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Author
Wu, Wenbin

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Essays on Monetary Economics

A dissertation submitted in partial satisfaction of the
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in

Economics

by

Wenbin Wu

Committee in charge:

Professor James Hamilton, Chair
Professor Thomas Baranga
Professor David Lagakos
Professor Rossen Valkanov
Professor Johannes Wieland

2017

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University of California, San Diego

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VITA

2009	Bachelor of Arts, Beijing Normal University, Beijing
2012	Master of Arts, Renmin University of China, Beijing
2012–2017	Teaching Assistant, Department of Economics University of California, San Diego
2017	Doctor of Philosophy, University of California, San Diego

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ABSTRACT OF THE DISSERTATION

Essays on Monetary Economics

by

Wenbin Wu

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Professor James Hamilton, Chair

Chapter 1 contributes to the recent debate about the importance of temporary price changes for monetary policy transmission. Although sales occur very frequently, macroeconomists often filter them out because sales are not responsive to economic shocks. Using micro data underlying CPI, I demonstrate that after sales, the price index of durables goes down gradually, and that the aggregation of sales of durable goods have a significant impact on the aggregate inflation. However, sales of nondurables – the focus of previous studies – do not show these results. To study the impact of sales, I then propose a two-sector menu-cost model with the feature of sales. The model is able to

match the pattern of sales and moments in the micro data. By contrast, failing to account for temporary sales in a menu-cost model would increase the output effect by 73%, and the Calvo model calibrated to the frequency of regular price changes triples the output effect.

Chapter 2 examines the impact of unconventional monetary policies on the stock market when the short-term nominal interest rate is stuck at the zero lower bound. Unconventional monetary policies appear to have significant effects on stock prices and the effects differ across stocks. In agreement with existing credit channel theories, I find that firms subject to financial constraints react more strongly to unconventional monetary policy shocks (especially large-scale asset purchases) than do less constrained firms. My results imply that the credit channel is as important as the interest rate channel in the transmission of unconventional monetary policies at the zero lower bound.

Chapter 3 investigates the time-varying effects of monetary policy shocks on financial markets. I show that the corporate bond market is highly responsive to monetary policy shocks throughout 2000 - 2012, implying a high pass-through of policy-induced movements in Treasury yields to private yields even during the zero lower bound period. While the long-term Treasury bond market is highly sensitive to monetary policy shocks throughout almost the entire sample, the short-term Treasury bond market is severely constrained by the zero lower bound. The stock market is less responsive from 2008 to 2010, but the responsiveness bounces back rapidly in 2011.

Chapter 1

Sales, Monetary Policy, and Durable Goods

Many empirical studies point out that the effects of monetary policy on economic activities are large in the short run (e.g., Christiano, Eichenbaum, & Evans 1999, Romer & Romer 2004). Thus, many macroeconomic models require that prices cannot adjust too frequently, because when prices adjust slowly, firms and retailers are unable to adjust prices fast enough to offset monetary policy shocks, and thus generating large short-run real effects of monetary policy.[1] Recently, many micro price datasets have become available to researchers, leading to a burst of studies that evaluate the level of price rigidity at the micro level. In contrast to high price rigidity used in a large class of macroeconomic models, prices are much more flexible at the micro level. [2]

Do volatile micro-level prices undermine the hypothesis of price rigidity used in

[1]For example, in the estimated dynamic stochastic general equilibrium (DSGE) models of Smets and Wouters (2003, 2007) and Christiano, Motto, and Rostagno (2014), prices change about once every year. Del Negro, Giannoni, and Schorfheide (2015) and Altig, Christiano, Eichenbaum, and Linde (2011) estimate that it takes more than two years for prices to change once. DiCecio and Nelson (2007) show that the duration for prices to change once is every four years in the UK, which implies that prices in the UK are even more sticky than in the US.

[2]Using Bureau of Labor Statistics (BLS) data, Bils and Klenow (2004), Klenow and Kryvtsov (2008) , and Nakamura and Steinsson (2008) find that prices change at least three to four times each year. Using Dominick's scanner data, Midrigan (2011) observes that prices change once every two months. Eichenbaum, Jaimovich and Rebelo (2011) (hereafter EJR) find that weekly prices change once every two weeks using other scanner data. For the UK, Kryvtsov and Vincent (2015) find that prices change once every 5 months, a little higher than the US but still much lower than the estimate in DiCecio and Nelson (2007).

many macroeconomic models? There is little consensus on the answer to this question. The controversy lies in how the prevalence of sales (i.e., temporary price cuts) affect the effects of monetary shocks, because most price changes in micro data are due to temporary sales (see, e.g., Nakamura & Steinsson 2008). In the macro literature, sales are often filtered out before prices are used to calculate the frequency of price changes, otherwise the frequency would become too high to generate large enough monetary policy effect. A convincing reason is that sales are unresponsive to economic shocks, at least to the aggregate shocks. For example, Anderson et al. (2016) use scanner data to show that although temporary sales account for 95% of price changes in their data, sales do not respond to wholesale cost changes. Klenow & Malin (2010) find that temporary sales account for very little variance for the dynamics of the aggregate inflation.

This paper challenges this view. Using the micro data underlying the UK CPI, I show that sales of durables are highly responsive to aggregate shocks, and have a significant impact on the aggregate inflation. However, sales of nondurables are not responsive to aggregate shocks. I then propose a two-sector menu-cost model with the feature of sales. The model is able to match the pattern of sales and moments in the micro data. Failing to account for temporary sales in a menu-cost model would increase the output effect by 73%, the Calvo model calibrated to the frequency of regular price changes triples the output effect.

I first show that after a sale, the price index of durables tend to decrease in the following periods, implying that sales reflect potential changes in marginal costs, which enables them to influence the dynamics of the aggregate inflation. But the price index of nondurables – the focus of previous studies – do not tend to decrease after sales, implying that they mainly reflect idiosyncratic forces[3], which tend to cancel out at the aggregate

[3]For example, temporary sales may reflect firms and retailers' idiosyncratic marketing strategies, and their idiosyncratic old information.

level[4]. While previous studies focus on temporary price changes of nondurable goods (e.g., Kehoe & Midrigan, 2015 ; Guimaraes & Sheedy, 2011; Eichenbaum, Jaimovich & Rebelo, 2011), this empirical finding suggests that it is important and necessary to distinguish nondurables from durables when we study temporary price changes.

I then propose a two-sector menu-cost model to study the impact of sales. The model is a combination of the standard menu-cost model (see Golosov and Lucas 2007, Gertler and Leahy 2008, and Midrigan 2011) with House, Kimball and Barsky's two-sector model with durables and nondurables. To be able to match the size of price changes and the pattern of sales in the data, firms face two types of idiosyncratic shocks: permanent productivity shock and temporary wholesale cost shock. permanent productivity is necessary in order to match the size of regular price changes in the data. When a retailer is shocked by a temporary wholesale cost shock, it can incur a costless sale and then revert to the original price after that period. This type of price adjustment strategy is motivated by the fact that sales are much more frequent than regular price changes, so that the cost for charging sale prices should be very low (see also Zbaracki et al. 2004, Zbaracki, Levy, and Bergen 2006). It is also motivated by Eichenbaum, Jaimovich, and Rebelo (2011) , in which they allow retailers to charge a price plan which consists of several different prices. Retailers can charge any price in the price plan without incurring any cost.

The model is then calibrated to match moments in the data to study the impact of sales. The benchmark model only allow sales of durables to respond to the aggregate shocks, while sales of nondurables only respond to idiosyncratic shocks. Even though only $1/3$ of sales (those of durables) are responsive to changes of aggregate shocks, they play an important role in affecting the transmission of monetary policy. The high

[4]This is consistent with Anderson et al. (2016). However, Anderson et al. are unable to look at nondurables and durables separately due to data limitation.

elasticity of intertemporal substitutability (EIS) of durables plays a key role in the model. Following an expansionary monetary policy shock, those households in the economy without temporary sales would expect prices to be consistently rising. Thus, they would purchase as many durables as they could during the first few periods, because they would be indifferent about when to purchase durables due to high EIS of durables. However, in an economy with a high frequency of temporary sales, households can rely on the existing stock of durables to wait for future temporary low prices to restock their durables. So, those households in an economy with temporary sales would not respond as much. In addition, I show that in the model even if temporary sales of nondurables reflect responses to marginal cost changes, the near-constancy of the shadow value of durables implies that the nominal nondurable output would be affected only through the price of durables. The shadow value of durables is near-constant because changes in durable expenditures barely affect the durable stock; this is because they are small relative to the size of durable stock due to the long service lives of durables. Therefore, the aggregate output is only affected by the price rigidity of the durable sector.

This paper has a similar view with Alvarez and Lippi (2016), Kryvtsov and Vincent (2015) and Hernaiz (2013). Alvarez and Lippi (2016) generalize EJR's model to a general equilibrium model, and find that temporary price changes substantially reduce the size and persistence of monetary policy shocks. Kryvtsov and Vincent (2015) argue that sales significantly increase aggregate price flexibility, thus generating a much smaller effect of monetary policy. Hernaiz (2013) introduces price promotions in a NK model where consumers differ in their price sensitivity and in their search for promotions. He finds that sales greatly reduce the effects of monetary policy. Both the magnitude and persistence of monetary policy effects are almost eliminated when sales are considered. We all conclude that sales play an important role in affecting the transmission of monetary policy, but we differ in two aspects: (1) I take into account that most sales (about $2/3$ of all sales) do not respond to the aggregate shocks; (2) I calibrate the model to the micro data.

Some other researchers have found that temporary sales are not important for monetary analysis. For example, Kehoe and Midrigan (2015) develop a model to match the pattern of price changes in the BLS data. They find that temporary price changes have a small influence on the real effects of monetary policy shocks. Guimaraes and Sheedy (2011) construct a macroeconomic model where sales are the endogenous results of heterogeneous customers. They argue that sales do not matter for monetary analysis because sales are not only transitory but also staggered. Eichenbaum, Jaimovich and Rebelo (2011) argue that price rigidity takes the form of ”reference price.” They construct a menu cost model to match the pricing pattern in the data, which generates a similar monetary non-neutrality to the standard menu cost model calibrated to the reference price changes. All of them do not consider durables, and Eichenbaum, Jaimovich and Rebelo (2011) only consider a partial equilibrium with nondurables. Anderson et al. (2016) use retailer scanner data to show that sales do not react to cost shocks, and thus they have a limited effect on macroeconomic variables. But their data contain mainly nondurable goods, and they do not investigate nondurables and durables separately using the BLS data.

This paper proceeds as follows. In Section 2, I describe the data used in this paper. In Section 3, I investigate the relationship between sales the aggregation inflation using the micro data. In Section 4, I develop a two-sector menu-cost model featuring sales and durable goods, describe the computation method to solve the model, and calibrate it to match moments in the data. Section 5 presents the analysis of the model, and compared it to the Calvo model, the Golosov and Lucas Model, the model without sales. Section 6 concludes.

1.1 Data

The micro data underlying UK CPI are used to calculate the frequency of price changes. This data set is maintained by the Office for National Statistics (ONS)[5]. It contains monthly surveys of over 1,100 individual goods and services from more than 14,000 retail outlets across 13 geographical areas in the UK. The surveys are carefully designed to exclude the influence from either housing expenditures or other non-final consumption expenditures. The published data are available to us from Jan. 1996. [6]

The data are collected and aggregated according to the Classification of Individual Consumption by Purpose (COICOP)[7], which includes 12 divisions and 71 classes. A class is a basic group category, such as "Bread and Cereals," "Meat," etc. The dataset also includes information on whether a product is "on sale" or "recovering from sale". The ONS labels a discount available for all customers as a sale. If a discount is only available to loyalty-card members, it is not labeled as a sale. The UK CPI is also compiled hierarchically according to the COICOP.[8]

Before estimation, I first clean the data in four steps: (1) I pool the data from Jan. 1996 to Dec. 2014, and build a unique id for each observation[9]; (2) I remove prices

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[5]See http://www.ons.gov.uk/ons/index.html.

[6]There are about 140 items not included in my data because they are centrally collected – price quotes are directly reported to the ONS without field work. The ONS is unable to publish price quote information for central collection, because samples are generally much smaller for centrally collected items, and thus it would be disclosive to release the information at this level. This isn't a big issue, since the majority of prices underlying CPI are from the local collection.

[7]The COICOP is an international hierarchical classification system for categorizing consumer expenditure.

[8]The lowest aggregate of prices is called elementary aggregate, and is stratified by locations and shops. Elementary aggregates are usually calculated using a simple geometric mean. They are then used to calculate higher level indices - item indices using stratum weights. Next, class indices are computed from item indices weighted by item weights. Finally, class indices are collated into the aggregate CPI using class weights. Living Costs and Food Survey (LCF) is a major source to update stratum weights and item weights. Class weights are computed from National Accounts Household Final Monetary Consumption Expenditure data two years prior to the current CPI year (See Sanderson et al. 2014). The CPI is chain-linked twice a year to take into account the update of the weights and items.

[9]It is hard to find a unique ID. Kryvtsov and Vincent (2014) delete items when they have the same item/region/store. I try to avoid doing this by using more information to identify the same item over time.

that are tagged as a non-comparable substitution, invalid, and have either a base price of zero or a current price of zero; (3) I remove price quotes with price relatives of either more than 10 or less than -0.8; [10] (4) and I drop all observations around dates of VAT changes[11]. All the estimations in this paper are weighted.

A sale is identified as a temporary deviation from the reference price, which is the most frequently observed price in a five-month period [12]. Appendix A provides a simple example of sales, and Appendix C presents the algorithm used by KM to identify regular prices.

1.1.1 Descriptive Statistics

Table 1.1 documents the moments of price changes in the micro data underlying the UK CPI [13]. The first column lists moments of the whole sample; the second column and the third column list those of durables and nondurables, respectively. We see that most price changes are sales. The frequency of regular price changes only accounts for about one fourth of all price changes. These frequencies are somewhat lower than those in the US, but still very large. We can also see that the mean size of prices change are large compared to annual 2% inflation rate. The mean size of regular price increases is about 12%, the mean size of sales is about 16%, and the size of price changes is highly dispersed. I also report probability that prices stay on the annual mode (about 73%), and the frequency that annual mode of prices changes (about 55%). Consistent with Bils and

First, I use item/region/store/struatum cell/shop type to identify the same item. Second, I use base price (Jan price) to deal with the remaining duplicates. My procedures allow me to keep most of the observations in the data.

[10]This procedure follows Bils, Klenow and Malin (2012). Less than 1% observations are removed.

[11]VAT are included in the price quotes. A change in VAT automatically leads to changes in all the prices. Two VAT changes happened in the data I used: (1) VAT rate from 17.5% to 15% at December 1st, 2008. (2) back to 17.5% starting January 1st, 2010. (3)VAT rate was raised from 17.5% to 20% on January 4, 2011.

[12]The reference price is proposed by Eichenbaum, Jaimovich and Rebelo (2010). To remedy the issue that the modal price can change even when the original price does not change, I follow the methodology proposed by Kehoe and Midrigan (2015) to calculate the reference price.

[13]I first map all the CPI categories to the COICOP, and then calculate the weighted moments of the data.

Klenow (2004), I find that approximately 20 percent of durable goods and 21 percent of nondurable goods change their prices each month. These results illustrate that the regular-price-change frequency and temporary-sales frequency of durable goods appear to be a little lower than those of nondurable goods. This presents a stark contrast to the literature, in which the prices of durable goods are often assumed to be more flexible than those of nondurable goods.

Table 1.1. Moments of Data

	All	Durable	Nondurable
Freq. of reg price changes	0.058	0.051	0.061
Mean size of reg price increases	0.109	0.124	0.100
Frac. of sales episodes	0.255	0.178	0.294
Mean size of price changes	0.157	0.196	0.145
Prob. at annual mode	0.735	0.764	0.721
Freq. of annual mode changes	0.588	0.536	0.611
Mean size of sales (abs.)	0.160	0.162	0.159
S.D. of price changes	0.166	0.184	0.162

Note: Calculated by the author, based on micro data underlying UK CPI.

1.2 Sales and Inflation

A widely held view by macroeconomists is that the transmission of monetary policy depends on the aggregate price flexibility. Without aggregate price rigidity, most New Keynesian models can't generate Phillips curves that link price changes to real output. So, if the aggregation of sales price changes does not contribute to the aggregate inflation, they are not important for monetary analysis (e.g., Klenow & Malin 2010), which is possible if sales purely reflect idiosyncratic forces, such as firms and retailers' idiosyncratic marketing strategies, and their idiosyncratic old information.

A typical Phillips curve takes the following form,

$$\pi_t = \beta E_t \pi_{t+1} + \lambda(\theta) mc_t,$$

where π_t is the inflation rate, θ is the frequency of price changes (or the frequency of idiosyncratic shocks in a menu-cost model, see Gertler and Leahy 2008), $\lambda(\theta)$ is a function of θ, and mc_t is the marginal cost (which can be rewritten in terms of output gap).

In this section, I find that sales of nondurables mainly reflect idiosyncratic forces, while those of durables reflect aggregate shocks. These empirical findings imply that we should discriminate sales of durables from those of nondurables. Existing studies either focus on sales of nondurables (e.g., Kehoe & Midrigan 2015, Guimaraes & Sheedy 2011, Alvarez & Lippi 2016, and Kryvtsov & Vincent 2015), or they do not look at nondurables and durables separately (e.g., Anderson et al. 2016, and Eichenbaum, Jaimovich & Rebelo 2011)[14].

Klenow and Malin (2010) provide the first attempt to assess whether sales contain macro content. They calculate the variance of the sale-related inflation[15] to evaluate whether sales can be canceled out when aggregated. They find that sales contribute very little to the aggregate inflation fluctuations. Klenow and Wills (2007) find that the size of price discounts is significantly correlated with cumulative inflation since the item last changed price, suggesting that sales are responsive to aggregate shocks. However, using scanner data, Anderson et al. (2016) find that sales do not respond to cost shocks.

In what follows, I will revisit this topic by using the micro-data underlying UK CPI.

[14]Empirical findings here complement those of Anderson et al. (2016) in which they mainly focus on nondurables.

[15]The sale-related inflation is defined as the difference between inflation and the regular-price inflation.

1.2.1 Do Sales Respond to Aggregate Shocks?

To test whether sales respond to aggregate cost shocks, we can check whether or not the aggregate price level goes down after sales. If sales are an indicator of decreases in the average cost, then after a sale, retailers must lower their regular prices, decrease the frequency or size of sales, or both. And given that sales are much more prevalent than regular price changes, one might expect that they would move the price level quickly after a sale. The price index is calculated as follows,

$$Aggregate\ price\ index \quad = \quad \sum_i w_{it}(p_{it} - p_{it-1})$$

where w_{it} is the CPI weight for good i at time t.

Figure (1.1) reports the price index after a sale. At month 0, there is a sale, so regular prices do not change. Therefore, all the price changes are relative to the month 0 regular prices. At month 0, the sharp decrease in the aggregate price level are entirely caused by sales. The figure shows a significant difference between nondurables and durables. For nondurables, the price level recovers and remains quite stable after sales. However, for durables, the aggregate price level starts to decrease after sales, indicating that sales play a similar role as regular price changes in the price adjustment process for durables, but not for nondurables.

we can also run a regression as follows,

$$\pi_t = a + \sum_{k=0}^{\infty} b_k \pi_{t-k}^S + \varepsilon_t \tag{1.1}$$

where a and b_k $(k \geq 0)$ are constants, $\pi_t^S = \sum_i w_{it} I_{it}^{sales}(p_{it} - p_{it-1})$, and I_{it}^{sales} is an indicator of sales. If sales are responsive to aggregate cost changes, we can see positive

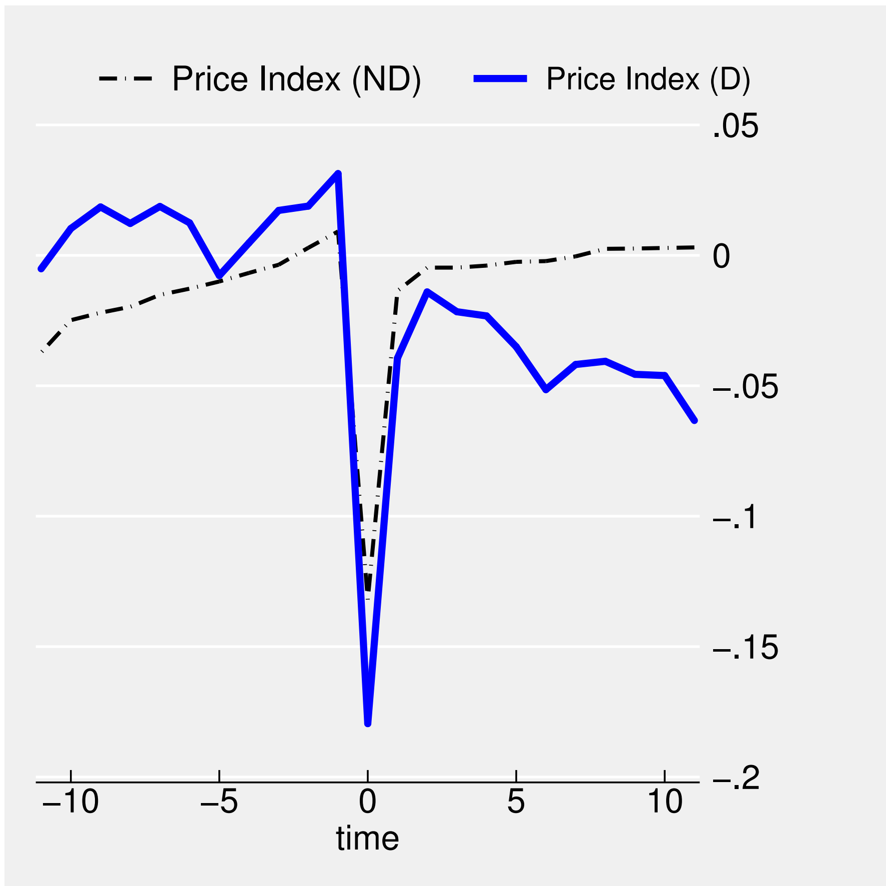

Figure 1.1. Price Indices After sales

Note: This figure plots the price indices before and after a sale for both the durable and nondurable sectors. Month 0 identifies the month in which the sale occurs.

coefficients after sales price index increases, i.e. sales become less frequent or the size of sales gets smaller. Otherwise, we should see negative coefficients.

Table 1.2. Regression of the aggregate price index on sale price index

	π_t (Durables)			π_t (Nondurables)		
π_t^S	2.066***	1.505***	1.442***	-2.126***	-0.898	-0.793
	(0.185)	(0.225)	(0.226)	(0.373)	(0.609)	(0.629)
π_{t-1}^S		0.646***	0.528**		-0.802	-0.639
		(0.233)	(0.240)		(0.643)	(0.678)
π_{t-2}^S		0.392*	0.192		-0.864	-0.602
		(0.225)	(0.244)		(0.609)	(0.687)
π_{t-3}^S			0.219			-0.268
			(0.240)			(0.678)
π_{t-4}^S			0.348			-0.363
			(0.226)			(0.630)
Observations	189	187	185	191	189	187
R^2	0.400	0.454	0.468	0.147	0.176	0.178

Note: This table reports the regression of the change in the aggregate price index on the sale price index. Positive coefficients indicate that more or larger sales move down the aggregate price index.

Table (1.2) shows the results for both durable and nondurable sector. Columns 1-3 report three different regressions for the durable sector, with different lags of sale price levels. It is evident that all the coefficients are positive, and that most of them are statistically significant. Positive coefficients indicate that more or larger sales move down the aggregate price index. Therefore, for the durable sectors, sales are very likely a reflection of aggregate cost changes.

Columns 4-6 show the results for the nondurable sector. In contrast to durables, all the coefficients are negative, with some of them being statistically significant. One possible explanation is that sales of nondurable goods are used as a tool to disguise the increase in regular prices. (For further discussion, see Anderson et al. 2016)

In sum, I find that sales of nondurables appear to move in the opposite direction of the changes in the aggregate price index. According to Anderson et al. (2016), this may be because (1) sales might follow "sticky plans," which are made only periodically; (2) sales are made in order to disguise the increases in regular prices. Nevertheless, sales of durables reflect changes in aggregate costs. While previous theoretical studies focus on the sales of nondurable goods (see Kehoe & Midrigan, 2015 ; Guimaraes & Sheedy, 2011; Eichenbaum, Jaimovich & Rebelo, 2011), this empirical finding suggests that we should focus on the sales of durables instead.

1.2.2 Aggregate Inflation and Sales

To determine how sales affect the aggregate inflation, Klenow and Malin (2010) calculate a "sale-related inflation," defined as the difference between the aggregate inflation and the regular-price inflation (see Appendix A for a simple example illustrating how to calculate the sale-related inflation). Following Klenow and Malin, I calculate the aggregate inflation and the regular-price inflation as

$$\begin{aligned}
\pi_t &= \sum_i w_{it}(p_{it} - p_{it-1}) \\
\pi_t^R &= \sum_i w_{it}(p_{it}^R - p_{it-1}^R) \\
\pi_t^S &= \sum_i w_{it}(p_{it}^S - p_{it-1}^S)
\end{aligned}$$

where w_{it} is the CPI weight for good i at time t, p_{it}^R is the regular price for good i at time t, and $p_{it}^S = p_{it} - p_{it}^R$ is the size of sales for good i at time t. Note that π_{it}^S equals zero if there are no sales. The sale-price inflation can also be backed out by taking the difference between the regular-price inflation and the posted-price inflation,

$$\pi_t^S = \pi_t - \pi_t^R$$

It is also evident that if sales represent some pure idiosyncratic forces each period, the average of $(p^S_{it} - p^S_{it-1})$ over i will converge to a constant. Klenow and Malin test this prediction by verifying whether the variance of π^S_t is small relative to the variance of the aggregate inflation.

To ensure that I correctly calculate the inflation, I first compare my calculation of the aggregate inflation with the published inflation in Figure A.2 (see Appendix B). We can see that although my calculation differs slightly, it closely tracks the published inflation.[16] As expected, inflation generally falls during recessions.

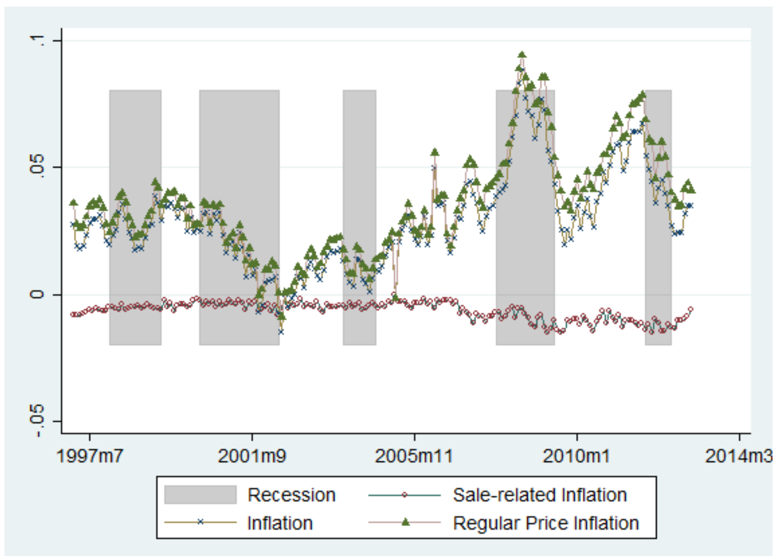

Figure 1.2. Decomposition of the inflation of the nondurable sector
This figure plots the decomposition of the inflation of the nondurable sector into sale-related inflation and regular-price inflation. The gray areas represent recession periods for the UK. The calculation is based on data underlying the UK CPI in the period of January 1997 to December 2013.

Figure 1.2 presents the decomposition of the aggregate inflation of the nondurable sector into regular-price inflation and sale-related inflation[17]. The regular-price inflation co-moves closely with the aggregate inflation (correlation with the posted-price inflation

[16]The differences might arise for two reasons: (1) centrally collected items are not available to us; (2) I do not use the chain-linking calculation.
[17]To calculate the variance, I took out separate monthly dummies in order to remove seasonal effects.

= 0.989), while the sale-related inflation shows a very small variation (correlation with the posted-price inflation = 0.007). The sale-related inflation is very much like a constant over time. The variance of sale-related inflation is small compared to the regular price inflation. The regular-price inflation accounts for 122% of the variance of the aggregate variance, implying that almost the entire variance of the aggregate inflation comes from the variation of the regular-price inflation, and that the sale-related inflation moves in the opposite direction of regular-price inflation. This is consistent with predictions that sales contain little macro content, and that they are used to disguise increases in regular prices.

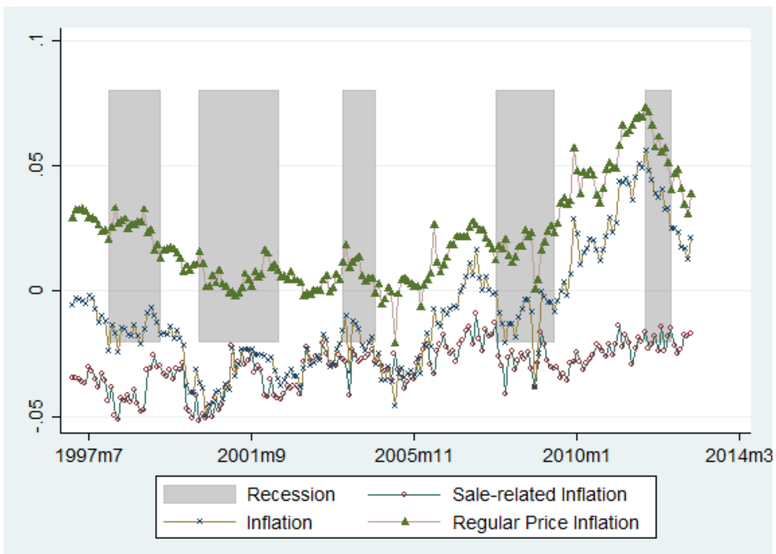

Figure 1.3. Decomposition of the inflation of the durable sector
This figure plots the decomposition of the inflation of the durable sector into sale-related inflation and regular-price inflation. The gray areas represent recession periods for the UK. The calculation is based on data underlying the UK CPI in the period of January 1997 to December 2013.

Figure 1.3 presents the result for the durable sector. Still, the regular-price inflation co-moves with the aggregate inflation (correlation = 0.931). However, the striking result is that the sale-related inflation co-moves closely with the aggregate inflation (correlation = 0.651). The regular-price inflation only accounts for 64.6 percent of the variance of the aggregate inflation for the durable sectors, implying that at least 35.4

percent of the variations in aggregate inflation is due to sales. Hence, unlike nondurable sectors, the sale-related inflation in the durable sectors cannot be canceled out when aggregated. Clearly, there is some macro content in the sale prices that moves with the aggregate inflation.

1.3 A Two-sector Menu-cost Model

In this section, I present a menu-cost model featuring the role of sales and durable goods. The model is then calibrated to match moments in the data to study the impact of sales.

As I have documented, although sales of nondurables essentially have no impact on the aggregate inflation, sales of durables seem to move the aggregate inflation significantly. However, previous studies only focus on the nondurable sector when they investigate the impact of sales on monetary policy transmission. To allow the model to study the impact of sales of durables, I combined the standard menu-cost model with House, Kimball and Barsky's two-sector model. Households not only consume nondurables, they also consume durables which depreciate at a rate of δ_d. If the durable sector is removed and the frequency of sales is set to 0, this model is reduced to a standard menu-cost model as in Golosov and Lucas (2007).

To be able to match the pattern of sales in the data, firms face two types of idiosyncratic shocks: permanent productivity shock and temporary wholesale cost shock. When a retailer is shocked by a temporary wholesale cost shock, it can incur a costless sale and then revert to the original price after that period. This type of price adjustment strategy is motivated by the fact that sales are much more frequent than regular price changes, so that the cost for charging sale prices should be very low (see also Zbaracki et al. 2004, Zbaracki, Levy, and Bergen 2006). It is also motivated by Eichenbaum, Jaimovich, and Rebelo (2011) , in which they allow retailers to charge a price plan which consists of several different prices. Retailers can charge any price in the price plan without incurring any cost. To be consistent with the empirical results documented in Section 3, I assume that sales of nondurables are only responsive to idiosyncratic shocks, while sales of durables are responsive to both idiosyncratic and aggregate shocks. Figure (1.4) presents a simulated price series generated by the model with sales, which is very similar to those observed in the data.

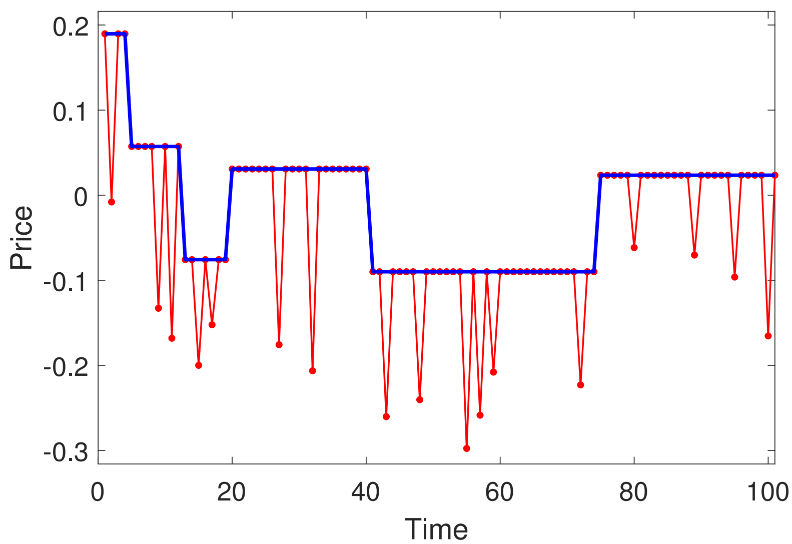

Figure 1.4. Price Series Generated by the Model

Note: This figure plots a simulated price series generated by the model.

1.3.1 Model Setup

Households The economy is composed of a continuum of representative households from 0 to 1. The time endowment of each household is normalized to 1. Households derive utility from the consumption of both nondurable and durable goods. Households supply labor to firms, and accumulate one-period bonds and a real money balance. Households also receive profits from firms because the firms are owned by households. Let C_t be the nondurable consumption at time t, and D_t be the durable consumption. Let

N_t be the labor supplied, and M_t/P_t be the real money balance. The household maximizes the present value of infinite-period utility:

$$\max_{C_t,N_t,B_{t+1},M_t} E_0 \sum_{t=0}^{\infty} \beta^t (U(C_t,D_t) - \psi N_t + \nu(\frac{M_t}{P_t})) \tag{1.2}$$

where $U(C_t,D_t) = (\chi_1 C_t^{(\rho-1)/\rho} + \chi_2 D_t^{(\rho-1)/\rho})^{\rho/(\rho-1)}$ is the utility derived from composite goods of nondurables and durables, ρ is the elasticity of substitution between durable goods and nondurable goods (which is set to 1 to simplify the computation).

The household is subject to the following budget constraint:

$$C_t + \frac{P_{x,t}}{P_{c,t}} X_t + \frac{Q_t}{P_{c,t}} B_{t+1} + \frac{M_t - M_{t-1}}{P_{c,t}} + \frac{P_{x,t}}{P_{c,t}} \mathscr{K}_t \leq \frac{W_t}{P_{c,t}} N_t + \frac{\Pi_t}{P_{c,t}} + \frac{B_t}{P_{c,t}} \tag{1.3}$$

where $\mathscr{K}_t = \kappa_x(\frac{D_t}{D_{t-1}} - 1)^2 D_{t-1}$ is the durable goods adjustment cost,[18] W_t is the nominal wage, B_t is the end-of-period t nominal one-period debt, Q_t is the bond price, and Π_t are the profits from the firms (households effectively own all final output or intermediate firms). The accumulation equation for durable goods is given as

$$D_t = D_{t-1}(1 - \delta_d) + X_t \tag{1.4}$$

[18]The adjustment of durable goods might be more costly than that of nondurable goods for the following reasons. First, durables are usually not fully used before they are replaced with new items. Used durables are sold in the secondary market, and households can also restore their durable stocks by purchasing used durables from this market. Thus, it is natural to assume that households need to pay an adjustment cost to purchase new durables if they frequently sell their used durables in the secondary markets. Second, some durables, such as cars and furniture, might be costly to replace, even when it is used, as these items are more expensive, and their damage or destruction can incur extra payment from the owners.

We may write the first-order conditions for N,C,B, as follows,

$$\psi P_{c,t}C_t = W_t \tag{1.5}$$

$$Q_t = \beta E_t \frac{C_t P_{c,t}}{C_{t+1}P_{c,t+1}} \tag{1.6}$$

$$\theta \frac{P_{c,t}C_t}{M_t} = 1 - Q_t \tag{1.7}$$

Equation (1.5) characterizes the labor supply condition for the households; and equation (1.6) is the Euler equation, which shows that the marginal utility of current consumption equals the marginal gain of shifting one unit of consumption to the next period; equation (1.7) shows that the marginal rate of substitution between money and nondurable consumption to their relative price. We can define γ_t as the multiplier on the accumulation equation of durable goods. Following Barsky, House, and Kimball (2007), I define $MU^D = \partial U(C_t,D_t)/\partial D_t$ as the marginal utility from one more unit of durable goods consumption.The optimal condition for X is[19]

$$\gamma_t = MU_t^D + \beta(1-\delta)E_t\gamma_{t+1} \tag{1.8}$$

Equation (1.8) represents the shadow value for durable goods. It is clear that a one-unit increase in investment in durable goods will provide households with direct utility during this period and indirect utility from the remainder of this investment in the next period.

Nondurable goods C_t and durable good purchases X_t are aggregated over intermediate goods $c_t(j)$ and $x_t(j)$,

$$C_t = (\int_0^1 [z_{ct}(j)c_t(j)]^{\frac{\varepsilon-1}{\varepsilon}} dj)^{\frac{\varepsilon}{\varepsilon-1}},\ X_t = (\int_0^1 [z_{xt}(j)x_t(j)]^{\frac{\varepsilon-1}{\varepsilon}} dj)^{\frac{\varepsilon}{\varepsilon-1}} \tag{1.9}$$

[19]Here, the adjustment cost of durables is assumed to be zero to simplify the equation and facilitate the interpretation. I consider this cost when I simulate the model.

where $c_t(j)$ and $x_t(j)$ are the intermediate goods produced by intermediate firm j, $z_{ct}(j)$ and $z_{xt}(j)$ are idiosyncratic shocks, and ε is the elasticity of the intermediate goods' substitution. The optimization gives us the demand function for each $c_t(j)$ and $x_t(j)$,

$$c_t(j) = z_{ct}^{\varepsilon-1}(j)(\frac{P_{c,t}(j)}{P_{c,t}})^{-\varepsilon}C_t,\ x_t(j) = z_{xt}^{\varepsilon-1}(j)(\frac{P_{x,t}(j)}{P_{x,t}})^{-\varepsilon}X_t \tag{1.10}$$

as well as the price index,

$$P_{c,t} = (\int_0^1 z_{ct}^{\varepsilon-1}(j)P_{c,t}(j)^{1-\varepsilon}dj)^{\frac{1}{1-\varepsilon}},\ P_{x,t} = (\int_0^1 z_{xt}^{\varepsilon-1}(j)P_{x,t}(j)^{1-\varepsilon}dj)^{\frac{1}{1-\varepsilon}} \tag{1.11}$$

Firms Intermediate goods are produced by firms and distributed by retailers. Firms face two types of idiosyncratic shocks: permanent productivity shocks[20] and temporary shocks (note that I will suppress the subscripts for sectors in this subsection because the calculations are exactly the same for both sectors),

$$y_t(j) = \frac{n_t(j)}{m_t(j)z_t(j)} \tag{1.12}$$

These intermediate firms minimize their costs given the demand function. The marginal cost to produce one more unit of product is

$$\varphi_t(j) = m_t(j)z_t(j)W_t \tag{1.13}$$

$m_t(j)$ is assumed to be discrete with values from $\{m_L, 1\}$. When firms are hit with m_L, they (actually retailers) can post a sale price without incurring any cost. $z_t(j)$ follows a random walk,

[20] This productivity shock also affect the production of final goods, so it can be interpreted as quality shocks for consumers due to shocks in production process. See also Midrigan (2011).

$$log(z_t(j)) = log(z_{t-1}(j)) + \varepsilon_t^z(j) \tag{1.14}$$

The profit of intermediate good firm j at time t can be written as

$$\Pi_t(j) = P_t(j)Y_t(j) - \varphi_t(j)Y_t(j) \tag{1.15}$$

Note that when firms are hit by m_L, the optimal sale price is completely determined by the marginal cost

$$P_{x,t}^S = \frac{\varepsilon}{\varepsilon - 1}\varphi_t(j) \tag{1.16}$$

In order to match the empirical results documented in previous section, I assume nondurable firms use sales to respond to idiosyncratic shocks but not aggregate shocks, while durable firms can set their sale prices to optimal prices. So, for nondurable firms, the optimal sale price is

$$P_{c,t}^S = \frac{\varepsilon}{\varepsilon - 1}\varphi_t(j)\frac{W_{t-1}}{W_t} \tag{1.17}$$

It turns out that this setting is not important since the determinant of the economy is the durable sector, which will be discussed below.

Intermediate firms are monopolistically competitive. They can choose prices to maximize the present value of their infinite periods of profits, subject to their product-specific demand function. Note that the firm's profit in period $t+s$ needs to be discounted by $Q_{t,t+s} = \beta^s \frac{P_{c,t}C_t}{P_{c,t+s}C_{t+s}} = \beta^s \frac{W_t}{W_{t+s}}$. If they were allowed to change their regular prices, firms maximize their infinite sum of profits,

$$\max_{P_t(j),\ p_t^R(j)} \sum_{s=0}^{\infty} Q_{t,t+s}(1-\nu_h)^s(\Pi_t(j) - W_t\phi \times I\{p_t^R(j) \neq p_{t-1}^R(j)\}) \tag{1.18}$$

where ϕ is the menu cost of change regular prices, and ν_h is the fraction of firms that exit each period, they are then replaced by new entrants which have $m_t(j) = 1$ and $z_t(j) = 1$.

Market Clearing and Monetary Policy The exogenous path for monetary policy shocks is modeled as

$$\Delta \ln M_t = \rho_m \Delta \ln M_{t-1} + \varepsilon_{m,t} \tag{1.19}$$

The good and labor market clear. The total final output (GDP) of the economy can be characterized as

$$Y_t = P_{x,t} X_t + P_{c,t} C_t \tag{1.20}$$

.

1.3.2 Computation Method

The utility function is assumed to be $log(C_t) + \chi log(D_t) - \psi N_t + \theta log(\frac{M_t}{P_t})$. Liner labor disutility arises when labor is indivisible.

To simplify the computation and notation, I rewrite the profit function as follows,

$$\Pi_{c,t}(j) = (\mu_t(j) - m_t(j))\mu_t(j)^{-\varepsilon}(\frac{P_{c,t}}{W_t})^{\varepsilon-1} P_{c,t} C_t, \tag{1.21}$$

$$\Pi_{x,t}(j) = (\mu_t(j) - m_t(j))\mu_t(j)^{-\varepsilon}(\frac{P_{x,t}}{W_t})^{\varepsilon-1} P_{x,t} X_t \tag{1.22}$$

where $\mu_t(j) = \frac{P_t(j)}{z_t(j)W_t}$. Note that unlike in Golosov and Lucas, and Midrigan (2011), $\mu_t(j)$ is not markup here. We need to divide it by $m_t(j)$ to get the markup of firm j. But I will refer to $\mu_t(j)$ as markup in what follows since this is not very misleading.

Now, the state of firms is captured by the regular price markup, which greatly simplify the computation. The aggregate state variables include the growth rate of money $g_t = \Delta ln(M_t)$, the distribution of firms' markups Ψ and last period durable goods.

Firms can incur three different pricing decisions each period: (1) change the regular price; (2) charge a sale price; and (3) do not change the price. We may characterize this problem in terms of Bellman equations,

$$
\begin{aligned}
V_S^j(\mu_{R,-1}(j);g,\Psi,D_{-1}) = \quad & \max_{\mu(j)} \ \{(\mu(j)-m(j))\mu(j)^{-\varepsilon}(\frac{P_x}{W})^{\varepsilon-1}\frac{P_xX}{W} \\
& +\beta(1-\nu_h)EV(\mu_R^*(j);g',\Psi',D)\} \\
V_R^j(\mu_{R,-1}(j);g,\Psi,D_{-1}) = \quad & \max_{\mu_R(j)} \ \{(\mu_R(j)-m(j))\mu_R(j)^{-\varepsilon}(\frac{P_x}{W})^{\varepsilon-1}\frac{P_xX}{W} \\
& -\phi+\beta(1-\nu_h)EV(\mu_R^*(j);g',\Psi',D)\} \\
V_N^j(\mu_{R,-1}(j);g,\Psi,D_{-1}) = \quad & (\mu_{R,-1}(j)-m(j))\mu_{R,-1}(j)^{-\varepsilon}(\frac{P_x}{W})^{\varepsilon-1}\frac{P_xX}{W} \\
& +\beta(1-\nu_h)EV(\mu_R^*(j);g',\Psi',D)
\end{aligned}
$$

where $V=\max\{V_S,V_R,V_N\}$, the value of $\mu_R^*(j)=\mu_{R,-1}exp(g'\times\varepsilon'^z)^{-1}$ if the regular price doesn't change, otherwise $\mu_R^*(j)=\mu_R exp(g'\times\varepsilon'^z)^{-1}$. I only list the value functions for a durable firm, value functions for nondurable firms are similar except that $\psi P_cC=W$.

I follow Krusell and Smith (1998) [21] by approximating the law of motion of the aggregate state variables to only rely on the growth rate of money supply and last period's aggregate price level normalized by money supply this period. For example, the aggregate price level for the durable sector normalized by money supply this period can be approximating by,

$$log(\frac{P_{x,t}}{M_t})=a_0+a_1g_t+a_2log(\frac{P_{x,t-1}}{M_t})+a_3log(\frac{P_{c,t-1}}{M_t})+a_4log(D_{t-1}) \qquad (1.23)$$

[21] See also Golosov and Lucas 2007, Midrigan 2011.

Starting from a guess for the coefficients in (1.23) and some other approximating equations, I solve the value functions and policy rules for nondurable and durable firms. Then, I simulate data from these value functions and policy rules to calculate new coefficients which are used as new coefficients for the next loop. The process continues until the coefficients converge.

1.3.3 Model Calibration

Assigned Parameters Table (2.2) lists the assigned parameters used in the model. The length of the model period is one month. The discount factor is $\beta = 0.96^{1/12}$. Following BHK, the weight on durables is set to 0.25, the elasticity of substitution ρ between durables and nondurables is set to 1. The depreciation rate of durables δ_d is set to 0.01. Following Kehoe and Midrigan (2016), I estimate the AR(1) growth rate of the UK money supply to be 0.40, with volatility 0.0017. The durable adjustment cost κ is set to 20, similar as that of capital.

Table 1.3. Assigned Parameters

Parameter	Value	Description
β	$0.96^{1/12}$	Discount Factor
D/Y	25%	Fraction of durables in steady state
δ_d	0.01	Durables and capital depreciation rates
κ_d	20	Adjustment cost of durables
ρ_m	0.40	Auto Corr. of money growth
σ_m	0.0017	Money growth rate shock
Period length	1 $Month$	Period length

Note: This table reports the assigned parameters used in the model.

Calibration and Data Moments I calibrate eight parameters (four parameters each sector) to match moments in the data, including the standard deviation of permanent shocks σ_z, the frequency of temporary shocks λ_s, the size of temporary shocks m_L, and the fixed menu cost of changing the regular prices. I choose the parameter values to minimize the differences between moments of the data and those of the model. Table (1.4) reports the calibration parameters. In the benchmark model, the menu costs are 0.1 and 0.0207 of the steady-state wage, respectively. The permanent shock has a volatility of about 0.028 for nondurables and 0.03 for durables. The temporary wholesale cost occur with a frequency of 0.3332 for nondurables and 0.1938 for durables, with size 0.1501 for nondurables and 0.1896 for durables.

Table (1.5) presents the data moments and those simulated from different models. Numbers with stars are targeted moments. The benchmark model is calibrated to match four moments of the data: frequency of regular price changes, mean size of regular price increases, fraction of sales episodes, and the mean size of abs. price changes. The Golosov and Lucas model and the model without sales are calibrated to match two moments of the data: frequency of regular price changes, and mean size of regular price increases.

The benchmark model match moments in the data quite well. The model also fit well some additional moments, such as frequency of annual model changes, and the size of sales. The estimate for standard deviation of price changes are smaller than that in the data, but it does much better job than GL model and the No Sales model. The GL model and No Sales model are able to match regular price moments, but they are unable to generate high frequency sales pattern as observed in the data, and they are more off from the data for other moments, too.

Table 1.4. Calibrated Parameters

Models	GL	No Sales		Benchmark	
	All	Nondurables	Durables	Nondurables	Durables
ϕ	0.0255	0.0183	0.0316	0.0100	0.0207
σ_z	0.0261	0.0261	0.0286	0.0280	0.0300
λ_s	–	–	–	0.3332	0.1938
m_L	–	–	–	0.1501	0.1896

Note: This table reports parameters calibrated according the moments in the data. GL model is the Golosov and Lucas (2007) model. Benchmark model is the model with two sectors and sales. No sales model refer to the model with two sectors but without sales. Numbers with stars are targeted moments.

1.4 Results

Table (1.6) reports the aggregate results[22] simulated from four different model: Golosov Lucas model (one sector), Calvo model with two sectors[23], benchmark model, and model with sales.

The standard deviation of total consumption is 0.22 in the benchmark model, while it is 0.38 in the model without sales, 73% more than in the benchmark model. The Calvo model – that most often used in the literature – generates 0.66 standard deviation in consumption, three times that of the benchmark model. Thus, accounting for sales makes the prediction of monetary models very different. Given that the benchmark model account for more moments in the data, it is more likely that the benchmark model produces the most plausible results. Table (1.6) also presents the standard deviation for nondurable and durable expenditures. As expected, durable expenditure is about three times more volatile than that of nondurables. And sales have effect on both nondurable and durable expenditures.

Sales represent another dimension of price adjustment for durables. In response

[22]Total consumptions are HP-filtered with parameter 14400.
[23]The price change frequency is calibrated to match the regular price change frequency for each sector.

Table 1.5. Data and Simulated Moments

	Data	GL	Data		Benchmark		No sales	
Moments	All	All	Durables	Nondurables	Durables	Nondurables	Durables	Nondurables
Freq. of reg price changes	0.058	0.058*	0.051	0.061	0.051*	0.061*	0.051*	0.061*
Mean size of reg price increases	0.109	0.106*	0.124	0.100	0.124*	0.100*	0.122*	0.101*
Frac. of sales episodes	0.255	0.009	0.178	0.294	0.175*	0.278*	0.008	0.013
Mean size of price changes	0.157	0.105	0.196	0.145	0.198*	0.152*	0.120	0.100
Prob. at annual mode	0.735	0.822	0.764	0.721	0.703	0.593	0.841	0.809
Freq. of annual mode changes	0.588	0.588	0.536	0.611	0.538	0.640	0.525	0.610
Mean size of sales (abs.)	0.160	0.103	0.162	0.159	0.198	0.150	0.112	0.088
S.D. of price changes	0.166	0.013	0.184	0.162	0.055	0.045	0.024	0.019

Note: This table compares moments in the data with those generated by different models. GL model is the Golosov and Lucas (2007) model. Benchmark model is the model with two sectors and sales. No sales model refer to the model with two sectors but without sales. Numbers with stars are targeted moments.

to a monetary policy shock, the firm's markup decreases. If they are shock by temporary whole shock, they will adjustment their posted to reflect changes in their idiosyncratic states and monetary policy shocks. Durables are sensitive to sales due to their high intertemporal elasticity of substitution[24]. Durable goods have a low depreciation rate, and thus a large change in the flow of durable goods would have a small impact on the stock of durables. Since consumers derive utility from the stock of durables instead of the flow of durables, they are more tolerant to large change in the flow of durables compared to nondurable consumption each period. The optimal strategy for consumers are to purchase durables when they have temporary sales, and wait and rely on the stock if they charge high prices.

The benchmark model and model with sales both produce larger standard deviations of consumption than that in the Golosov and Lucas model. This is because the addition of a durable sector make the economy more sensitive to monetary policy shock though the durable sector only account for 25% of the total output. Because the output $Y_t \approx P_{xt}(\frac{1}{\gamma} + X_t)$ almost entirely depends on the price and consumption of durables. [25].

However, similar as in Golosov and Lucas (2007), both the benchmark model and the model without sales cannot produce as high volatility in consumption as the corresponding Calvo model. Again, the same as their explanation, the selection effect is large when the model allows idiosyncratic shocks. The addition of a durable sector do not alleviate this selection.

[24]The EIS for nondurable goods is about 0.2 (see Cashin & Unayama 2012, Hall 1998). The EIS for durable goods is much higher (Adda & Cooper 2000, and Erceg & Levin 2006).

[25]Accurately, $Y_t = P_{xt}(\frac{P_{ct}}{P_{xt}} C_t + X_t) = P_{xt}(\frac{1}{\gamma_t} + X_t)$. According to BHK, the shadow value γ_t is nearly constant over time. Recall that from equation (1.8), the shadow value of good X is $\gamma_t = E_t\left[\sum_{i=0}^{\infty} \beta^i (1-\delta_d)^i MU_{t+i}^D\right]$. If β is very close to 1 and δ_d is very close to 0, γ_t is heavily influenced by the marginal utility of durable flows MU_{t+i}^D in the distant future. After a temporary shock, MU_{t+i}^D is close to its steady-state value in the future. Thus, the changes in γ_t would be limited even if the first few terms of MU_{t+i}^D change, which would not change much due to high durable stock to flow ratio.

Table 1.6. Simulated Aggregate Results

Models	GL	Calvo	No Sales	Benchmark
σ_y	0.18	0.66	0.38	0.22
σ_c	0.18	0.41	0.21	0.13
σ_x	–	1.40	0.89	0.61

Models	GL	Calvo		No Sales		Benchmark	
Law of motion	$\frac{P(t)}{M(t)}$	$\frac{P_x(t)}{M(t)}$	$\frac{P_c(t)}{M(t)}$	$\frac{P_x(t)}{M(t)}$	$\frac{P_c(t)}{M(t)}$	$\frac{P_x(t)}{M(t)}$	$\frac{P_c(t)}{M(t)}$
g_t	-0.566	-0.916	-0.900	-0.528	-0.490	-0.285	-0.183
$\frac{P(t)}{M(t)}$	0.741	–	–	–	–	–	–
$\frac{P_c(t)}{M(t)}$	–	0	0.939	0	0.820	0	0.835
$\frac{P_x(t)}{M(t)}$	–	0.949	0	0.857	0	0.863	0
D(t-1)	–	0	–	0.042	0	0.096	0
R^2	98.6	1	1	98.3	97.2	96.1	92.3 [a]

Note: This table reports the aggregate implications of different models, and the law of motion for the aggregate inflation. GL model is the Golosov and Lucas (2007) model. Calvo model is a two-sector Calvo model as in BHK, the price change frequency is calibrated to match the regular price change frequency for each sector. Benchmark model is the model with two sectors and sales. No sales model refer to the model with two sectors but without sales. Numbers with stars are targeted moments. Output and consumptions are HP-filtered with parameter 14400.

[a] The R square is not satisfactory, I am still working on this.

1.5 Conclusions

Recent studies argue that volatile micro-level prices can be consistent with high price rigidity used in many macroeconomic models, because most price changes are due to temporary sales and temporary sales reflect pure idiosyncratic forces which cancel out at the aggregate level. My investigation reveals that while temporary sales of nondurables may be due to idiosyncratic forces, temporary sales of durable goods do respond significantly to aggregate shocks, which enables the aggregation of temporary sales to affect the dynamics of the aggregate inflation.

I then develop a two-sector menu-cost model which features the roles of durables and sales. The model is able to reproduce documented moments and the pattern of sales in the data. Failing to account for temporary sales would increase the output effect by 73%. The difference in responses to monetary policy shock is due to the high intertemporal elasticity of substitution of durable goods. The model also points out that the Calvo model calibrated to the frequency of regular price changes would generate triple size of output effect compared to the benchmark model with sales.

1.6 Acknowledgements

Chapter 1, “Sales, Monetary Policy, and Durable Goods”, in part, is currently being prepared for publication of the material. Wenbin Wu. The dissertation author was the sole author of this paper.

Chapter 2

The Credit Channel at the Zero Lower Bound Through the Lens of Equity Prices

In order to stimulate the economy after the Great Recession, the Federal Reserve (Fed) lowered the target for the federal funds rate nearly to zero[1], which is often referred to as the zero lower bound (ZLB). Before the ZLB, monetary policy was conducted mainly through the federal funds rate, which was set by the Federal Open Market Committee (FOMC). But once the ZLB was reached, the federal funds rate was no longer an effective policy tool[2]. In order to stimulate the economy further at the ZLB, the Fed used several unconventional measures: (1) large-scale asset purchases (LSAPs, often referred to as quantitative easing, QE), where the Fed purchased a large amount of U.S. Treasury securities, agency mortgage backed securities (MBS), and other securities with medium to long maturity; (2) forward guidance, where the Fed promised to keep the federal funds target rate low for a long period of time in order to affect the expectation of future rates;

[1] The actual range is 0 to 25 basis points.

[2] Sweden's Riksbank was the first to cut the repo rate to below zero. Danmarks Nationalbank, Swiss National Bank, European Central Bank and the Bank of Japan have also implemented this policy. Recently, the Fed has discussed negative interest rates in speeches, see http://money.cnn.com/2016/02/11/news/economy/negative-interest-rates-janet-yellen/. Anderson and Liu (2013) discussed this problem and gave several reasons that the Fed should not implement a negative policy rate.

and (3) operation twist, where the Fed sold a large amount of short-term bonds and used the proceeds to buy long-term bonds in an effort to bring down long term interest rates.

Were these unconventional monetary policies effective? Most existing studies of unconventional monetary policies have focused on their impact on interest rates[3]. But the neoclassical interest rate channel is not the only way that conventional monetary policy may have influenced economic activity. Bernanke and Gertler (1989) and Kiyotaki and Moore (1997) propose an important alternative transmission mechanism operating through the credit channel. They show that agency cost and credit constraints can make external funds more costly than internal funds for firms. In this situation a shock to external funds would exert a stronger effect on firms that are more financially constrained. Bernanke, Gertler and Gilchrist (1999) incorporate this idea into a New Keynesian framework to study the interaction between monetary policy shocks and the credit market. They emphasize the role of a financial accelerator, which helps amplify and propagate monetary policy shocks. The credit channel is distinct from the neoclassical cost of capital channel, which works primarily through changes in interest rates.

These models predict that financially constrained firms react more strongly to monetary shocks than do less constrained firms. This prediction can be used to test for the role of the credit channel at the ZLB. One basis for the prediction is the following reasoning. Firms have two types of assets: cash savings in a bank and physical capital. If firms can only borrow up to part of the value of their physical capital, then in a financial crisis, they may deplete all of their cash savings and need to borrow external funds. As a result, firms will not operate at the optimal level if they cannot borrow enough to buy and maintain equipment[4]. However, firms that do not need external funds will not be

[3]For UK evidence, see Breedon, Chadha and Waters (2012). For US evidence, see D'Amico (2011), Gagnon et al. (2011), Neely (2010), Krishnamurthy and Vissing-Jorgensen (2011), Hamilton and Wu (2012), and Williams (2011).

[4]A similar example is used in Kocherlakota (2000), where the "optimal" level refers to the best possible level that firms can reach in a world without any financial constraints.

adversely affected in this manner. If there is an unanticipated favorable shock to the economy, entrepreneurs who are financially constrained can invest in more physical capital and operate at a level closer to the optimal state, whereas firms that are not financially constrained would be less affected since they are already in the optimal state. This difference becomes even larger when the capital price starts to rise and constrained firms are able to borrow more because their net worth increases.

Investigating the relationship between unconventional monetary policies and the credit channel is important for several reasons. First, the credit channel allows for small shocks to be amplified into large and persistent business fluctuations, and could be one of the most important ways that unconventional monetary policies mattered for real economic activity. Second, even if we find that unconventional monetary policies significantly affect long-term interest rates and asset prices, we cannot determine whether or not they have a large and desirable effect on the economy (see Jiménez et al. 2014, and Araújo, Schommer and Woodford 2015).

In the present study, I use stock market data to show that the credit channel plays a role in the transmission of unconventional monetary policy shocks at the ZLB. First I examine whether the stock market responds to unconventional monetary policy announcements. Next I analyze the pattern of this impact by investigating which type of firm reacts more strongly to these monetary policy surprises[5]. To gauge the intensity of financial constraints, I use four different measures: market capitalization, number of employees, debt to total capital ratio, and long-term debt rating. I demonstrate that firms that are more financially constrained react more strongly to monetary policy surprises than those that are less constrained. These findings imply that the impact of unconventional monetary policies on the stock market works through the non-neoclassical credit channel

[5]The firms considered in this study are relatively large because they are all S&P 500 index companies. In this context, financial constraint is a relative concept, i.e., firms that are classified as financially constrained are only more financially constrained than other firms.

as well as through the neoclassical channel. Additionally, I detect a credit channel effect from LSAPs, but not from forward guidance or operation twist.

The remainder of this paper is organized as follows. In Section 2, I describe the data and reexamine the relationship between the stock market and unconventional monetary policy. In Section 3, I test the credit channel effect by using a simple event study, an ordinary least squares (OLS) estimation, and a heteroskedasticity-based estimation. Section 4 concludes.

2.1 Data and Reexamination

2.1.1 Data

Following Wright (2012) and Kiley (2014), I use Federal Open Market Committee (FOMC) announcements as events to identify monetary policy surprises. In the baseline intraday analysis I will study the change in stock prices between 10 minutes before the FOMC announcement and 20 minutes after. I also explore longer windows up to a full day.

I extract certain important events as the baseline event set, which I compare to the full event set. The full event set (as described in Gagnon et al. 2011) consists of 33 FOMC announcements between December 16, 2008 and December 31, 2012.[6] The baseline event set is as follows[7]:

• November 25, 2008: The Fed first announced that it would start a program to purchase agency debt and MBS.

• December 16, 2008, and March 18, 2009: The FOMC made statements giving important information about QE1.

[6]The full event set is described in Table A.1 in the online appendix to this paper.

[7]All of these events were included in the baseline event set in Gagnon et al. (2011), and they were also used in Krishnamurthy and Vissing-Jorgensen (2011). January 18, 2009 was excluded because the expectation of the public was not met, e.g., for more details, see Neely (2010) .

• August 10, 2010, and September 21, 2010: The FOMC made statements giving important information about QE2[8].

• August 9, 2011: Forward guidance announced[9].

• September 21, 2011: Operation twist announced.

• June 20, 2012: Operation twist extended.

• August 31, 2012: Ben Bernanke made a speech about QE3.

• September 13, 2012: $40 Billion per month QE3 announced.

Xia (2014) summarized all of the relevant event dates for unconventional monetary policies based on Gagnon et al. (2011), Krishnamurthy and Vissing-Jorgensen (2011), Neely (2010) , and others. The full event set includes all the event dates listed in these studies prior to December 2012. The baseline event set is built by expanding the event set used in Gagnon et al. (2011) and Krishnamurthy and Vissing-Jorgensen (2011)[10].

The data used in this study are compiled from several sources. The Trade and Quote (TAQ) database provides tick-by-tick equity prices for stocks traded on the NYSE. The market value and the S&P long-term debt ratings are acquired from the Compustat database. Other firm characteristics (such as the number of employees and the debt to total capital) are obtained from Datastream. Intra-day changes in long-term interest rates are constructed from the Chicago Board Options Exchange (CBOE) 10-year Treasury note index. I exclude financial firms (SIC Codes 6000-6999), but my results are robust if they are included.

[8]November 3, 2010 was not included in this study because it was widely anticipated, and thus it had little effect. See Krishnamurthy and Vissing-Jorgensen (2011), for more details.

[9]See Xia (2014) for more details.

[10]We did not include December 1, 2008 in the baseline event set. It was not suitable for studying the effect of unconventional monetary policy on the stock market because some large negative information about the economy was also released at the same time that might have biased the simple event study estimate. An important nonmonetary policy shock occurred at the same time: the National Bureau of Economic Research (NBER) officially declared that the nation was in a recession. Neely (2010) provides more details about the events on December 1, 2008.

2.1.2 Reexamining the Reaction of the Stock Market to Unconventional Monetary Policies

Prior to the ZLB, researchers measured the impact of monetary policy surprises on the stock market using OLS regression (see Kuttner 2001, Gürkaynak, Sack and Swanson 2005, and Bernanke and Kuttner 2005). The basic model is

$$\Delta \ln(P(t)) = \alpha_1 + \beta_1 \Delta SR(t) + \varepsilon(t), \tag{2.1}$$

where $\Delta SR(t)$ is the unanticipated change in the policy rate, $\Delta \ln(P(t))$ is the stock market return, $\varepsilon(t)$ is the error term, and α_1 and β_1 are parameters.

Unexpected policy changes are usually proxied by the changes in the federal funds future rates (Kuttner 2001, Gürkaynak, Sack and Swanson 2005) or in short-term interest rates (Rigobon and Sack 2004). Unfortunately, the federal funds rate and its future rate have been insensitive to macro news since it hit the ZLB. Hence, conventional methods for measuring the impact of monetary policy are no longer effective because unconventional monetary policies are not tied directly to the federal funds rate or to other short-term rates. In order to measure the unanticipated changes in unconventional monetary policies, Wright (2012) and Kiley (2014) employ long-term interest rates instead of the federal funds rate (or short-term interest rates). The key issue of measuring monetary policy shocks using long-term interest rates is the volatile error term in long-term interest rates during the FOMC event windows, which will be discussed in more detail in the next section.

In this paper, I follow Wright (2012) and Kiley(2014) by using long-term interest rates to measure the unanticipated changes in unconventional monetary policies[11]. The

[11] We also conducted an event study to examine the impact of unconventional monetary policies on the stock market. See online appendix A.2.1 for details.

resulting model[12] is

$$\Delta \ln(P(t)) = \alpha_2 + \beta_2 [\Delta LR(t) - e(t)] + \upsilon(t),$$

where $\Delta LR(t)$ is the change in the long-term rate, $\Delta \ln(P(t))$ is the change in the equity price, $e(t)$ and $\upsilon(t)$ are idiosyncratic shocks, and $\Delta LR(t) - e(t)$ is defined as the unobserved unconventional monetary policy shock as in Kiley (2014). In this way, I normalize the unobserved unconventional monetary policy shock to lower the10-year Treasury yield by 100 basis points (see Wright 2012, Fuhrer and Olivei 2011, and Kiley 2014)[13]. If $e(t)$ is negligible, we simply revert back to equation (2.1), and thus OLS can still be applied. Because of the narrow event windows that I use and the rapid reaction of the financial market, the changes in the long-term rate ($\Delta LR(t)$) should approximate monetary policy surprises well (i.e. $e(t)$ is likely to be a very small value). Hence, I use a simple OLS estimation as a benchmark.

I also examine the case when the error term $e(t)$ is non-negligible which could cause an errors-in-variables problem. Kiley (2014) used an instrumental variable (IV) to mitigate this bias, while I address it by using a heteroskedasticity-based estimator implemented using IV.[14]

Table 2.1 reports the intra-day and daily[15] estimation results of both the full

[12]The model used by Kiley (2014) is

$$\Delta LR(t) = b^1 \Delta H(t) + e(t)$$
$$\Delta \ln(P(t)) = b^2 \Delta H(t) + \upsilon(t),$$

where $\Delta H(t)$ is the unobserved monetary policy shock. We can plug the first equation into the second to obtain the resulting model.

[13]We used this normalization because most previous studies found that there was a significant impact of these unconventional measures on the yield curve (D'Amico 2011, Gagnon et al. 2011, Neely 2010, Krishnamurthy and Vissing-Jorgensen 2011, and Hamilton and Wu 2012). See Williams (2011) for a summary of previous studies on the effects of unconventional monetary policies on the yield curve.

[14]See the online appendix for more details.

[15]The intra-day estimations use event windows as mentioned in the previous subsection, which start 10 minutes before the FOMC announcement and end 20 minutes after the announcement. The daily

event set and the baseline event set. The intraday estimates suggest that in response to a 100-basis-point decrease in the 10-year yield the overall stock market increases by about 3 percent, and these estimates are highly statistically significant. These results are similar for both the full event set and the baseline event set and whether I use OLS or heteroskedasticity-based estimation. By contrast, the daily estimates are more volatile, which may be attributable to significant news that affects the stock market on a given day besides the FOMC announcement. I regard the intraday estimations as more accurate, and will use intraday windows in all the subsequent estimates reported.

Table 2.1. OLS Results Based on Event Study

	Full Event Set			Baseline Event Set		
	Daily	30min (OLS)	30min (Het)	Daily	30min (OLS)	30min (Het)
Coef.	-0.631	-2.760***	-2.968***	-7.496*	-3.028***	-3.547***
S.E.	4.496	0.839	0.825	3.998	0.872	0.751

Note: The dependent variable is the stock market return within the event window and the regressor is the change in the 10-year yield within the same event window. Robust standard errors are reported, *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The intra-day estimations use event windows which start 10 minutes before the FOMC announcement and end 20 minutes after the announcement. The daily estimations use daily event windows. Intraday(Het) is the results of heteroskedasticity-based estimation (see online appendix A.2.2).

For a robustness check, I also used event window lengths ranging from 9 minutes to 90 minutes, which allows us to determine the effects of event window misspecification. I find that the estimation results became quite stable when the event window exceeds 12 minutes. Overall, this evidence shows that unconventional monetary policy is not neutral and had a large impact on the stock market during the narrow announcement windows.

estimations use daily event windows.

2.2 Evidence on the Credit Channel

Next I analyze the details of the response of individual stocks to monetary policy shocks. In particular, I check whether more financially constrained firms respond more strongly to monetary policy surprises compared to less financially constrained firms. Firms subject to more severe financial constraints are more likely to be small firms, firms with more debt, and firms with a low long-term debt rating (see Ehrmann and Fratzscher 2004, Lamont, Polk and Saa-Requejo 2001, and Kaplan and Zingales 1997). Hence I use four proxies to measure the intensity of financial constraints: the firm size as measured by both the market value and the number of employees, the ratio of debt to total capital, and the S&P long-term debt rating.

2.2.1 Event Study

Although simple and intuitive, event studies are suitable methods for assessing the effects of unconventional monetary policies because: (1) given that the data are high frequency and the event window is quite narrow, it is very likely that monetary policy news would dominate other non-monetary news within the announcement window; (2) it is plausible that the stock market would fully reflect the monetary policy shocks within the event window since it reacts rapidly to news. Nevertheless, an event study is inappropriate if monetary policy news can not dominate other shocks within the event window, or if the stock market reacts slowly to monetary policy surprises. I relax these assumptions to a certain extent in the next subsections by using OLS estimation and heteroskedasticity-based estimation.

I form three portfolios based on each measure of financial constraint to see whether portfolios of more financially constrained firms respond more during the FOMC event windows. I look for this pattern by summing up all the returns around the FOMC announcement dates for all portfolios.

Table 2.2 shows the findings from the event study for various financial constraint measures. The four measures of financial constraints (i.e., market value, number of employees, debt to total capital ratio, and the S&P long-term debt rating) are used to divide the firms into three different groups that range from low to high financial constraint intensity[16]. Panel A and Panel B show the estimated results based on two types of categorization. Panel A uses an equal division, i.e., $< 33.3\%$, 33.3–66.7%, and $>$ 66.7% , while Panel B uses an unequal division, i.e., $< 10\%$, 10–90%, and $> 90\%$ (see Ehrmann and Fratzscher 2004 for more details). All of the results are obtained using the baseline event set[17].

The results in Table 2.2 exhibit a clear pattern in agreement with the prediction of the credit channel. The last column shows the differences between the high financial constraint intensity group and the low intensity group. All of the values in this column are positive and most are significant, which implies that firms with more financial constraints respond more strongly to monetary policy surprises. Regardless of the method by which financial constraint is measured (market cap, debt to total capital ratio, long-term debt rating), the differences between the high, medium, and low groups are clear. For example, if we consider the market cap, it is clear that there is a strictly decreasing pattern: the cumulative return changed from 3.72 percent, to 3.44 percent, and then to 3.35 percent when the market caps of firms were categorized as small, medium, and large, respectively (Panel A)[18]. As expected, the differences between the most financially constrained firms and the least financially constrained firms increase and become more significant when

[16]We performed this division on a daily basis to control for the asymmetries of monetary policy over time.

[17]As discussed above, the full event set was always too noisy to obtain accurate estimates for the event study, so we only studied the baseline event set. However, we considered the full event set when we developed methodologies to deal with noise.

[18]The corresponding financial constraint level would be high, medium and low.

Table 2.2. Cumulative returns of portfolios sorted by financial constraints

Panel A: Equal Division	Intensity of Financial Constraint			
	High	Medium	Low	High-Low
Market Cap	3.77***	3.51***	3.35***	0.42**
Employees	3.74***	3.38***	3.33***	0.41**
Debt to Total Capital	3.56***	3.46***	3.24***	0.32
S&P Long-term Debt Rating	4.02***	3.72***	3.31***	0.71***

Panel B: Unequal Division	Intensity of Financial Constraint			
	High	Medium	Low	High-Low
Market Cap	3.89***	3.54***	3.29***	0.60*
Employees	3.91***	3.38***	3.36***	0.55
Debt to Total Capital	3.88***	3.40***	2.85***	1.03***
S&P Long-term Debt Rating	4.49***	3.46***	3.39***	1.10***

Note: All of the results were computed using the baseline event set. I used a 30-min event window, i.e., 10 min before and 20 min after the announcements. I categorized the firms as: (1) equal division, i.e., $<$33.3%, 33.3–66.7%, and $>$66.7% ; and (2) unequal division, i.e., $<$10%, 10–90%, and $>$ 90% (see [21] for more details). Four financial constraint measures were used to divide the firms into three different groups that ranged from low to high. I performed the divisions on a daily basis to control for the asymmetries of monetary policy over time. I bootstrapped the p-values by comparing the returns from the baseline event dates to those drawn randomly from September 5, 2008 to December 31, 2012. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

we use unequal categorization ($< 10\%$, 10–90%, and $> 90\%$). In Panel B, the pattern is exactly the same as that in Panel A, except that the differences between the high and low groups are greater. To check the robustness of these results, financial firms are included in my data and the event study estimates are repeated. The credit channel pattern remains significant, i.e., more financially constrained firms react more strongly to monetary policy news. Overall, this is solid evidence that financial constraints play an important role in the transmission of monetary policy through equity prices.

Given that we only perform a simple event study, it is surprising that almost all of the results in Table 2.2 agree with the prediction of the credit channel. The only qualification is that the differences between the medium group and the low group are almost zero when we use the number of employees to proxy financial constraints. One possible reason is that the number of employees is not a good proxy for financial constraints, because I only consider firms in the S&P 500 index. Alternatively, this may be due to non-negligible errors that occur within the event window when the responses of stock returns are not measured precisely. To address the second issue, I employ OLS estimation, as described in the next subsection. The responses of stock returns can be measured more accurately based on their sensitivity to monetary policy surprises, which may be approximated by changes in the long-term interest rate within a narrow event window.

The analysis described above focuses on the total effect of unconventional monetary policies. In addition, it is important to determine which unconventional tool is most responsible for the credit channel effect. As reported in the online appendix, I examined different effects of LSAPs, forward guidance, and operation twist. I found that the credit channel effects are due mainly to LSAPs, whereas forward guidance and operation twist appear to have negative effects on the stock market. However, the results obtained for forward guidance and operation twist may be unreliable due to the limited number of observations.

2.2.2 OLS Estimation

The results of event studies are unreliable if the return of the stock market at the event windows is contaminated by non-monetary policy shocks, which is likely to happen because the stock market is very volatile. We can address this issue by using OLS estimation, which would only extract the part of the stock return related to the monetary policy shock. To facilitate comparisons with the results of the heteroskedasticity-based estimations, I conduct the OLS estimation on a stock-by-stock basis. I regress the stock returns of individual firms in S&P 500 on monetary policy surprises to determine their sensitivity to monetary policy surprises. The relationship between stock returns and unconventional monetary policy shocks is given by[19]

$$\Delta \ln(P_i(t)) = \alpha_3 + \beta_3 \left[\Delta LR(t) - e(t)\right] + u(t),$$

where $\Delta \ln(P_i(t))$ is the stock return for firm i, $\Delta LR(t)$ is the change in the long-term interest rate, and $e(t)$, $u(t)$ are idiosyncratic shocks. The coefficient of the change in the long-term yield (β_3) can be used to measure the sensitivity of stock returns to monetary policy surprises. We can interpret β_3 as the size of the change in the average stock price when a monetary policy surprise raises the long-term yield by 1%. As described in the previous subsection, I perform OLS regression of firm i's stock returns on the changes in the long-term rate where $e(t)$ is negligible, which I relax to some extent when the

[19]Similar to the previous section, we derived our model from that used by Kiley (2014)

$$\Delta LR(t) = b^1 \Delta H(t) + e(t)$$
$$\Delta \ln(P_i(t)) = b^2 \Delta H(t) + u(t),$$

where $\Delta H(t)$ is the unobserved monetary policy shock. We plugged the first equation into the second to obtain our model.

heteroskedasticity-based estimator is used, as discussed in the next subsection.

Figure 2.1 shows the distribution of the estimated sensitivity of stock returns to a 1 percent decrease in the 10-year Treasury yield $(-\beta_3)$[20]. There is huge heterogeneity in the response across the firms. But most of the values are between -10 and 10, and skew to the right with a mean of 2.475.

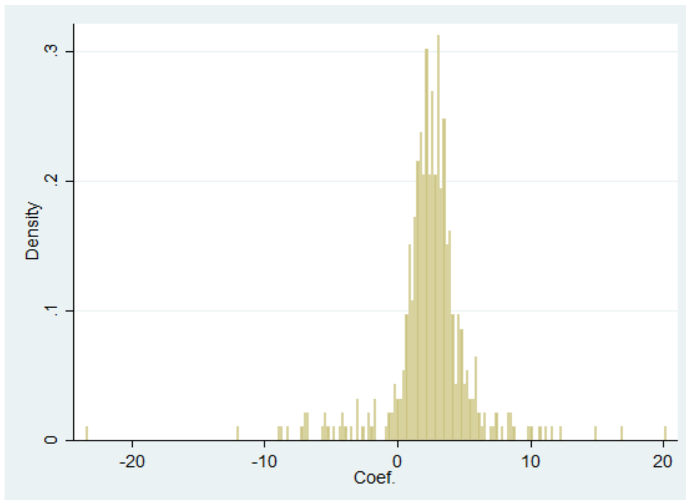

Figure 2.1. Distribution of the responses based on the event study

Next, I regress these responses $(-\beta_3)$ on the measures of financial constraint[21] in an effort to explain the observed heterogeneity in terms of the various financial constraint measures. If the credit channel is important, we expect to find a significant difference between financially constrained firms and financially unconstrained firms.

It should be noted that there is no need to use joint estimation. Two-stage regression is suitable because the estimated value $-\beta_3$ is used as the dependent variable not as a regressor. Hence, errors from the first stage would not bias the estimate obtained in the second stage.

[20]This figure uses the full event set. The distribution is less spread out for the baseline event set.

[21]Ehrmann and Fratzscher (2004) discussed this approach and compared it to the single equation approach, where the coefficient of the interaction term of the monetary policy shock and the financial constraint measure were most important. This approach allowed us to implement heteroscedasticity-based estimation. In fact, these two approaches are equivalent if we use outdated firm characteristics data to measure financial constraints.

The results for the full event set are shown in Table 2.3. The results obtained from the baseline event set are similar. All of the estimates are significant at the 1 percent level. I add the cash flow-to-sales ratio (CFS) in the fourth regression to control for the profitability of firms. I only add CFS to the fourth regression because the other financial constraint proxies are less affected by the firms' profitability[22]. For example, low rated firms may result from low profitability or high financial constraints, but the size of firms and the debt ratio appear to have no relationship with profitability.

As expected, a 1 percent increase in size decreases the responses (or sensitivities) by 0.062 or 0.058 depending on the measure of size used. Thus, larger firms that are less likely to be financially constrained respond less strongly to monetary policy shocks. Firms in the S&P 500 index are relatively large and healthy, which makes it very difficult for us to detect significant evidence of the credit channel. Nevertheless, it is interesting that my results still confirm the presence of the credit channel even in this case.

Firms with a higher debt to total capital ratio tend to be more financially constrained because they raise more money externally. Column (3) of Table 2.3 shows that the response is stronger with a higher debt to total capital ratio. I convert the long-term debt rating into a conventional numeric value before the regression[23]. High scores correspond to low ratings, so it is clear that firms with lower ratings tend to respond more strongly to monetary policy shocks than those with better debt ratings from column (4) of Table 2.3.

Overall, I find evidence that the credit channel was working at the ZLB when the Fed conducted unconventional monetary policies because financially constrained firms

[22]When CFS was added to the other regressions, the results did not change and the coefficients for CFS were generally insignificant.

[23]As described in Avramov et al. (2007), we transformed the S&P ratings into conventional numeric scores as follows: AAA = 1, AA+ = 2, AA = 3, AA- = 4, A+ = 5, A = 6, A- =7, BBB+ = 8, BBB = 9, BBB– = 10, BB+ = 11, BB = 12, BB– = 13, B+ = 14, B = 15, B– = 16, CCC+ = 17, CCC = 18, CCC– = 19, CC = 20, C = 21, and D = 22.

Table 2.3. Event Study Estimation and Responses to Monetary Policy

	(1)	(2)	(3)	(4)
log(MV)	-0.062***			
	(0.018)			
log(Emp)		-0.058***		
		(0.013)		
log(DTTC)			0.343***	
			(0.021)	
Ratings				0.115***
				(0.012)
Time Dummy	Yes	Yes	Yes	Yes
Observations	11,124	11,067	10,618	9,756

Note: The dependent variable is the sensitivity of stock returns to unconventional monetary policy shocks. Columns (1)–(4) correspond to regressions with different regressors: (1) log(market value); (2) log(number of employees); (3) debt to total capital ratio; (4) S&P long-term debt rating and cash flow to sale ratio. I added the cash flow to sales ratio (CFS) in the fourth regression to control for the profitability of firms. Robust standard errors are shown in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$. As described in Avramov et al. (2007), I transformed the S&P ratings into conventional numeric scores as follows: AAA = 1, AA+ = 2, AA = 3, AA- = 4, A+ = 5, A = 6, A- =7, BBB+ = 8, BBB = 9, BBB– = 10, BB+ = 11, BB = 12, BB– = 13, B+ = 14, B = 15, B– = 16, CCC+ = 17, CCC = 18, CCC– = 19, CC = 20, C = 21, and D = 22.

appear to respond more intensely to monetary policy shocks than less constrained firms. As a robustness check, I also obtain estimates for samples with 45-minute and 60-minute event windows. The results are qualitatively similar to those obtained with a 30-minute event window above.

2.2.3 Heteroskedasticity-based Estimation

The event study can generate biased estimates if the error terms are not negligible and if there exists a simultaneity problem, as described in Rigobon and Sack (2003, 2004). To address these potential issues, I employ a heteroskedasticity-based estimator to ensure the robustness of my results. Note that my model generalizes that of Rigobon and Sack (2004) in two ways: (1) I use the long-term interest rate instead of the short-term interest rate to measure the size of monetary policy surprise; (2) I allow monetary policy shocks to influence the long-term interest rate and the stock market returns simultaneously. In general, my method is similar to that of Wright (2012), except that I obtain my estimates at a high frequency level with no lags in the predictive regressions.

The identification steps are similar to those in the previous section[24]. We can show that if the monetary policy shock is the only shock whose variance differs across two regimes the system can be reduced to[25]

$$\Delta \ln(P_i(t)) = \alpha_4 + \beta_4 [\Delta LR(t) - T(t)] + \varepsilon(t)$$

where $\Delta LR(t) = T(t) + \Delta H(t)$. $T(t)$ is an expression in terms of $\Delta Z(t), e(t), \upsilon(t)$ and $u(t)$. $T(t)$ can be correlated with $LR(t)$ but it needs to be homoskedastic across two regimes. Hence, we go back to single equation identification which has already been

[24]In order to implement this new estimator, we used the IV approach (see Appendix A.5 for more details).

[25]See Appendix A.4 for more details.

shown in the previous section.

I repeat the regression described in the previous subsection to test whether the credit channel was at work during the ZLB. Table 2.4 shows the heteroskedasticity-based estimations. All of the estimates are similar to those shown in Table 2.3, thereby implying that my results are quite robust to various specifications.

Table 2.4. Heteroskedasticity-based Estimation and Responses to Monetary Policy

	(1)	(2)	(3)	(4)
log(MV)	-0.066***			
	(0.018)			
log(Emp)		-0.059***		
		(0.014)		
log(DTTC)			0.327***	
			(0.021)	
Ratings				0.126***
				(0.012)
Time Dummy	Yes	Yes	Yes	Yes
Observations	11,124	11,067	10,618	9,756

Note: The dependent variable is the sensitivity of stock returns to unconventional monetary policy shocks. Columns (1)–(4) correspond to regressions with different regressors: (1) log(market value); (2) log(number of employees); (3) debt to total capital ratio; (4) S&P long-term debt rating and cash flow to sale ratio. I added the cash flow to sales ratio (CFS) in the fouth regression to control for the profitability of firms. Robust standard errors are shown in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$. As described in Avramov et al. (2007), I transformed the S&P ratings into conventional numeric scores as follows: AAA = 1, AA+ = 2, AA = 3, AA- = 4, A+ = 5, A = 6, A- =7, BBB+ = 8, BBB = 9, BBB– = 10, BB+ = 11, BB = 12, BB– = 13, B+ = 14, B = 15, B– = 16, CCC+ = 17, CCC = 18, CCC– = 19, CC = 20, C = 21, and D = 22.

The instrumental variable approach of Kiley (2014) and principal component approach of Wright (2012) can potentially address the non-negligible error problem if the monetary policy shock is the only common shock for both the stock market and the long-term interest rates within the event window. Otherwise, the IV approach and principal component approach would not be appropriate because they might pick up the effects of non-monetary shocks[26].

Overall, I find that there is large heterogeneity in the response to monetary policy across firms, which is explained well by firms' level of financial constraint. Firms with more financial constraints respond more intensely to unconventional monetary policy surprises than do relatively unconstrained firms.

2.3 Conclusions

Since the federal funds rate was stuck at the ZLB, the Fed has used unconventional monetary policies to stimulate the economy. These unconventional policies include the LSAP program, the operation twist, and forward guidance. In contrast to the federal funds rate prior to the ZLB, no simple measure can be used to summarize the stance of unconventional monetary policies. Therefore, I normalized the intensity of unconventional monetary policies to lower the 10-year yield by 1 percent (100 bp), and then studied its effects on equity prices. The linkage between bond yield changes and stock market returns is important because the spillover to equity prices represents the first important step where unconventional monetary policies affect the real economy. More importantly, the stock market provides us with a natural experiment to test the existence of the credit channel for the transmission of unconventional monetary policies. The high heterogeneity among the responses of stock returns to monetary policy shocks allows us to test whether the credit channel was at work at the ZLB. My results show that more

[26]Kiley (2014) used 2- and 5-year Treasury yields as instrument variables for the 10-year yield, which would fail if the 2- or 5-year yields correlated with the 10-year yield before (or after) the event window when there was assumed to have no monetary policy shocks. We examined this possibility by analyzing the correlation between the 10-year yield change and the 5-year yield change in the *prewindow*, which started 60 minutes before FOMC announcements and ended 20 minutes before FOMC announcements. We found that the coefficient was significantly different from zero.

financially constrained firms have significantly greater responses to unconventional monetary policy surprises (especially large-scale asset purchases) than less constrained firms. These findings complement those of Ehrmann and Fratzscher (2004) by examining the credit channel effect at the ZLB. The findings of this study provide additional evidence for the effectiveness of unconventional monetary policies.

2.4 Acknowledgements

Chapter 2, "The Credit Channel at the Zero Lower Bound Through the Lens of Equity Prices", in part, has been submitted for publication of the material as it may appear in Journal of Money, Credit and Banking, 2017, Wenbin Wu. The dissertation author was the sole author of this paper.

Chapter 3

Are Financial Markets Less Responsive to Monetary Policy Shocks at the Zero Lower Bound?

Many studies have documented that monetary policy shocks have an important impact on the stock market, the Treasury yields, and the corporate yields(see, for example, Thorbecke (1997), Rigobon and Sacks(2004), Bernanke and Kuttner (2005), Wright (2012), Kiley (2013, 2014) and Gilchrist, López-Salido and Zakrajšek (2015)). However, few of the existing studies have further investigated the time-varying effect of monetary policies on these variables. In this paper, we estimate the time-varying effect of monetary policy shocks on a range of economic and financial variables using a similar approach to that employed by Swanson and William (2014).

The consideration of the time-varying effect of monetary policy shocks is important because: (1) The way the Fed makes its move is evolving over time. Conventionally, the fed funds rate serves as a policy instrument. At the zero lower bound (ZLB)[1], the Fed turned to other unconventional instruments (for example, ”large-scale asset purchases”, ”forward guidance”, and ”operational twist”)[2]. (2) An outstanding open question is

[1]The zero lower bound refers to the period during which the fed funds rate is set at the range between 0 to 25 basis points.

[2]The Fed funds rate is no longer an effective tool at the ZLB. In order to lower long-term interest rates to give more stimulus to the economy, the Fed conducted several rounds of large-scale asset purchases

whether or not monetary policies become less powerful over time, especially at the ZLB. One way to look at this problem is to investigate the time-varying responsiveness of the economic and financial variables to the monetary policy shocks.

Using the methodology developed in Swanson and William (2014), we show that the sensitivities of all these measures to monetary policy shocks vary over time. The corporate bond market remained highly responsive to monetary policy shocks throughout the entire sample, implying that the Treasury yield changes induced by monetary policy shocks were largely passed through to private yields in the ZLB periods. The long-term Treasury bond market was highly reactive in the ZLB periods[3], but the short-term Treasury bond market was severely constrained by the ZLB. The stock market responded less strongly from 2008 to 2010 compared to the ”normal” period (which will be clear in the next section), but the sensitivity bounced back quickly in 2011.

Related Literature: The paper most relevant to mine is Swanson and William (2014). They develop a new method of measuring the time-varying sensitivity of interest rates to a range of macroeconomic announcements. We find that this methodology is also useful to investigate the power of monetary policy shocks at the ZLB. Kiley (2013) and Gilchrist, López-Salido and Zakrajšek (2015) also examine the pass-through from Treasury yields movement induced by monetary policies to private yields. My work complement theirs by allowing the pass-through to vary over time.

The remainder of this paper is organized as follows. In Section 2, we describe the data and present the methodology. In Section 3, we report the results. In Section 4, we

(LSAPs), where it purchased a large amount of Treasury bonds, agency debt and mortgage backed securities (MBS), and other securities with medium to long maturity. The Fed also used other unconventional policy instruments to influence the economy, including: (1) forward guidance, where the Fed promised to keep the Fed funds target rate low for a long period of time in order to affect the expectation of future rates; and (2) operation twist, where the Fed sold a large amount of short-term bonds and used the proceeds to buy long-term bonds in an effort to bring down their term premiums.

[3]It reacted less in the Great Recession periods (2007-2008), during which the fed funds rate was higher than the ZLB.

give our conclusions.

3.1 Data and Methodology

Kuttner(2001) and Gürkaynak et al.(2005) show that economic and financial variables only respond to unanticipated changes in monetary policies. So, we follow the convention by using Federal Open Market Committee (FOMC) announcements and minutes[4] as events for identifying monetary policy surprises. We first document the daily changes of 1,2,5,7,10 year Treasury yields around these event dates. Next, we extract a factor from rolling three year samples of these yield changes[5]. The factor is then normalized to have 1 to 1 relationship with 2 year Treasuries and used to measure the monetary policy surprises. The reason that we do not use short-end Treasuries or the fed funds rate is that these interest rates essentially are constrained at the ZLB, while the longer term interest rates are still very flexible. Therefore, many recent studies use changes in long term interest rates to measure the stance of monetary policy shocks in order to be able to capture the variation of monetary policy shocks at the ZLB (See for example, Wright (2012), and Kiley (2014)). The data used in this study are downloadable from the website of the Federal Reserve Bank of St. Louis. The release dates of FOMC minutes (1996-2012) can be acquired from the website of the Federal Reserve Board. We pin down other release dates (1990 - 1995) by looking up news in the Factiva Database.

We study the impact of monetary policy shocks on three markets (six variables): the corporate bond market (AAA yields, BAA yields), the Treasury bond market (2 year

[4]We must thank the referee to point out that the sample size is small if only FOMC announcement dates are used. While the results are similar with or without FOMC minute dates, it is meaningful to add them because the sample size becomes larger. As noted in Rosa (2013), FOMC minutes do contain important new information about monetary policies.

[5]The referee pointed out that it is problematic to extract the first principal component using the covariance matrix of the data over the entire sample, because there is a sharp break in the correlation matrix before and after the ZLB(See Kiley (2014)). Therefore, we extract the first principal component from rolling three year samples. It is worth noting that the results are quantitatively and qualitatively similar if we use the entire sample.

Treasury yields, 10 year Treasury yields), the stock market (S&P 500 index and VIX index)[6]. We now specify the steps to estimate the time-varying sensitivity of a economic variable to monetary policy surprises. Following Swanson and William (2014), we first estimate this sensitivity over a benchmark sample, 1990-2000, which is supposed to be free from the ZLB restriction. We next estimate the rest of the sample, 2001-2012, which is then compared to the benchmark case to determine whether or not the power of monetary policy surprises decreases at the crisis or the ZLB.

Our model of measuring the sensitivity of a economic variable h_t to monetary policy shocks M_t takes the form of

$$\Delta h_t = \alpha + \beta M_t + \varepsilon_t \tag{3.1}$$

where t indexes days, ε_t is an error term.

To measure the time-varying sensitivity β^i ($i = 1990$ to 2012), we run regressions year by year from 1990 to 2012[7]. We estimate the time-varying regression of the form

$$\Delta h_t = a^{d_i} + \delta^{d_i} b M_t + \varepsilon_t \tag{3.2}$$

where a^{d_i} and δ^{d_i} are time-varying parameters, b is the constant part of the sensitivity. i indexes years[8], d indexes days within year i. Our focus is δ^{d_i}, which measures the time-varying sensitivity of h_t to monetary policy surprises M_t. Note that in order to separately identify δ^{d_i} and b, we need to normalize δ^{d_i}. Following Swanson and William

[6]At first, we also wanted to look at TIPS and breakeven inflation rates, but the lengths of these samples are too short.

[7]As pointed out by Swanson and William (2014), this approach may deliver volatile estimates because of the small sample problem. Swanson and William (2014) deal with this small-sample problem by imposing a restriction that the relative magnitude of sensitivity for different macroeconomic announcements are constant over time. As discussed in footnote 3, we overcome the small sample problem by including FOMC minute dates.

[8]$i \in \{1990, 1991, ..., 2012\}$.

(2014), we normalize δ^{d_i} such that the average of δ^{d_i} over 1990-2000[9] to be 1. In the subsequent periods, if δ^{d_i} exceed 1, variable h is more sensitive to monetary policy shocks compared to that of 1990-2000; if δ^{d_i} is smaller than 1, variable h becomes less sensitive to monetary policy shocks.

In order to determine finer estimates of δ^{d_i}, we follow Swanson and William (2014) by estimating daily rolling regressions as follows:

$$\Delta h_t = a^d + \delta^d \tilde{M}_t + \varepsilon_t \tag{3.3}$$

where $\tilde{M}_t = \hat{b}M_t$, $\hat{b}$ is estimated from the regression (2). The regression (3) estimates δ^d for each day from Jan 1990 to the end of sample over one-year rolling windows. Because δ^d is estimated at the second stage ($\hat{b}$ is estimated at the first stage), we also take into account this two-stage estimation error following Swanson and William (2014) when the standard error is calculated.

3.2 Estimation Results

Table B.1 reports the results for the regression (1) over the "normal" sample from 1990 to 2000 (results are very similar for the entire sample from 1990 - 2012). These results are robust to whether or not we add lags of M_t. Note again that one unit increase in monetary policy shock is normalized to increase 2 year Treasuries by the same amount. Over the period of 1990 - 2000, 1 percent increase in monetary policy shock increase AAA yields, BAA yields, 2 year Treasuries and 10 year Treasuries by 0.5431 percent, 0.5723 percent, 1.1285 percent and 0.9031 percent, respectively, all of which are significant. As expected, it increases the VIX index by 0.2119 percent, but lowers the stock market return by 4.4505 percent.

[9] As noted by Swanson and William (2014), this period is supposed to be a "normal" period during which monetary policies are not constrained by the zero lower bound.

Table 3.1. Coefficient Estimates β From The Linear Regression (1) Over 1990-2000

Variables	AAA Yields	BAA Yields	2 yr Treasuries	10 yr Treasuries	SP500	VIX
MP Shock	0.5431	0.5723	1.1285	0.9031	-4.4505	0.2119
	(0.0860)	(0.0699)	(0.0475)	(0.0686)	(1.2886)	(0.0773)
Obs.	5731	5731	5729	5729	5719	5713
Event Dates	366	366	366	366	366	366
R^2	0.02	0.02	0.05	0.03	< 0.01	< 0.01

Note: MP shock denotes monetary policy shock. It is measured by the first principle component of three-year rolling sample of the daily changes of 1,2,5,7,10 year Treasury yields around the FOMC announcement and minute dates. It is normalized to have 1 to 1 relationship with 2 year Treasuries. Heteroskedasticity-consistent t statistics in parentheses.

The estimation results in Table 3.2 show the coefficient estimates b from the regression (2). Results are similar to those in Table B.1. The estimates for the sensitivity of the stock return and VIX index become larger. We also report the R squares and the p value of testing whether δ^{d_i} is constant over time[10]. Consistent with the model, the hypotheses that δ^{d_i} is constant over time are rejected for all specifications.

Figure 3.1 and 3.2 report the time-varying sensitivity coefficients δ^{d_i} from the regression (3). The blue solid line in each plot is the estimated value of δ^{d_i} on each date d. The dotted lines are the 95% confidence intervals along time. Horizontal line at 1 is drawn for each panel in order to make a contrast with the benchmark period. The lightly shaded regions (yellow) depict periods during which δ^{d_i} is significantly below 1 but significantly larger than zero. The red shaded regions denote periods during which δ^{d_i} is significantly below 1 and not significantly different from zero.

Panel A of figure 3.1 depicts the sensitivity of AAA yields to monetary policy shocks. It shows that the sensitivity does not fall significantly below 1 at the ZLB

[10]We do not need to test the hypothesis that relative b is constant over time because we only have one regressor.

Table 3.2. Constant Coefficient *b* Estimates From The Time-Varying Regression (2)

Variables	AAA Yields	BAA Yields	2 yr Treasuries	10 yr Treasuries	SP500	VIX
MP Shock	0.6048	0.5822	1.0812	0.9746	-9.0091	0.2516
	(0.0542)	(0.0539)	(0.0349)	(0.0442)	(3.0047)	(0.1575)
Obs.	5731	5731	5729	5729	5719	5713
Event Dates	366	366	366	366	366	366
R^2	0.0306	0.0318	0.0659	0.0560	0.0112	0.0082
$H_0 : \delta$ constant	0	0	0	0	0	0

Note: MP shock denotes monetary policy shock. It is measured by the first principle component of three-year rolling sample of the daily changes of 1,2,5,7,10 year Treasury yields around the FOMC announcement and minute dates. It is normalized to have 1 to 1 relationship with 2 year Treasuries. Heteroskedasticity-consistent t statistics in parentheses. δ constant is for the hypothesis that $\delta^d = 1$ for all years in the sample.

though it varies over time. Actually, the sensitivity mostly stays above 1 during the ZLB period. Wright (2012) also found that corporate bond yields responded significantly to unconventional monetary policy shocks. We complement Wright (2012) by pointing out that this responsiveness is also as strong as in the normal period 1990-2000. The results for BAA yields are reported in Panel B of figure 3.1. It is clear that the sensitivity of BAA yields is similar as AAA yields. It is worth noting that although the confidence intervals get larger at the ZLB, the response of BAA yields remain quite sensitive to monetary policy shocks even at 2012[11].

Panel C of figure 3.1 presents the results for 2 year Treasuries. Two year Treasury yield was very insensitive to monetary policy shocks at the ZLB, reflecting a large constraint of the ZLB on the short-term bond yields. However, the ZLB posed little constraints on the yields of long term bonds as can be seen from Panel D of figure 3.1[12].

[11]During 2002-2003, BAA yields are quite insensitive to monetary policy shocks.

[12]The long-term Treasury yields reacted less in the Great Recession periods (2007-2008), during which the fed funds rate was higher than the ZLB.

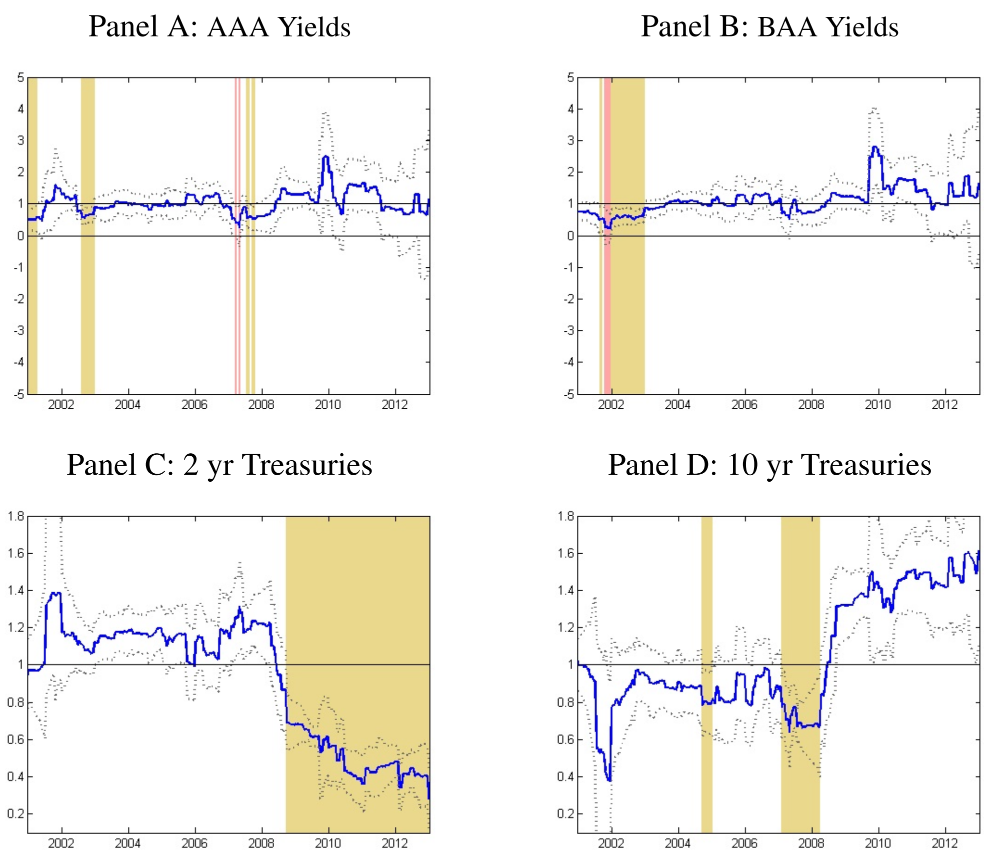

Figure 3.1. Time-varying Sensitvity Coefficients δ^d

At the ZLB, the traditional policy instrument – fed funds rate – was no longer effective. The unconventional monetary policies the Fed conducted during this period aim to bring down long-term interest rates. That is the reason why long-term interest rates were still quite responsive to monetary policy shocks in the ZLB period, while short-term interest rates were largely constrained.

Panel A: S&P500 Panel B: VIX

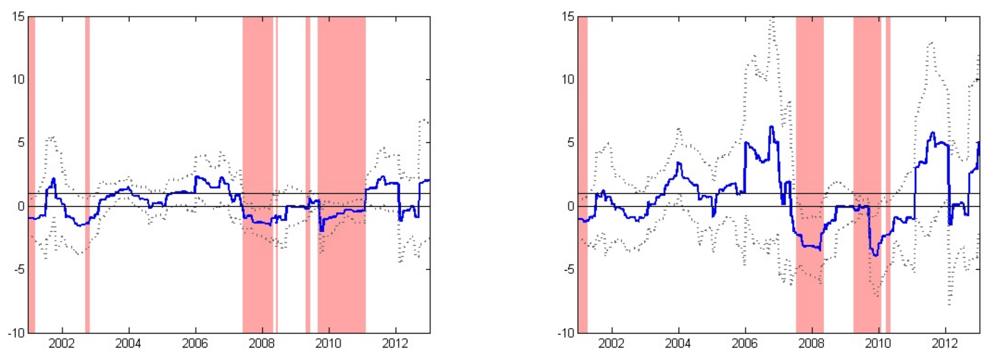

Figure 3.2. Time-varying Sensitvity Coefficients δ^d

Figure 3.2 presents the results for the VIX index and the S&P 500 index, which strongly contrasts figure 3.1. The Great Recession and the ZLB appear to pose a serious constraint on the power of monetary policies to affect the stock market. Although the estimates are quite volatile, they remained largely over 1 prior to the ZLB period for both the VIX index and the S&P 500 index. During 2008-2010, the sensitivity dropped immensely implying the limitation of monetary policies on affecting the stock market. However, the sensitivity bounced back quickly after 2010 when the economy started to recover.

3.3 Conclusions

Have monetary policy shocks become less powerful over the period of 2000-2012, especially during the ZLB? This paper attempts to answer this question by studying the time-varying effect of monetary policy shocks. We find that the corporate bond market stayed highly sensitive to monetary policy shocks throughout the Great Recession and the ZLB. While the 2 year Treasury yield was severely constrained by the ZLB, the 10 year Treasury yield remained highly responsive to monetary policy shocks over the entire sample except a short period in the Great Recession. The stock market became less responsive to monetary policy shocks from 2008 to 2010. But this sensitivity recovered quickly after 2011. Overall, our findings imply that monetary policy still has large power even at the ZLB period, although its effect on the stock market and the short-term Treasury bond market is qualified.

3.4 Acknowledgements

Chapter 3, “Are Financial Markets Less Responsive to Monetary Policy Shocks at the Zero Lower Bound?”, in full, is a reprint of the material as it appears in Economics Letters 2016, 145: 258-261. Wenbin Wu. The dissertation author was the sole author of this paper.

Appendix A

Chapter 1

A.1 A Simple Example of Sales

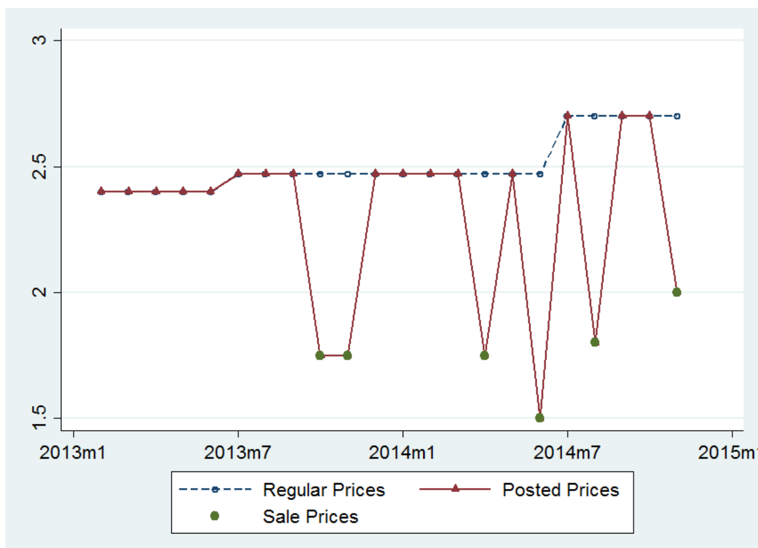

Figure A.1. The Price of *WHOLE SPONGE CAKE NOT FROZEN*

Note: This figure plots the prices of WHOLE SPONGE CAKE NOT FROZEN from January 2013 to December 2014.

Figure A.1 provides an example to illustrate sales , posted price, and regular price. I plot the prices of *whole sponge cake (not frozen)* in the period January 2013 to December 2014. Temporary prices are represented by the red points in Figure A.1. The regular prices are the posted prices that are carried forward from the previous non-sale period. They are depicted by the blue dashed line. The posted prices are represented by the solid red line.[1]

To illustrate how to compute the sale-related inflation, assume there is only one good in the economy. Before the first sale at October 2013, the aggregate inflation equals the regular-price inflation $\pi_t = \pi_t^R$, $\pi_t^T = 0$. The first sale lasted for two periods, from October 2013 to November 2013, and the price dropped from \$2.49 to \$1.75. From September 2013 to October 2013, the aggregate inflation equals the sale-related inflation $\pi_t = \pi_t^T = -29.7\%$, and $\pi_t^R = 0$. From October to November, . Then, from November to December, . Other sales episodes are calculated using the same algorithm.

A.2 Additional Figures and Tables

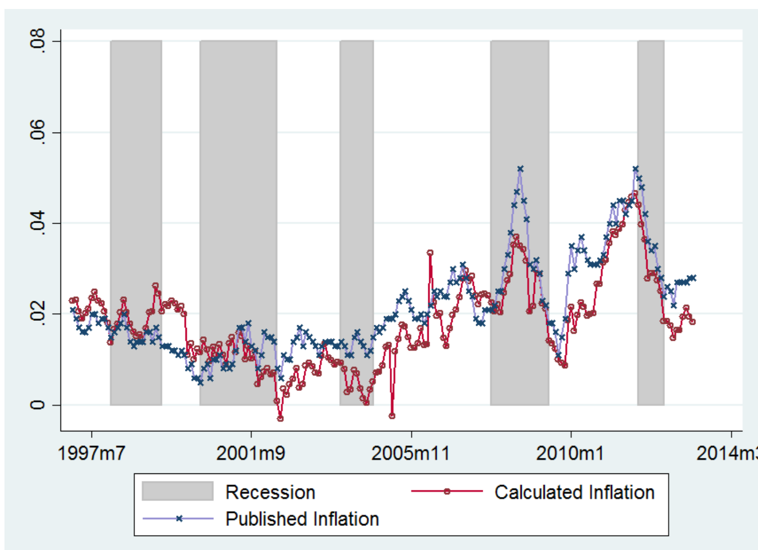

Figure A.2. The Calculated Inflation and the Published Inflation

Note: This figure plots calculated inflation against published inflation. The gray areas represent recession periods for the UK. The calculated inflation is based on data underlying the UK CPI over the period of January 1997 to December 2013.

[1]See Section 2 for more discussion of the different treatment of sales and regular prices.

A.3 KM's Algorithm to Construct Temporary Price Changes

Kehoe and Midrigan (2015) modify the algorithm of EJR to identify temporary price changes (or equivalently regular price changes). This algorithm is applied to each good or service separately. The basic idea is to identify those price changes that temporarily deviate from the "reference price," which is defined as the modal price in a window of five months. I list the steps of constructing the temporary price changes as follows:

Step 1: Compute the modal prices p_t^M within a window of five months for each good or service. The modal price is set to be missing if the number of periods within the window is less than 2.

Step 2: Compute the regular price p_t^R as the modal price p_t^M if at least one-third of the prices are equal to the modal price in the window that includes two periods, both before and after. Otherwise, I set the regular price equal to p_{t-1}^R. [2]

Step 3: Adjust regular prices, p_t^R obtained from Step 2 so that regular prices do not change if the actual prices do not change. This step strictly follows Kehoe and Midrigan (2015). I set last period's regular price p_{t-1}^R equal to this period's actual price p_t if $p_{t-1}^R \neq p_t^R$ and $p_t^R = p_t$ (p_t^R, p_{t-1}^R not missing). Also, I set this period's regular price p_t^R equal to the last period's actual price, p_{t-1} if $p_{t-1}^R \neq p_t^R$ and $p_{t-1}^R = p_{t-1}$ (p_t^R, p_{t-1}^R not missing).

For more details, see Kehoe and Midrigan (2015).

[2] The initial regular price is set to the modal price.

Appendix B

Chapter 2

B.1 FOMC dates

Table B.1. FOMC dates

Date	Event	Time	Date	Event	Time
12/16/2008	FOMC Meeting	14:15	1/26/2011	FOMC Meeting	14:15
1/28/2009	FOMC Meeting	14:15	3/15/2011	FOMC Meeting	14:15
3/18/2009	FOMC Meeting	14:15	4/27/2011	FOMC Meeting	12:30
4/29/2009	FOMC Meeting	14:15	6/2/2011	FOMC Meeting	12:30
6/24/2009	FOMC Meeting	14:15	8/9/2011	FOMC Meeting	14:15
8/12/2009	FOMC Meeting	14:15	9/21/2011	FOMC Meeting	14:15
9/23/2009	FOMC Meeting	14:15	11/2/2011	FOMC Meeting	12:30
11/4/2009	FOMC Meeting	14:15	12/13/2011	FOMC Meeting	14:15
12/16/2009	FOMC Meeting	14:15	1/25/2012	FOMC Meeting	12:30
1/27/2010	FOMC Meeting	14:15	3/13/2012	FOMC Meeting	14:15
3/16/2010	FOMC Meeting	14:15	4/25/2012	FOMC Meeting	12:30
4/28/2010	FOMC Meeting	14:15	6/20/2012	FOMC Meeting	12:30
6/23/2010	FOMC Meeting	14:15	8/1/2012	FOMC Meeting	14:15
8/10/2010	FOMC Meeting	14:15	9/13/2012	FOMC Meeting	12:30
9/21/2010	FOMC Meeting	14:15	10/24/2012	FOMC Meeting	14:15
11/3/2010	FOMC Meeting	14:15	12/12/2012	FOMC Meeting	12:30
12/14/2010	FOMC Meeting	14:15			

Note: Data are collected by the author from website of Federal Reserve Board.

B.2 Did The Stock Market React to Unconventional Monetary Policy?

B.2.1 Simple event study

Table B.2 reports the estimation results from the event study. The results from daily and intraday estimations are listed. The daily and 30min intraday estimates give us the upper and lower bound of the effect of unconventional monetary policy shocks during the FOMC announcements.

B.2.2 Heteroskedasticity-based estimation

As in the OLS estimation, a long term interest rate is also used to normalize monetary policy shock. Heteroskedasticity-based estimation is able to address several potential issues: (1) long term interest rates tend to be affected by more shocks than short term rates. Consequently, using the changes in long term interest rates at the FOMC dates(or announcement windows) to approximate monetary policy shock might be inappropriate if monetary policy news does not dominate other shocks. (2)Because long term rates are not commonly recognized as the policy instrument and is not the only way through which monetary policy affects the stock market, monetary policy shock may affect the stock market indirectly through changes in interest rates and directly through other channels. Therefore, a more general way to model the relationship between stock market returns and unconventional monetary policy shocks is given as

$$
\begin{aligned}
\Delta LR(t) &= a_1 \Delta \ln(P(t)) + \Delta H(t) + \Delta Z(t) + e(t) \\
\Delta \ln(P(t)) &= a_2 \Delta LR(t) + b \Delta H(t) + c \Delta Z(t) + \upsilon(t)
\end{aligned}
$$

where $\Delta Z(t)$ is an non-monetary common shock, $\Delta H(t)$ is modeled explicitly as unconventional monetary policy shock that simultaneously affects long term interest rate and

Table B.2. Stock Returns around The Baseline and The Full Event Set Announcements

				S&P500 Return		10year yield	
Date	Event	Baseline	Time	Daily	Intraday	Daily	Intraday
11/25/2008	Initial Announcement	1	8:15	0.19	-	-8	-
12/16/2008	FOMC Meeting	1	14:15	4.67	1.58	-14	-10.9
3/18/2009	FOMC Meeting	1	14:15	2.34	1.48	-48	-44.1
8/10/2010	FOMC Meeting	1	14:15	-0.17	0.67	-3	-6.2
9/21/2010	FOMC Meeting	1	14:15	-0.27	0.60	-9	-1.4
8/9/2011	FOMC Meeting	1	14:15	4.56	-0.94	-21	-2.4
9/21/2011	FOMC Meeting	1	14:15	-3.11	-0.26	-5	-5.8
6/20/2012	FOMC Meeting	1	12:30	-0.17	-0.06	0	-3.5
8/31/2012	Bernanke Speech	1	10:00	0.46	-0.10	-8	-1.8
9/13/2012	FOMC Meeting	1	12:30	1.62	0.61	2	7.7
12/1/2008	Bernanke Speech	0	13:15	-8.50	-0.74	-16	-11.7
1/28/2009	FOMC Meeting	0	14:15	3.30	-0.11	10	1.4
4/29/2009	FOMC Meeting	0	14:15	1.94	0.74	9	6.4
6/24/2009	FOMC Meeting	0	14:15	0.52	-0.55	3	9.9
8/12/2009	FOMC Meeting	0	14:15	1.18	-0.21	4	2.8
9/23/2009	FOMC Meeting	0	14:15	-1.11	0.53	-6	-7.7
11/4/2009	FOMC Meeting	0	14:15	-0.06	0.10	4	2.5
12/16/2009	FOMC Meeting	0	14:15	0.05	-0.09	1	3.4
1/27/2010	FOMC Meeting	0	14:15	0.51	0.07	1	2.3
3/16/2010	FOMC Meeting	0	14:15	0.75	0.19	-6	-1.7
4/28/2010	FOMC Meeting	0	14:15	0.57	0.23	4	1.4
6/23/2010	FOMC Meeting	0	14:15	-0.32	0.34	-6	0
11/3/2010	FOMC Meeting	0	14:15	0.35	-0.43	-1	7.1
12/14/2010	FOMC Meeting	0	14:15	-0.02	-0.01	13	2.6
1/26/2011	FOMC Meeting	0	14:15	0.36	-0.08	5	1.7
3/15/2011	FOMC Meeting	0	14:15	-0.51	0.33	9	2
4/27/2011	FOMC Meeting	0	12:30	0.53	0.14	2	-1.6
6/22/2011	FOMC Meeting	0	12:30	-0.65	0.08	3	2.4
11/2/2011	FOMC Meeting	0	12:30	1.49	-0.17	-4	0.5
12/13/2011	FOMC Meeting	0	14:15	-0.90	-0.70	-8	-1.6
1/25/2012	FOMC Meeting	0	12:30	0.88	0.35	-4	-5.4
3/13/2012	FOMC Meeting	0	14:15	1.74	-0.05	6	4.1
4/25/2012	FOMC Meeting	0	12:30	1.35	-0.05	-1	1.9
8/1/2012	FOMC Meeting	0	14:15	-0.29	-0.22	5	1.9
10/24/2012	FOMC Meeting	0	14:15	-0.32	-0.06	-1	-0.4
12/12/2012	FOMC Meeting	0	12:30	0.04	0.38	4	3.4
Baseline cumulative change				10.12*	3.59***	-114***	-68.4***
Full event set cumulative change				12.99	3.62*	-84*	-40.8***

Note: Daily change is calculated by taking the difference between the close and open quote at the announcement date[1]. Yields are in basis points. Returns are measured in percentage. I bootstrap the p-value based on the data from 9/15/2008 to 12/31/2012. *** p<0.01, ** p<0.05, * p<0.1.

the stock market return, and $e(t)$,$\upsilon(t)$ are idiosyncratic shocks. This model has several appealing features: (1) simultaneity is modeled explicitly; (2) there are other common shocks $\Delta Z(t)$ for both the stock market return and interest rate yield; (3) unconventional monetary policy shock $\Delta H(t)$ is allowed to directly affect the stock market returns.

The identification of this model requires a simple assumption, as follows. First, I simplify my model to be

$$\begin{aligned} LR(t) &= \Delta H^*(t) + \Delta Z^*(t) + e^*(t) \\ \Delta \ln(P(t)) &= \beta^*\left[\Delta LR(t) - c^*\Delta Z^*(t) - e^*(t)\right] + c^*\Delta Z^*(t) + \upsilon^*(t) \end{aligned}$$

where variables with * are normalized again[2]. β^* is the parameter we are interested in because $\Delta LR(t) - c_1^*\Delta Z(t) - e^*(t) = \Delta H^*(t)$ – the renormalized monetary policy shock. We may further simplify the system to

$$\Delta \ln(P(t)) = \beta^*\left[\Delta LR(t) - T(t)\right] + \varepsilon(t)$$

where $T(t) = c^*\Delta Z^*(t) + e^*(t)$. $T(t)$ is allowed to be correlated with $LR(t)$, but it must satisfy the homoskedasticity assumption below.

[2]It is easy to see that

$$\begin{aligned} \beta^* &= \frac{a_2 + b}{a_1 b + 1} \\ \Delta H^*(t) &= \frac{a_1 b + 1}{1 - a_1 a_2}\Delta H(t) \\ \Delta Z^*(t) &= \frac{a_1 c + 1}{1 - a_1 a_2}\Delta Z(t) \\ e^*(t) &= \frac{1}{1 - a_1 a_2}e(t) + \frac{a_1}{1 - a_1 a_2}\upsilon(t) \\ \upsilon^*(t) &= \frac{1}{1 - a_1 a_2}\upsilon(t) + \frac{a_2}{1 - a_1 a_2}e(t) \\ c^* &= \frac{a_2 + c}{a_1 c + 1} \end{aligned}$$

Second, we need to identify two subsamples, which are denoted as M and NM. M is the narrow event window around the FOMC announcements and NM represents the *prewindows*, which have the same length as the event window but immediately precede it. We also need an assumption regarding the second moment of the shocks present in my model.

Assumption 1: $\sigma_H^M > \sigma_H^{NM}$, $\sigma_T^M = \sigma_T^{NM}$.

A similar assumption was used in Rigobon and Sack (2004). The assumption $\sigma_H^M > \sigma_H^{NM}$ should hold intuitively since monetary policy shocks are larger around the FOMC announcements than they are in other periods. In order to implement this new estimator, I use the IV approach (see Appendix A5 for more details). The announcement event windows and their corresponding prewindows are chosen to serve as two subsamples. The event window starts 10 minutes before and ends 20 minutes after the FOMC announcement, while the pre-window starts 40 minutes before and ends 10 minutes before the announcement.

B.3 Disaggregate Effect of Unconventional Monetary Policy

See Table (B.3) and Table (B.4).

Table B.3. Unconventional Monetary Policy Announcement Dates

Date	Event	Category	Time
11/25/2008	*Initial Announcement*	*LSAP 1*	*8:15*
12/16/2008	FOMC Meeting	LSAP 1	14:15
3/18/2009	FOMC Meeting	LSAP 1	14:15
8/10/2010	FOMC Meeting	LSAP 2	14:15
9/21/2010	FOMC Meeting	LSAP 2	14:15
8/9/2011	FOMC Meeting	Forward Guidance	14:15
9/21/2011	FOMC Meeting	Operation Twist	14:15
6/20/2012	FOMC Meeting	Operation Twist	12:30

Note: QE3 dates are not included because of their little impact on the yield curve and the stock market.

B.4 Evidence on the Credit Channel

As described in the Section 2, I use the long-term interest rate to normalize monetary policy shocks. I model the relationship between individual stock returns and unconventional monetary policy shocks by[3]

$$\Delta LR(t) = a_1 \Delta \ln(P(t)) + b_1 \Delta H(t) + c_1 \Delta Z(t) + e(t)$$

$$\Delta \ln(P(t)) = a_2 \Delta LR(t) + b_2 \Delta H(t) + c_2 \Delta Z(t) + \upsilon(t)$$

$$\Delta \ln(P_i(t)) = a_3 \Delta \ln(P(t)) + a_4 \Delta LR(t) + b_3 \Delta H(t) + c_3 \Delta Z(t) + u(t),$$

where $\Delta H(t)$ represents unconventional monetary policy shock that affects the change in long-term interest rate $\Delta LR(t)$, the stock market return $\Delta \ln(P(t))$, and individual stock returns $\Delta \ln(P_i(t))$ simultaneously. $\Delta \ln(P_i(t))$ is the stock return of firm i. $\Delta Z(t)$ is another common shock that is homoskedastic. $e(t)$, $\upsilon(t)$ and $u(t)$ are idiosyncratic shocks.

[3] See online appendix A.2.2 for a similar but simpler model, which we used to examine the relationship between the stock market and monetary policy shocks.

Table B.4. Estimation Results from Heteroskedasticity Estimation

LSAP				
	High	Medium	Low	Diff(H-L)
Market Cap	4.72***	4.33***	4.13***	0.58*
Employee	4.58***	4.17***	4.34***	0.25
Debt to Total Capital	4.74***	4.20***	3.73***	1.01**
Long term debt rating	4.77***	4.29***	4.24***	0.53*
Forward Guidance				
	High	Medium	Low	Diff(H-L)
Market Cap	-1.11	-0.85	-0.75	-0.36
Employee	-0.73	-0.82	-0.8	0.07
Debt to Total Capital	-0.92	-0.77	-0.92	0
Long term debt rating	-0.71	-0.88	-0.66	-0.05
Operation Twist				
	High	Medium	Low	Diff(H-L)
Market Cap	-0.55	-0.64	-0.51	-0.04
Employee	-0.45	-0.56	-0.62	0.17
Debt to Total Capital	-0.53	-0.62	-0.37	-0.16
Long term debt rating	-0.37	-0.61	-0.62	0.25

Note: All of the results are computed using the baseline event set. I use a 30-minute event window, i.e., 10 minute before and 20 minute after the announcements. I categorize the firms as unequal division, i.e., $< 10\%$, 10–90%, and $> 90\%$. Four financial constraint measures are used to divide the firms into three different groups ranging from low financial constraint intensity to high financial constraint intensity. I perform the divisions on a daily basis to control for the asymmetries of monetary policy over time. I bootstrap the p-values by comparing the returns from the baseline event dates to those drawn randomly from September 5, 2008 to December 31, 2012. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

This model considers the fact that individual stock returns are affected by both the market return and interest rate changes. Moreover, it also considers other common shocks $\Delta Z(t)$, and the direct effect of a monetary policy shock $\Delta H(t)$. Essentially, the OLS estimation is equivalent to my heteroskedasticity-based estimation if $\Delta Z(t)$ and all idiosyncratic shocks $e(t), \upsilon(t)$ and $u(t)$ are very small (close to zero), i.e., if monetary policy shocks dominate all other shocks. My model is probably more robust due to its generality, but it cannot be identified unless some assumptions are allowed.

Following the steps similarly in the Section A.2.2, it is easy to simplify the above model to

$$\Delta \ln(P_i(t)) = \alpha_4 + \beta_4 [\Delta LR(t) - T(t)] + \varepsilon(t)$$

where $\Delta LR(t) = T(t) + \Delta H(t)$. $T(t)$ is an expression in terms of $\Delta Z(t), e(t), \upsilon(t)$ and $u(t)$. $T(t)$ can be correlated with $LR(t)$ but I need it to be homoskedastic across two regimes. Hence, we go back to single equation identification, which has already been shown in the previous section.

B.5 Implementation methods - IV approach

My model is[4]

$$\Delta \ln P_t = \alpha_1 + \beta_1 [\Delta LR_t - e_t] + \upsilon_t$$

It is easy to see that α_1 can be normalized to 0 if we demean both sides of the previous equation. Rewrite the model as

$$\begin{aligned} \Delta \ln P_t &= \beta_1 \Delta H_t + \upsilon_t, \\ \Delta LR_t &= \Delta H_t + e_t \end{aligned} \tag{B.1}$$

where ΔLR_t is the change in the long-term rate and $\Delta \ln P_t$ is the change in the equity price, ΔH_t is unobservable unconventional monetary policy shock. e_t and υ_t are idiosyncratic shocks.

Note that my model generalizes Rigobon and Sack (2004) as follows: (1) I use long term interest rate instead of short term interest rate to measure the size of monetary policy surprise; (2) I allow monetary policy shock to influence both long term interest rate and the stock market return simultaneously.

Heteroskedasticity-based estimation – We may be concerned about the effect of the non-negligible error term e_t, which might cause an error-in-variable problem.

To deal with this problem, we need to identify two subsamples, which are denoted as M and NM. M is the narrow event window around the FOMC announcements and NM represents the *prewindows*, which have the same length as the event window but

[4]To keep the derivation more clear, we move the time notation from the parenthesis to the subscript.

immediately precede it. We also need an assumption regarding the second moment of the shocks present in my model.

Assumption 1: $\sigma_H^M > \sigma_H^{NM}$, $\sigma_e^M = \sigma_e^{NM}, \sigma_\upsilon^M = \sigma_\upsilon^{NM}$.

Assumption 2: $E\left[\Delta H_t e_t\right] = E\left[\Delta H_t \upsilon_t\right] = 0$.

This implementation is very similar to Rigobon and Sack (2004), except that I use a different model and want to identify different parameters. Denote the variance covariance matrix of each subsample as

$$\begin{aligned} \Omega^M &= E\left[\left[\Delta LR_t^M \ \Delta \ln P_t^M\right]' * \left[\Delta LR_t^M \ \Delta \ln P_t^M\right]\right] \\ \Omega^{NM} &= E\left[\left[\Delta LR_t^{NM} \ \Delta \ln P_t^{NM}\right]' * \left[\Delta LR_t^{NM} \ \Delta \ln P_t^{NM}\right]\right] \end{aligned} \tag{B.2}$$

It is clear that

$$\begin{aligned} \Omega^M &= E\begin{bmatrix} \left(\Delta LR_t^M\right)^2 & \Delta LR_t^M \Delta \ln P_t^M \\ \cdot & \left(\Delta \ln P_t^M\right)^2 \end{bmatrix} \\ &= \begin{bmatrix} \left(\sigma_H^M\right)^2 + \left(\sigma_e^M\right)^2 & \beta_1\left(\sigma_H^M\right)^2 \\ \cdot & \beta_1^2\left(\sigma_H^M\right)^2 + \left(\sigma_\upsilon^M\right)^2 \end{bmatrix} \end{aligned}$$

The second equality follows from $E\left[\Delta H_t e_t\right] = E\left[\Delta H_t \upsilon_t\right] = 0$.

If we take the difference between these two covariance matrices and let $\left(\sigma_H^M\right)^2 - \left(\sigma_H^{NM}\right)^2 = \lambda$, we have

$$\begin{aligned}
\Delta\Omega &= \Omega^{M}-\Omega^{NM} \\
&= \begin{bmatrix} \lambda & \beta_1\lambda \\ \cdot & \beta_1^2\lambda \end{bmatrix} \\
&= \lambda \begin{bmatrix} 1 & \beta_1 \\ \cdot & \beta_1^2 \end{bmatrix}
\end{aligned}$$

Then, it is clear that β_1 can be estimated as follows,

$$\hat{\beta}_1 = \frac{\Delta\hat{\Omega}_{12}}{\Delta\hat{\Omega}_{11}} \quad \text{or} \quad \tilde{\beta}_1 = \frac{\Delta\hat{\Omega}_{22}}{\Delta\hat{\Omega}_{12}}$$

Now,

$$\begin{aligned}
\hat{\beta}_1 &= \frac{\Delta\hat{\Omega}_{12}}{\Delta\hat{\Omega}_{11}} \\
&= \frac{cov\left(\Delta LR_t^{M}, \Delta\ln P_t^{M}\right) - cov\left(\Delta LR_t^{NM}, \Delta\ln P_t^{NM}\right)}{var\left(\Delta LR_t^{M}\right) - var\left(\Delta LR_t^{NM}\right)} \\
&= \frac{E\left[\left(\Delta LR_t^{M}, -\Delta LR_t^{NM}\right)\left(\Delta\ln P_t^{M}, \Delta\ln P_t^{NM}\right)'\right]}{E\left[\left(\Delta LR_t^{M}, -\Delta LR_t^{NM}\right)\left(\Delta LR_t^{M}, \Delta LR_t^{NM}\right)'\right]}
\end{aligned}$$

That is to say, we may use IV approach below to implement this estimator. For $S_1 \in M, S_2 \in NM$, let $\Delta R = \left[\Delta R'_{S_1} \;\; \Delta R'_{S_2}\right]'$, $\Delta P = \left[\Delta\ln P'_{S_1} \;\; \Delta\ln P'_{S_2}\right]'$, and $w_i = \left[\Delta R'_{S_1} \;\; -\Delta R'_{S_2}\right]'$, then

$$\hat{\beta}_1 = \left(w_i'\Delta R\right)^{-1}\left(w_i'\Delta P\right)$$

Intuitively, why $\left(\Delta LR_t^{M}, -\Delta LR_t^{NM}\right)$ is able to instrument $\left(\Delta LR_t^{M}, \Delta LR_t^{NM}\right)$? First, it is clear that they are correlated. Second, $\left(\Delta LR_t^{M}, -\Delta LR_t^{NM}\right)$ does not correlate with

$\left(e_t^M, e_t^{NM}\right)$, because

$$\begin{aligned} & E\left[\left(\Delta LR_t^M, -\Delta LR_t^{NM}\right)\left(e_t^M, e_t^{NM}\right)'\right] \\ = & \left(\sigma_e^M\right)^2 - \left(\sigma_e^{NM}\right)^2 = 0 \end{aligned}$$

where the second equality follows from Assumption 1.

A similar approach is applicable for another estimator $\tilde{\beta}_1$. I follow Rigobon and Sack (2004) to report only the first estimator. Empirically, the reason might be that $\left(\Delta LR_t^M, -\Delta LR_t^{NM}\right)$ is a better instrumental variable for $\left(\Delta LR_t^M, \Delta LR_t^{NM}\right)$ than $\left(\Delta \ln P_t^M, -\Delta \ln P_t^{NM}\right)$ because the former one has a higher correlation and thus is more relevant.

B.6 Distribution of the responses (Het)

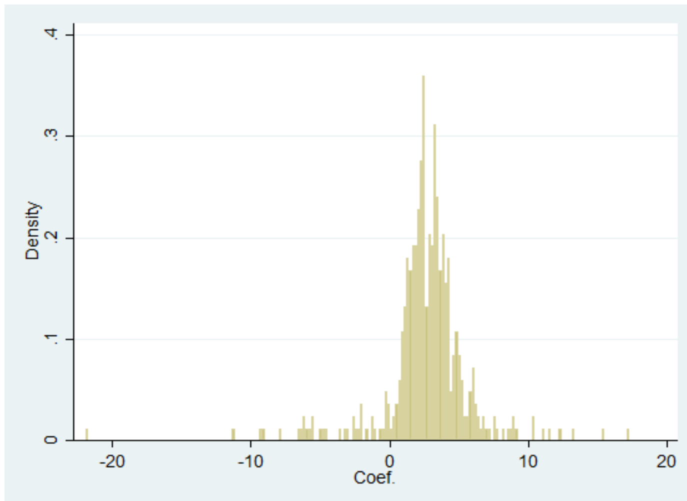

Figure B.1. Distribution of the responses from heteroskedasticity-based estimation

Figure B.1 shows the distribution of the estimated responses of individual stock return on unconventional monetary policies normalized by 10 year yield rate.

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