(5.33)	(88.51)	(11.33)	(83.12)	(9.59)	(84.17)	(21.18)	(26.87)	(32.93)
FPA	0.41	0.09	0.54*	0.02	1.01*	0.48	2.23	0.90	5.48*	1.66
	(0.34)	(0.18)	(0.31)	(0.10)	(0.58)	(0.34)	(1.38)	(0.82)	(2.68)	(3.22)
Correction for outliers	No	Yes	No	Yes	No	Yes	No	Yes	No/Yes	No/Yes
R^2	0.12	0.12	0.11	0.13	0.14	0.13	0.12	0.16	0.15	0.04
Number of firms	760	760	694	694	742	742	738	738	705	713
Observations	57,541	57,441	45,891	45,775	24,752	24,676	15,580	15,525	3,407	3,300

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

Table 5: **Response of the Constituents of the S&P500 to Monetary Policy Shocks (firm & industry level controls)**

This table reports the results of regressing squared percentage returns of the constituents of the S&P500 in a 30 minutes window bracketing the FOMC press releases on the federal funds futures based measure of monetary policy surprises calculated according to equation (2), v_t^2, the frequency of price adjustment, FPA, as well as their interactions. See specification (3). Equally weighted frequencies of price adjustments are calculated at the firm level using the microdata underlying the producer price index. pcm is the price cost margin defined as sales minus cost of goods sold over sales, $4F - conc\ ratio$ is the 4 firm concentration ratio, bm is the book to market ratio and size is the logarithm of the market capitalization. std sale is the volatility of annual sales growth at the quarterly frequency, nondur, serv, invest, gov and nx follow the durable goods classification of Gomes et al. (2009), dura is the durability measure of Bils et al. (2012), labor share is the share of total staff expenses in sales, FC2Y is fixed costs to sales, RecPay2Y is receivables minus payables to sales, I2Y is investment to sales and D2A is depreciation and amortization over total assets. engel are the Engel curve slopes of Bils et al. (2012), sync is the degree of synchronization in price adjustment at the firm level, #prod is the number of products in the producer price data, Rat is the S&P long term issuer rating and KZ the Kaplan-Zingales index. The full sample ranges from February 1994 through December 2009, excluding the release of September 17th 2001, for a total of 137 observations. Driscoll-Kraay standard errors are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
v_t^2	76.59***	53.49***	83.02***	48.19	−185.60***	57.33***	81.12***	70.80***	83.23***
	(15.13)	(18.92)	(16.31)	(33.61)	(30.83)	(11.43)	(10.75)	(17.03)	(7.90)
$FPA \times v_t^2$	−69.05***	−43.62***	−67.94***	−66.98***	−63.72***	−71.98***	−57.56***	−58.82***	−100.60***
	(5.04)	(7.84)	(7.05)	(5.42)	(4.86)	(8.72)	(14.06)	(6.92)	(28.12)
$v_t^2 \times pcm$		50.42 * *							
		(20.42)							
$v_t^2 \times 4F - conc\ ratio$			−46.87***						
			(10.24)						
$v_t^2 \times bm$				−1.97					
				(1.69)					
$v_t^2 \times size$					16.31***				
					(2.54)				
$v_t^2 \times std\ sale$						338.90***			
						(60.12)			
$v_t^2 \times nondur$							−33.93***		
							(5.19)		
$v_t^2 \times serv$							−27.46***		
							(4.17)		
$v_t^2 \times invest$							7.3		
							(9.01)		
$v_t^2 \times gov$							28.01***		
							(5.97)		
$v_t^2 \times nx$							−0.75		
							(10.47)		
$v_t^2 \times dura$								11.77***	
								(2.27)	
$v_t^2 \times labor\ share$									0.42
									(14.11)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Correction for outlier	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of firms	760	728	670	760	760	728	565	633	181
Observations	57,440	51,929	50,123	57,440	57,442	51,941	42,990	47,421	15,594

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

continued on next page

Table 5: **Continued from Previous Page**

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
v_t^2	46.45*	76.50***	74.50***	84.99***	19.99	95.92***	83.05***	145.80***	71.83***	−224.90***	−147.40***
	(23.94)	(15.24)	(12.82)	(16.04)	(25.53)	(16.59)	(15.31)	(15.51)	(16.53)	(69.66)	(49.55)
$FPA \times v_t^2$	−24.07***	−72.58***	−61.55***	−62.56***	−25.60***	−50.45***	−26.68***	−63.81***	−74.98***	−112.20***	−113.80**
	(4.65)	(6.01)	(5.23)	(6.27)	(4.84)	(6.25)	(9.34)	(5.94)	(6.94)	(20.76)	(48.54)
$v_t^2 \times pcm$										−17.25	−52.25***
										(13.81)	(17.74)
$v_t^2 \times 4F - conc\ ratio$										8.92	−92.83***
										(7.08)	(22.19)
$v_t^2 \times bm$										−1.87	−0.34
										(1.29)	(1.09)
$v_t^2 \times size$										20.90***	16.84***
										(5.10)	(4.59)
$v_t^2 \times std\ sale_a$										565.90***	−234.50***
										(82.78)	(88.53)
$v_t^2 \times nondur$										−39.01***	−54.58***
										(3.78)	(13.31)
$v_t^2 \times serv$										−51.25***	−61.03***
										(14.82)	(22.14)
$v_t^2 \times invest$										2.11	−37.78***
										(5.73)	(12.76)
$v_t^2 \times gov$										14.04	−54.16***
										(8.78)	(10.48)
$v_t^2 \times nx$										62.93***	−0.76
										(11.12)	(24.10)
$v_t^2 \times dura$											
$v_t^2 \times labor\ share$											−11.11
											(31.34)
$v_t^2 \times FC2Y$	136.50**										
	(55.74)										
$v_t^2 \times RecPay2Y$		−1.75*								19.47	139.40***
		(1.01)								(30.07)	(46.88)
$v_t^2 \times I2Y$			−12.42							−8.87	−75.92
			(37.62)							(42.46)	(160.70)
$v_t^2 \times D2A$				−251.60**						194.00	425.70***
				(108.00)						(138.90)	(103.50)
$v_t^2 \times engel$					56.20***						
					(13.65)						
$v_t^2 \times sync$						−65.94**				22.32	101.10
						(28.53)				(27.81)	(71.44)
$v_t^2 \times \#prod$							−0.38***			0.1	−0.02
							(0.03)			(0.15)	(0.12)
$v_t^2 \times Rat$								−21.18***		−24.90***	−3.1
								(2.98)		(6.01)	(2.34)
$v_t^2 \times KZ$									5.80**	−0.2	1.83
									(2.83)	(2.31)	(1.12)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Correction for outlier	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of firms	746	737	723	737	633	759	760	743	746	473	94
Observations	56,474	55,884	55,565	56,145	47,415	57,322	57,431	53,283	56,352	33,067	7,187

Standard errors in parentheses

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

Table 6: **Response of the Constituents of the S&P500 to Monetary Policy Shocks (within industry and controlling for return sensitivity to monetary policy surprises)**

This table reports the results of regressing squared percentage returns of the constituents of the S&P500 in a 30 minutes window bracketing the FOMC press releases on the federal funds futures based measure of monetary policy surprises calculated according to equation (2), v_t^2 and the interaction term with the frequency of price adjustment, FPA, in Panel A. Panel B regresses squared percentage returns of the constituents of the S&P500 in a 30 minutes window bracketing the FOMC press releases on the federal funds futures based measure of monetary policy shocks, the frequency of price adjustment, as well as their interactions controlling for the sensitivity of returns to monetary policy shocks, β_{v_t}. See specification (3). Equally weighted frequencies of price adjustments are calculated at the firm level using the microdata underlying the producer price index. The full sample ranges from February 1994 through December 2009, excluding the release of September 17th 2001, for a total of 137 observations. Driscoll-Kraay standard errors are reported in parentheses.

Panel A. Within Industry

	All		Agro	Mnfg	Util	Trade	Finance	Service	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
v_t^2	127.50***	76.59***	81.73*	71.85***	73.68***	74.38***	86.48***	61.28***	80.15***
	(22.80)	(15.13)	(45.87)	(12.33)	(20.59)	(15.99)	(19.15)	(13.08)	(13.78)
$FPA \times v_t^2$	−168.00 **	−69.05***	−106.60*	−35.98***	−125.0 ***	−54.99*	−20.11	168.6 ***	33.97
	(75.55)	(5.04)	(58.58)	(11.55)	(16.28)	(29.91)	(24.98)	(53.54)	(69.23)
Correction for outliers	No	Yes	No	No	No	No	No	No	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of firms	760	760	58	346	112	50	140	77	77
Observations	57,541	57,440	3,629	27,887	7,394	3,839	9,836	4,856	4,815

Panel B. Controlling for Return Sensitivities to Monetary Policy Surprises

	baseline		sq return sens		return sens		abs return sens		sq rel return sens	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
v_t^2	128.50***	76.95***	93.83***	62.03***	117.10***	70.63***	71.95 **	49.89 **	89.98***	58.08***
	(23.05)	(15.25)	(20.05)	(19.62)	(24.32)	(20.66)	(27.93)	(24.58)	(21.05)	(19.61)
$FPA \times v_t^2$	−169.80 **	−67.26***	−157.90 **	−62.11***	−160.80 **	−61.02***	−170.70 **	−62.17***	−147.30 **	−52.86***
	(78.50)	(5.33)	(68.89)	(8.64)	(65.63)	(4.70)	(77.89)	(7.29)	(63.68)	(5.58)
FPA	0.41	0.09	0.81*	0.28	0.47	0.01	0.61	0.16	0.77*	0.26
	(0.34)	(0.18)	(0.46)	(0.19)	(0.38)	(0.14)	(0.39)	(0.19)	(0.45)	(0.20)
$\beta_{v_t}^2 \times v_t^2$			5.537*	2.706**						
			(2.93)	(1.09)						
$\beta_{v_t} \times v_t^2$					−13.52	−6.42				
					(19.11)	(7.92)				
$\beta_{v_t}^{abs} \times v_t^2$							35.20*	17.21 **		
							(19.43)	(7.90)		
rel $\beta_{v_t}^2 \times v_t^2$									4.37*	2.30 **
									(2.38)	(0.99)
Correction for outliers	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.12	0.12	0.15	0.14	0.12	0.09	0.14	0.13	0.14	0.14
Number of firms	760	760	760	760	760	760	760	760	760	760
Observations	57,541	57,441	57,541	57,433	57,541	57,436	57,541	57,429	57,541	57,433

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

Table 7: **Response of the Constituents of the S&P500 to Monetary Policy Shocks (relative and pseudo event volatilities)**

This table reports the results of regressing the ratio of squared percentage returns of the constituents of the S&P500 in a 30 minutes window bracketing the FOMC press releases over the squared percentage returns in a pseudo event window between adjacent event dates on the federal funds futures based measure of monetary policy surprises calculated according to equation (2), v_t^2 *and the interaction term with the frequency of price adjustment, FPA in Panel A. Panel B regresses squared percentage returns of the constituents of the S&P500 in a 30 minutes pseudo event window between adjacent event dates on the federal funds futures based measure of monetary policy surprises calculated according to equation (2),* v_t^2 *and the interaction term with the frequency of price adjustment, FPA. See specification (3). Equally weighted frequencies of price adjustments are calculated at the firm level using the microdata underlying the producer price index. The full sample ranges from February 1994 through December 2009, excluding the release of September 17th 2001, for a total of 137 observations. Driscoll-Kraay standard errors are reported in parentheses.*

	Tight Window		Firm FE		Event FE		Firm & Event FE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Relative Volatilities								
v_t^2	0.57∗∗∗	0.32∗∗∗	0.57∗∗∗	0.33∗∗∗				
	(0.08)	(0.05)	(0.07)	(0.05)				
$FPA \times v_t^2$	−1.07∗∗∗	−0.65∗∗∗	−1.05∗∗∗	−0.64∗∗∗	−1.06∗∗∗	−0.57∗∗∗	−1.05∗∗∗	−0.56∗∗∗
	(−0.19)	(0.17)	(0.17)	(0.16)	(0.19)	(0.18)	(0.17)	(0.18)
FPA	0.00∗∗∗	0.00∗∗∗			0.00∗∗∗	0.00∗∗∗		
	(0.00)	(0.00)			(0.00)	(0.00)		
Event Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	No	Yes	Yes	No	No	Yes	Yes
Correction for outliers	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.07	0.02			0.12	0.10		
Number of firms	758	758	758	758	758	758	758	758
Observations	53,682	53,547	53,682	53,547	53,682	53,507	53,682	53,507
Panel B. Pseudo Event Volatilities								
v_t^2	2.26	2.01	2.33	2.04				
	(3.79)	(2.96)	(3.14)	(2.68)				
$FPA \times v_t^2$	5.68	−2.046	5.25	−2.11	5.96	−2.19	5.51	−2.33
	(7.60)	(4.33)	(6.78)	(3.35)	(7.83)	(4.11)	(6.83)	(3.20)
FPA	−0.17∗∗∗	−0.15∗∗∗			−0.17∗∗∗	−0.15∗∗∗		
	(0.04)	(0.05)			(0.05)	(0.05)		
Event Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	No	Yes	Yes	No	No	Yes	Yes
Correction for outliers	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.00	0.00			0.06	0.07		
Number of firms	758	758	758	758	758	758	758	758
Observations	53,262	53,248	53,262	53,248	53,262	53,247	53,262	53,247

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

Table 8: **Response of the Constituents of the S&P500 to Monetary Policy Shocks (profitability)**

This table reports the results of regressing squared percentage changes in mean quarterly operating income before depreciation between quarters $t+H$ till $t+H+3$ and $t-4$ till $t-1$ normalized by $t-1$ total assets of the constituents of the S&P500 in a 30 minutes window bracketing the FOMC press releases on the federal funds futures based measure of monetary policy surprises calculated according to equation (2) and accumulated to quarterly frequency, $\tilde{v}_t^2$, the frequency of price adjustment, FPA, as well as their interaction. See specification (5). Equally weighted frequencies of price adjustments are calculated at the establishment level using the microdata underlying the producer price index. The full sample ranges from February 1994 through December 2009, excluding the release of September 17th 2001, for a total of 137 observations. Driscoll-Kraay standard errors are reported in parentheses.

	H = 0	H = 1	H = 2	H = 3	H = 4	H = 5	H = 6	H = 7	H = 8
$\tilde{v}_t^2$	2.47*	1.75	−0.03	−2.10	−3.69	−7.98**	−10.51*	−15.99***	−21.55***
	(1.35)	(1.66)	(1.81)	(2.04)	(2.90)	(3.61)	(5.46)	(5.89)	(7.00)
$FPA \times \tilde{v}_t^2$	−19.68***	−23.98***	−25.62***	−30.91**	−36.81**	−35.18**	−41.58**	−29.98	−29.68
	(5.24)	(7.42)	(9.06)	(11.87)	(15.17)	(15.39)	(19.50)	(20.23)	(22.85)
FPA	2.10***	2.68***	3.24***	3.78***	4.07***	4.01**	4.77**	4.70*	4.88
	(0.39)	(0.59)	(0.86)	(1.16)	(1.43)	(1.70)	(2.24)	(2.70)	(3.34)
Correction for outlier	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Number of firms	685	682	678	671	668	661	660	653	642
Observations	20,756	20,428	20,117	19,814	19,646	19,449	19,295	18,921	18,475

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

Table 9: **Multi-sector model**

This table shows in Panel A calibrated parameter values for the dynamic New Keynesian multisector model described in Section V, the sectoral distribution of the frequency of price adjustment in Panel B and the parameter estimates of equation (8) with simulated data from the model in Panel C.

Panel A. Calibration

Parameter	Value	Source
η	2	Ashenfelter et al. (2010)
σ	2	standard
θ	7	standard
β	0.99	standard
ϕ_π	1.5	Taylor (1993)
ϕ_y	0.5	Taylor (1993)
ρ_{mp}	0.9	Coibion and Gorodnichenko (2012)
$std(v_t)$	0.0043	Coibion et al. (2012)

Panel B. Sectoral Distribution

Sector k	Share	Frequency of Price Adjustment
1	0.2	0.094
2	0.2	0.164
3	0.2	0.277
4	0.2	0.638
5	0.2	0.985

Panel C. Simulation Results

Calibration	$\hat{b}_1$	$\hat{b}_2$	$\hat{b}_3$
baseline	163.2	-178.8	-0.006
$\sigma = 3$	117.0	-118.2	-0.004
$\eta = 1$	348.8	-401.5	-0.011
$\theta = 6$	81.7	-77.5	-0.003
$\phi_\pi = 2$	85.7	-98.3	-0.003
$\phi_y = 0.75$	181.7	-203.7	-0.007
$\rho_{mp} = 0.91$	321.2	-378.6	-0.011
$std(v_t) = 0.004$	143.1	-154.8	-0.004