Reference Prices, Costs and Nominal Rigidities*

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Abstract

We assess the importance of nominal rigidities using a new weekly scanner data set. We find that nominal rigidities are important but do not take the form of sticky prices. Instead, they take the form of inertia in reference prices and costs, defined as the most common prices and costs within a given quarter. Reference prices are particularly inertial and have an average duration of roughly one year, even though weekly prices change roughly once every two weeks. We document the relation between prices and costs and find sharp evidence of state dependence in the probability of reference price changes and in the magnitude of these changes. We use a simple model to argue that reference prices and costs are useful statistics for macroeconomic analysis.

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1. Introduction

A central question in macroeconomics is whether nominal rigidities are important. In addressing this question the literature generally assumes that these rigidities take the form of sticky prices, i.e. prices that do not respond quickly to shocks. An important new literature discussed below assesses the importance of nominal rigidities by measuring how often prices change. In this paper we argue that nominal rigidities are important but they do not necessarily take the form of sticky prices or, for that matter, sticky costs. Instead, they take the form of inertia in 'reference prices' and 'reference costs.' By reference price (cost) we mean the most often quoted price (cost) within a given time period, say a quarter.[1] In our data set prices and costs change very frequently: the median duration is only three weeks for prices and two weeks for costs. However, the duration of reference prices is almost one year, while the duration of reference costs is almost two quarters. So both reference prices and reference costs are much more inertial than weekly prices and weekly costs.

What determines the duration of reference prices? Our analysis focuses on the relation between prices and costs paying particular attention to their reference values. We rely on a unique data set that consists of weekly observations on price and cost measures for each item sold by a major U.S. retailer in over 1,000 stores. We find that prices are systematically but imperfectly related to costs. Strikingly, prices rarely change unless there is a change in cost. However, prices do not always change when costs change, so there is substantial variation in realized markups.

Our analysis suggests that the retailer chooses the duration of reference prices

[1] The existence of reference prices has been noted by various authors in the industrial organization literature (see, for example Warner and Barsky (1995), Slade (1998), Ariga, Matsui, and Watanabe (2001), Pesendorfer (2002), Hosken and Reiffen (2004), and Goldberg and Hellerstein (2008)). With the exception of Goldberg and Hellerstein (2007) who use the Dominick's data on the cost of beer, the other papers do not have data on cost.

so as to limit markup variation. We base this inference on three findings. First, in over 90 percent of the observations the realized weekly markup is between plus and minus 10 percent of the average markup.[2] Significantly, this pattern holds for groups of goods with different reference price durations. Second, there is sharp evidence of state dependence in the probability of reference price changes. The probability of a reference price change is increasing in the difference between the markup that would obtain if the price did not change and the average value of the markup. Third, when the retailer changes reference prices it re-establishes the value of the unconditional markup, i.e. the retailer passes through all the changes in reference costs that have occurred since the last reference price change. Taken together, these findings support the view that the retailer chooses the duration of reference prices to keep markups within relatively narrow bounds.

We argue that our evidence is inconsistent with the three most widely used pricing models in macroeconomics: flexible-price models, standard menu-cost models, and Calvo-style pricing models. There is, however, a simple pricing rule that is consistent with our evidence. This rule can be described as follows. Prices do not generally change unless costs change. The unconditional markup and the duration of the reference price is good specific. For any given good the nominal reference price is on average a particular markup over nominal reference cost. The retailer resets the reference price so as to keep the actual markup within plus/minus 10 percent of the desired markup over reference cost. On average when the retailer changes the reference price it reestablishes the unconditional markup. With this rule reference prices can exhibit substantial nominal rigidities even though weekly prices change frequently.

Our results raise an obvious question: why should a macroeconomist care

[2] Our agreement with the retailer does not permit us to report information about the level of the markup for any one item or group of items.

about reference prices and costs? One possibility is that macroeconomists can safely abstract from high-frequency movements in prices and costs when analyzing the nature of the monetary transmission mechanism. From this perspective, significant persistence in reference prices and costs are a manifestation of a type of rigidity not present in conventional macro models. Another possibility is that high-frequency movements in prices and cost are important for understanding the monetary transmission mechanism.

To explore these issues we develop a simple partial-equilibrium model which captures key features of the data that we document in our empirical work. In our set up the firm chooses a 'price plan' which consists of a small set of prices. The firm can move between prices in this set without incurring any cost. However, there is a fixed cost of changing the price plan. The model is calibrated so that, amongst other things, it is consistent with the observed duration of weekly and reference price changes. We mimic the effect of a monetary policy shock by considering a shock that, absent pricing frictions, would have no effect on quantities. In the presence of sticky plans a monetary policy shock has a large effect on quantities and very little effect on prices. So, monetary policy has important real effects in our model even though prices change frequently.

Taking our model as the true data-generating process we proceed in the spirit of Kehoe and Midrigan (2007) and address the question: do simpler models provide a good approximation to the real effects of monetary policy? We focus attention on two calibrations of the standard menu-cost model. In the first calibration we choose the menu cost so that the model matches the frequency of observed weekly price changes. As a result, prices are quite flexible and the model generates the misleading conclusion that a monetary policy shock has a very small effect on the level of economic activity. In the second calibration we choose the menu cost so that the model reproduces the observed frequency of reference price changes.

As a result, prices are quite sticky and the model does a very good job of reproducing the real effects of a monetary policy shock. These results suggest that the frequency of reference price changes are more revealing about the underlying nature of nominal rigidities than the simple frequency with which prices and costs change.

Our paper is related to the recent literature which uses micro data sets to measure the frequency of price changes. The seminal article by Bils and Klenow (2004) argues that prices are quite flexible. Using monthly consumer prices index (CPI) data, they find that median duration of prices is 4.3 months. This estimate has became a litmus test for the plausibility of monetary models.[3] In contrast, Nakamura and Steinsson (2007) focus on non-sale prices and argue that these prices are quite inertial. When sales are excluded, prices change on average every eight to 11 months. Kehoe and Midrigan (2007) also examine the impact of sales on price inertia. They use an algorithm to define sales prices that they apply to weekly supermarket scanner data. They find that, when sales observations are excluded, prices change once every 4.5 months. When sales are included, prices change every three weeks. Excluding 'sales prices' from the data has a major impact on inference about price inertia. Not surprisingly, there is an ongoing debate in the literature about how to define a sale and whether one should treat 'regular' and 'sales' prices asymmetrically. An advantage of working with reference prices is that we do not need to take a stand on what sales are or whether they are special events that should be disregarded by macroeconomists.

This paper is organized as follows. Section 2 describes our data and discusses the relation between our measure of cost and marginal cost. In Section 3 we compare the behavior of weekly prices and reference prices. In Section 4 we

[3] See, for example, Altig, Christiano, Eichenbaum, and Linde (2004), and Golosov and Lucas (2006).

contrast the behavior of weekly costs and reference costs. In Section 5 we examine the relation between cost and price changes. In Section 6 we document additional features of the data that are useful for evaluating the plausibility of different pricing models. In Section 7 we discuss the implications of our empirical findings for various price-setting models. In Section 8 we present a simple sticky-plan model which we use to discuss the relevance of reference prices and costs. Section 9 concludes.

2. Data

Our analysis is primarily based on scanner data from a large food and drug retailer that operates more than $1,000$ stores in different U.S. states. The sample period is 2004 to 2006. We have observations on weekly quantities and sales revenue for roughly $60,000$ items in each of the retailer's stores. By an item we mean a good, as defined by its universal product code (UPC), in a particular store. We only include items that are in the data set for a minimum of 12 weeks in every quarter of the entire three-year period. This requirement reduces our sample to 243 stores and 405 thousand UPC-store pairs. Most of the items in our data set are in the processed food, unprocessed food, household furnishings, and 'other goods' categories of the CPI.[4] The retailer classifies items as belonging to one of 200 categories (e.g. cold cereal) and we use the retailer's category classification in our analysis.

We use our data on sales revenue and quantities sold to compute the price for each individual item. The retailer adjusts prices on a weekly basis, so daily movements in prices are not a source of measurement error in our weekly prices measures. Despite the high quality of scanner data there are several potential

[4]Examples of items in the 'other goods' category include laundry detergents, flowers, and magazines.

sources of measurement error associated with our price measure. First, some items are sold at a discount to customers who have a loyalty card. Second, some items are discounted with coupons. Third, there are two, or more, for one promotions. If there are changes over time in the fraction of customers who take advantage of these types of discounts, then our procedure for computing prices would induce spurious price changes. For these reasons, our estimates of the duration of weekly and reference prices provide lower bounds on the true duration statistics.

We construct a weekly measure of the retailer's cost for each item in each store, using data on sales and adjusted gross profit. The latter is defined as:

$$\text{Adjusted gross profit} = \text{Sales} - \text{Cost of goods.}$$

The cost of goods is the vendor cost net of discounts and inclusive of shipping costs. This measure is the most comprehensive cost measure available to us. This cost measure is viewed by the retailer as measuring the replacement cost of an item and it is the cost measure which they use in their pricing decisions.

The relation between our cost measure and marginal cost depends on the nature of the retailer's production function. Suppose, for example, that to sell one unit of an item, the retailer must have one unit of that item and one unit of a composite factor produced using labor and capital. We denote by L the number of units of the composite factor and by w the price of this factor. The wholesale price of the item is given by c. We assume that in the short run L is predetermined. Suppose that the cost of selling Y units of the item is given by:

$$C(Y) = \begin{cases} wL + cY & \text{if } Y \leq L, \\ wL + cL + \psi(Y - L) & \text{if } Y > L. \end{cases}$$

The firm chooses a scale of operation which is summarized by its choice of L. At any point in time, the number of customers entering the store, Y, need not equal L. When Y is greater than L the cost of providing the extra $Y - L$ goods is ψ. We assume that $\psi > w + c$. We can interpret $\psi - (w + c)$ as the implicit cost of a stockout, or the cost of meeting unusually high demand, say by hiring overtime labor and obtaining rush orders from the wholesaler. Nothing of importance that follows depends on this admittedly simplistic model of the cost of meeting unusually high demand.

The retailer chooses L to minimize the expected cost of selling Y units:

$$\min_L E\left[C(Y)\right] = \int_0^L \left(wL + cY\right) f(Y)dY + \int_L^\infty \left[wL + cL + \psi(Y - L)\right] f(Y)dY,$$

where $f(y)$ is the probability density function of Y. Here we make the simplifying assumption that c is known when L is chosen. The optimal value, L^*, satisfies:

$$F(L^*) = 1 - \frac{w}{\psi - c},$$

where $F(.)$ denotes the cumulative density function of Y. Realized total cost is given by:

$$C(Y) = \begin{cases} wL^* + cY & \text{if } Y \leq L^*, \\ (w + c)L^* + \psi(Y - L^*) & \text{if } Y > L^*. \end{cases}$$

As long as $Y \leq L^*$, marginal cost is given by c and our cost measure is a very good proxy for marginal cost. When $Y > L^*$ our cost measure understates actual marginal cost.

There are other production functions for which our cost measure may not correspond closely to marginal cost. For example, suppose that retail output, Y, is given by:

$$Y = AL^{1-\alpha}Q^\alpha,$$

where Q is the number of items purchased by the retailer from the wholesaler. The cost of each item is given by c. As above, suppose that L is predetermined but optimally chosen. Then, short run marginal cost is given by:

$$C'(Y) = \frac{w^{1-\alpha} c^{\alpha} Y^{(1-\alpha)/\alpha}}{\alpha^{\alpha} (1-\alpha)^{1-\alpha} A \left[\int_0^{\infty} (Y^{1/\alpha}) f(Y) dY\right]^{1-\alpha}}.$$

Note that, absent uncertainty, marginal cost is constant.[5] The presence of uncertainty makes marginal cost an increasing function of output. As α goes to one, short-run marginal cost approaches c. So, the higher α is the better our cost measure is as a proxy for marginal cost. In the remainder of the paper we proceed under the assumption that our cost measure is a reasonable proxy for marginal cost.

As a robustness check we use a second data set obtained from Dominick's, a chain of grocery stores in the Midwest with 100 outlets. This data set has been used in a variety of other studies (e.g. Chevalier, Kashyap, and Rossi (2003) and Midrigan (2006)). The Dominick's data set includes weekly observations on price and sales revenue for $3,500$ items over the period 1989-1997. This set includes a cost measure. However, this measure does not correspond to the replacement cost or the last wholesale price at which Dominick's bought the item, but rather the average acquisition cost of the items in inventory. Consequently, we do not use this cost measure.

Our scanner data has advantages and disadvantages relative to the CPI data used by authors such as Bils and Klenow (2004) and Nakamura and Steinsson (2007). A disadvantage is that our data sets do not cover all of the goods in the CPI. However, the median frequency of price change is the same for the items in our data sets and the CPI basket. In this sense, the items in our data set are not unrepresentative of those in the CPI basket. An important advantage of our scanner data is that it is available at a weekly frequency and includes information about quantities and costs, as well as prices.

[5] In this case, $C'(Y) = w^{1-\alpha} c^{\alpha} / \left[A \alpha^{\alpha} (1-\alpha)^{1-\alpha}\right]$.

Given the large number of items in our data set we must adopt a procedure to parsimoniously report our findings. Unless stated otherwise, the statistics that we report are computed as follows. First, we calculate the median value of a statistic across all items in a given category. We then compute the median of the 200 category medians. As a robustness check we also report results for revenue-weighted medians across categories.

3. The behavior of weekly prices and reference prices

In this section we compare the behavior of weekly and reference prices. Recall that the reference price of an item is the most commonly observed price for that item within a quarter. We refer to all other prices as nonreference prices. Our basic findings in this section are twofold. First, according to various metrics reference prices are important. Second, reference prices are much more persistent than weekly prices.

Reference prices Within a given quarter, weekly prices typically fluctuate between reference and nonreference prices. To summarize these within-quarter fluctuations we estimate a two-state Markov chain. In state one the weekly price is equal to the reference price. In state two the weekly price is different from the reference price. The average estimated Markov chain across categories is given by:[6]

$$M_p = \begin{bmatrix} 0.74 & 0.26 \\ 0.31 & 0.69 \end{bmatrix}. \tag{3.1}$$

[6] We estimate the transition matrix for the Markov chain for each item in every quarter in our sample and take the average over all quarters. We then compute the average transition matrix for items within a category. Finally, we compute the average transition matrix across categories.

It is evident from M_p that, for most weeks in a given quarter, the weekly price coincides with the reference price. Interestingly, the matrix M_p is consistent with the notion that weekly prices have 'memory.' When prices move away from their reference value they have a tendency to return to that value. In particular, nonreference prices return to a given reference price with 31 percent probability.

The matrix M_p pertains to within-quarter price fluctuations. We now quantify the importance of reference prices using statistics calculated across quarters. Unless otherwise indicated these statistics are reported in Table 1. First, 29 percent of all price changes involve movements from a nonreference price to a reference price. Second, the weekly price is equal to the reference price in 62 percent of the weeks. Third, half of the total quantities sold are sold at reference prices. Fourth, 54 percent of the revenue is collected at reference prices. Fifth, the standard deviation of quantities sold at reference prices is roughly the same as the standard deviation of quantities sold at nonreference prices (42 versus 43 percent, see Table 2). The first three observations imply that prices are often equal to reference prices and price movements are often movements toward reference prices. The last two observations imply that reference prices are important in terms of the level and volatility of quantities sold.

There is substantial heterogeneity in the importance of reference prices across categories. To illustrate this point Figure 1 displays the distribution of weeks spent and quantities sold at the reference price.[7] For more than 75 percent of the categories the price of the median item within a category is equal to the reference price more than 50 percent of the time. However, there are some extreme outlier categories. For magazines the price never changes in our sample. In contrast,

[7] Recall that for a given item in a given quarter to be included in the data set we require that there be either 12 or 13 weeks of observations for that item and for that quarter. This rule implies that there are only 24 possible values (1/12, 2/12,...12/12, 1/13, 2/13, ... 12/13) for the percentage of weeks spent at the reference price.

for the categories grapes, bananas, and pears the weekly price coincides with the reference price only eight percent of the time. The right panel of Figure 1 shows that, for 70 percent of the categories, the quantity of the median item sold at the reference price is above 40 percent of total sales. Again, magazines, bananas and pears are outlier categories.

Throughout this paper we calculate the reference price of an item as the most common price for that item within a quarter. We choose the quarter as the unit of time since most quantitative macro models use quarterly data. However, the basic reference phenomenon emerges even when we define reference prices as the most common price in a month. During the 36 months included in our sample 42 percent of the monthly reference prices are identical. So, even at the monthly frequency, there is a reference price that serves as an attractor around which weekly prices fluctuate.

Price persistence We now contrast the persistence properties of weekly prices and reference prices. According to Table 3 the probability of a weekly price change is 0.43. The implied duration of a weekly price is 2.3 weeks or 0.18 of a quarter.[8] The top panel of Figure 2 displays the distribution of the duration of weekly prices across categories.[9] Clearly, weekly prices are not sticky.

In sharp contrast to weekly prices, the probability of a reference price change is 0.27. So, the implied duration of reference prices is roughly 3.7 quarters (see Table 3).[10] The bottom panel of Figure 2 displays the distribution of the duration

[8] To facilitate comparisons with other estimates in the literature we calculate duration as the inverse of the frequency of price change. A shortcoming of this calculation is that it abstracts from the bias associated with Jensen's inequality (see Campbell and Eden (2005) for a discussion).

[9] Since magazine prices never change in our sample, they have an infinite weekly price duration. For this reason we excluded magazines from Figure 2.

[10] Intriguingly, this duration roughly coincides with the modal response that Blinder, Canetti, Lebow, and Rudd (1998) obtained when they asked firms: how often does the price of your most

of reference prices across categories.[11] This figure shows that 80 percent of the categories have reference price duration greater than 20 weeks. Clearly, there is substantial inertia in reference prices. These prices exhibit nominal rigidities that are not revealed by studying weekly prices.

One might be concerned that reference prices just correspond to 'sticky prices.' For example, if prices were literally constant, a reference price would account for 100 percent of the price observations. In fact, reference prices do not necessarily correspond to 'sticky prices.' The median percentage of quarters across categories in which weekly prices are constant for an entire quarter is only ten percent. In fact, reference prices are quite volatile. According to Table 2 reference prices are roughly 60 percent as volatile as weekly prices. This result is robust to whether we work with log levels or growth rates.[12]

Nonreference prices and sales prices Nonreference prices do not necessarily correspond to 'sales prices.' In fact, 21 percent of nonreference prices in our sample are actually *higher* than the corresponding reference price (see Table 1).

In principle, the finding that many nonreference prices are higher than reference prices could be spurious for the following reason. Our procedure for defining a reference price assumes that the firm makes decisions on a quarterly basis. This assumption might be incorrect. Suppose that the retailer increases the actual reference price towards the end of a given quarter. Our procedure would clas-

important product change in a given year?

[11] Recall that for an item to be included in our data set we require that there be 12 quarters of data for this item. This rule implies that there are only 11 possible values for the frequency of reference price changes. The number of reference price changes can be equal to one, two,..., 11. Consequently there are 12 possible values for the quarterly frequency of reference price change, 0, 1/11, 2/11, ... 11/11. There are also 12 possible values for the duration of reference prices: ∞, 11, 11/2, 11/3,... 1. In Figure 2 these quarterly durations are multiplied by 13 to convert them to weekly durations.

[12] We obtain a similar finding for the relative volatility of new weekly prices and new reference prices (see Table 2).

sify those prices as nonreference prices that are higher than the reference price. Similarly, suppose the retailer lowers the reference price near the beginning of the quarter. Our procedure would classify the actual old reference prices that occur in the beginning of the quarter as higher than the measured reference price for that quarter.

To produce an upper bound on the quantitative importance of these two scenarios we compute the fraction of the high nonreference prices that are not equal to the reference price in the previous or subsequent quarter. We find that this fraction is equal to 60 percent. So, a lower bound for the fraction of nonreference prices that are actually higher than the corresponding reference price is 12 percent (0.21 times 0.60). Taken as a whole our results indicate that nonreference prices are not necessarily 'sale prices.'

Some robustness checks As discussed above there can be spurious changes in prices in our data set associated with the time-varying use of loyalty cards, coupons, and promotions. Consequently, our estimate of the duration of weekly prices (0.18 of a quarter) is a lower bound on the true duration of weekly prices. From this perspective prices could be more inertial than suggested by our point estimates. We use two approaches to assess the potential impact of measurement error on our duration estimates.

First, we recompute the probability of a price change assuming that an actual price change occurs only when our price measure changes by more than x percent, for $x = 1, 2, \ldots, 5$. Weekly price duration is an increasing function of x and peaks at 0.27 of a quarter when $x = 5$ (recall that our benchmark value of weekly price duration is 0.18 of a quarter). Significantly, the reference price duration remains equal to our benchmark estimate of 3.7 quarters for all the values of x that we consider. So, the basic finding that reference prices are much more persistent than weekly prices is unaffected by this type of measurement error.

Second, we use an additional data set from the retailer that contains the actual price associated with each transaction for 374 stores in Arizona, California, Colorado, Oregon, Washington, and Wyoming. Because prices are observed directly, there is no measurement error associated with the time-varying use of discounts, coupons, loyalty cards, and other promotions. This data set is only available for a short time period (January 4 to December 31, 2004). The average number of days in which we observe the same item is 14. So, while we cannot use this data set to compute price duration, we can use it to quantify the bias introduced by the use of unit-value prices.

For the new data set we identify all UPCs that are sold three or more times in the same store in the same day and are included in the data for at least seven days. There are 1.7 million such observations. In 70 percent of these observations the same good is sold at the same price in all transactions that occur in the same store and on the same day. So, in this data set, measurement error can at most affect 30 percent of the observations. We can use this statistic to quantify the impact of measurement error on the duration of weekly prices. The probability of a weekly price change is 0.41. Suppose that 30 percent of these changes are indeed spurious. Then, the true probability of a weekly price change is $0.7 \times 0.41 = 0.29$. This probability of a weekly price change implies a duration of weekly prices of 0.27 quarters. Interestingly, this estimate coincides with the one we obtained using our first method for assessing the importance of measurement error.

This new data set is not long enough to allow us to compute reference prices. But any correction for measurement error would only increase the duration of reference prices. So, by correcting the duration of weekly prices but not the duration of reference prices we are providing a conservative estimate of the difference between the two. This estimate is 3.43 quarters $(3.7 - 0.27)$. We conclude that, even taking measurement error into account, the duration of reference prices is much longer than the duration of weekly prices.

Our main results pertain to statistics calculated using medians across categories. To assess the robustness of these results we also compute statistics using revenue-weighted medians across categories. We find that, with one possible exception, our results are robust to this alternative procedure. The one exception is that the point estimate of the duration of reference prices goes from 3.7 to 2.7 quarters. The duration of weekly prices is essentially unchanged. So, the basic qualitative result that reference prices are much more persistent than weekly prices is unaffected.

Results for Dominick's data set We conclude this section by briefly discussing the results that we obtain with the Dominick's data set. As Tables 1 through 3 show, these results are very similar to those obtained with our primary data set. Reference prices are important. First, weekly prices are often equal to reference prices (77 percent of the weeks). Second, price movements are often movements toward reference prices. The fraction of price changes that are from a nonreference price to a reference price is 41 percent. Third, reference prices continue to be important in terms of the fraction of quantities sold at reference prices (66 percent) and the volatility of quantities sold at reference prices (41 percent).

Finally, we find the same sharp contrast between the duration of weekly and reference prices. The duration of weekly prices is 0.32 quarters while the duration of reference prices is roughly three quarters.

4. The behavior of weekly costs and reference costs

In this section we compare the behavior of weekly and reference costs. The latter is defined as the most commonly observed cost for that item within a quarter. We refer to all other costs as nonreference costs. Our basic findings in this section can be summarized as follows. First, judging by various measures, reference cost are important. Second, reference costs are much more persistent than weekly costs. Third, reference costs are less persistent than reference prices.

The importance of reference costs We summarize within-quarter fluctuations in costs using a two-state Markov chain with the following states. In state one the weekly cost is equal to the reference cost. In state two the weekly cost is different from the reference cost. The average Markov chain across categories is given by:

$$M_c = \begin{bmatrix} 0.70 & 0.30 \\ 0.25 & 0.75 \end{bmatrix}.$$

The estimated Markov chain for costs is quite similar to the analogue Markov chain for prices. In most weeks in a given quarter, the weekly cost coincides with the reference cost. As with prices, nonreference costs often return to a given reference cost.

To quantify the importance of reference costs we use statistics calculated across quarters. First, 25 percent of all cost changes involve movements from a nonreference cost to a reference cost (see Table 1). Second, the weekly cost is equal to the reference cost in 54 percent of the weeks in our sample (see Table 1). As with prices, there is substantial heterogeneity in the importance of reference costs across categories. Figure 3 displays the distribution across categories of weeks in which the weekly cost is equal to the reference cost. There are some extreme outlier categories. For magazines the cost never changes in our sample. In contrast, for the categories grapes, bananas, and pears the weekly cost coincides with the reference cost only eight percent of the time. Recall that these categories are also outliers in terms of the fraction of weeks in which the weekly price is equal to the reference price.

Cost persistence As with prices, there is a sharp contrast between the persistence properties of weekly costs and reference costs. From Table 3 we see that the probability of a weekly cost change is 0.49. So, the implied duration of a weekly cost is 0.16 of a quarter, or roughly 2.1 weeks. The top panel of Figure 4 displays the distribution of duration of weekly costs across categories. Clearly, weekly costs are not sticky.

The probability of a reference cost change is 0.45. So, the implied duration of reference costs is roughly 2.2 quarters. The bottom panel of Figure 4 displays the distribution of reference cost duration across categories. Roughly two-thirds of the categories have reference cost duration exceeding 20 weeks. Clearly, there is substantial inertia in reference costs. The existence of stickiness in costs would not be revealed by analyzing weekly costs.

As with reference prices, one might be concerned that reference costs just correspond to sticky costs. This concern is not warranted. Across all categories, the median percentage of quarters in which weekly costs are constant is only six percent. In fact reference costs are quite volatile. According to Table 2 reference costs are roughly 60 percent as volatile as weekly costs.[13]

We conclude this section by noting that our weekly cost measures can have an endogenous component associated with trade promotions. As discussed in Maratou (2006) and Maratou, Gómez, and Just (2004), there are basically two types of trade promotions: performance-based contracts and discount-based contracts. Performance-based contracts give retailers incentives to sell the manufacturer's product. These incentives are tied to a measure of retailer performance (e.g.,

[13]We obtain a similar finding for the relative volatility of new weekly costs and new reference costs (see Table 2).

units sold, displayed or price discounts in effect during a given period). We think of these contracts as exogenous price schedules that are non-linear in nature. The main impact of this non-linearity is to potentially introduce measurement error into our analysis by driving a wedge between the retailer's average and marginal cost.

Discount-based promotions can induce a different type of endogeneity. These promotions generally take the following form: suppliers provide merchandise to retailers at a discount, usually for a brief, specified period (two to three weeks is standard). Changes in cost and prices induced by these types of promotions are likely to be transitory in nature. For this reason they are unlikely to affect reference costs and prices, which have an average duration of six months and one year, respectively.

5. The determinants of price changes

In this section we investigate the relation between reference prices and costs and find that there is a very important form of state dependence in reference prices. Specifically, the duration of reference prices is chosen to limit markup varation. This finding is based on four observations that we document below. First, the duration of reference prices is such that the variation of markups within the spell of a reference price is within $\pm 10\%$ of the average markup. Second, there is evidence of state dependence in the probability of reference price changes. Third, when the retailer changes reference prices it reestablishes the value of the unconditional markup. Finally, in periods in which the reference price is constant before it rises (falls), the markup falls (rises).

The relation between prices and cost changes A striking property of our data is that prices generally do not change absent a change in costs. The probability that the weekly price changes without a change in the weekly cost is only three percent (see Table 1). The probability that the reference price changes without a change in reference cost is 15 percent.

We do not find an important lag or lead in the relation between changes in costs and changes in prices. We assess whether there is a lag in the response of prices to changes in cost by computing the probability of a price change at time $t+1$, conditional on a cost change occurring at time t, no price change occurring at time t, and no cost change occurring at $t+1$. This probability is four percent and 15 percent for weekly and reference prices, respectively. So, there does not seem to be an important lag in the response of prices to changes in costs.

To see if there is a lead in the response of prices to changes in cost we compute the probability of a price change at time $t-1$, conditional on a cost change occurring at time t, no price change occurring at time t, and no cost change occurring at $t-1$. This probability is four percent and 16 percent for weekly and reference prices, respectively. These results suggest that there are no important leads in the response of prices to changes in costs.

While prices generally do not change absent a change in costs, a change in cost is not sufficient to induce a change in price. This fact means that there are substantial variations in markups. According to Table 2 the standard deviation of the weekly markup is 11 percent. The standard deviation of the reference markup, defined as the standard deviation of the ratio of reference prices to reference costs, is 9 percent.

We now analyze deviations of the markup from its average value. To this end, we compute the percentage difference between the realized weekly markup and the mean unconditional markup for weeks in which the weekly price coincides with the reference price. Figure 5 displays the distribution of this statistic. Interestingly, 90 percent of the probability mass is between plus and minus ten percent of the average markup. This finding suggests that the retailer resets its reference prices so that variations in the realized markup fall within a reasonably small interval.

To assess this hypothesis, we compute the analogue of Figure 5 for different categories of goods, classified according to the median duration of the reference price. The results are displayed in Figure 6 for groups of goods with median durations ranging from one to twelve quarters. These distributions are generally similar to those displayed in Figure 5. This finding is consistent with the hypothesis that the retailer chooses the duration of the reference price for each item to keep realized markups within similar small bounds. Figure 7 provides further evidence in support of this hypothesis. This figure shows that categories with a high probability of a reference cost change have a high probability of a reference price change.[14]

State dependence in reference prices A natural question to ask is whether there is any state dependence in the probability of reference price changes. To address this question, we define the 'hypothetical reference markup' as the reference markup that would obtain if the retailer did not change its reference price between quarter $t-1$ and quarter t. Thus, the hypothetical reference markup is the ratio of the reference price in quarter $t-1$ to the reference cost in quarter t. The top panel of Figure 8 displays the median probability that the reference price changes as a function of the percentage deviation of the hypothetical reference markup from the average markup. The probability that the reference price changes when the hypothetical reference markup is equal to the mean markup is very low. Strikingly, the larger is the percentage difference between the hypothetical reference markup and the average markup, the larger is the probability of a change in reference prices. So, there is clear evidence of a selection effect with

[14] Recall that there are only 12 quarters in our sample, so the probability of a change in reference price or cost can only take a discrete number of values.

regards to changes in reference prices. Figure 9 and 10 shows that this selection effect continues to be present when we group individual items by reference price duration (Figure 9) and cost volatility (Figure 10). However, this selection effect is weaker in the categories that have short price durations.[15] We interpret the similarity between Figures 9 and 10 as reflecting the negative correlation between price duration and cost volatility.

Suppose that a decision has been made to change the reference price. By how much does the reference price change? The bottom panel of Figure 8 displays the realized markup as a percentage deviation from the mean markup, conditional on the reference price changing. From this figure we see that the retailer sets the reference price so as to re-establish the average markup. Put differently, once the retailer decides to change its reference price, on average it passes through 100 percent of the cumulative change in reference cost that occurred since the last reference price change.

Figures 8 through 10 provide cross-sectional evidence on state dependence in the decision of changing reference prices. To provide time-series evidence on state dependence, we first compute the percentage deviations of the realized markup in periods with no price changes relative to the realized markup at the time of the price change. Figure 11 reports our results as a function of the number of periods prior to a price change. The key finding is that the markup falls (rises) monotonically over time as a function of the number of periods prior to a price increase (decrease).[16]

Taken together, these results support the hypothesis that the retailer chooses a reference price duration for each item to keep realized markups within bounds that are similar for different items.

[15] We exclude the goods with duration zero and infinity from Figure 9. The price of goods with duration zero always changes. The price of goods with infinite duration never changes.

[16] We thank one of the referees for suggesting that we produce this figure.

6. Other features of the data

In this section we document two additional features of the data that are useful for evaluating the plausibility of different pricing models.

Volatility of prices and marginal cost In our data set prices are more volatile than our measure of marginal cost. This result holds for weekly prices and costs as well as for reference prices and costs. The basic intuition for this result is that prices often do not change much in response to small changes in cost. But small cost changes that cumulate and create large deviations from the average markup can trigger very large changes in price. This pattern of behavior generates prices that have a larger standard deviation than cost.

The median of the ratio of the standard deviation of log(weekly price) to the standard deviation of log(weekly cost) is 1.08. The median of the ratio of the standard deviation of log(reference price) to the standard deviation of log(reference cost) is 1.15. We also find that prices are more volatile than costs if we focus on new prices and new costs or if we work in growth rates (see Table 2). We conclude that, regardless of whether we work with weekly or reference prices and costs, the volatility of prices generally exceeds that of marginal cost.

Demand shocks Conditional on the weekly price being constant and equal to the reference price, the standard deviation of quantities sold is roughly 42 percent.[17] This conditional volatility is roughly 79 percent of the unconditional volatility of quantities sold. We infer that demand shocks are quantitatively important.

[17] A caveat to our calculation is that we are conditioning on the nominal price being constant instead of the real price being constant. By real price we mean the price of the good relative to the CPI basket. Since we focus on a short time period during which inflation is quite low, it seems unlikely that inflation effects are important for this calculation.

7. Reconciling different pricing models with our findings

In this section we discuss the implications of our empirical findings for three pricing models that are widely used in macroeconomics: flexible price models, menu cost models, and Calvo models.

Flexible price models The Dixit-Stiglitz model of monopolistic competition lies at the core of many flexible price macroeconomic models. In this model, the elasticity of substitution across different goods is constant. The optimal policy for each monopolist is to set the price (P_t) equal to a constant markup (μ) over marginal cost (C_t), $P_t = \mu C_t$. This model is clearly inconsistent with our data, since it implies that there should be no variation in the markup. Table 2 indicates that the standard deviation of the logarithm of the realized weekly markup and reference markup is 0.11 and 0.09, respectively.

It is possible to reconcile a flexible price model with the data by introducing demand shocks that generate markup fluctuations. But, matching the data requires an incredible configuration of cost and demand shocks. Consider the following simple specification in which demand is linear:

$$P_t = a_t - b_t Q_t,$$

where Q_t represents the quantity sold. The variables a_t and b_t are stochastic demand shifters. Variable profits, π_t are given by: $\pi_t = P_t Q_t - C_t Q_t$, where C_t is the monopolist's cost. The monopolist's optimal price and quantity are given by:

$$P_t^* = \frac{a_t + C_t}{2},$$

$$Q_t^* = \frac{a_t - C_t}{2b_t}.$$

Changes in b_t only affect the quantity sold. Changes in a_t affect both price and quantity. Given observations on P_t^*, Q_t^*, and C_t, we can deduce the time series for a_t and b_t such that P_t^* and Q_t^* match the data exactly. We perform this calculation for each of the items in our sample. Three key results emerge. First, the median standard deviation of $\log(a_t)$ and $\log(b_t)$ are 0.16 and 0.77, respectively. So, to match the data the variable a_t must be roughly as as volatile as prices and cost (see Table 2). The volatility of b_t must be higher than the volatility of quantities and roughly four times more volatile than prices and costs. We conclude that an empirically plausible flexible price specification must allow for volatile demand shocks. Second, the correlation between $\log(a_t)$ and $\log(b_t)$ is positive (0.7). This positive correlation helps the model match the negative unconditional correlation between prices and quantities, reported in Table 4, while allowing for volatile demand. Third, and most importantly, matching the data requires an implausible pattern of comovement between a_t and C_t. In at least 40 percent of our observations the same price corresponds to different costs.[18] To match these observations, the change in a_t must *exactly* offset the change in C_t. Although possible, this pattern of shocks strikes us as incredible.

A similar argument applies to Dixit-Stiglitz demand with stochastic elasticity of substitution between goods. This specification generates variability in markups. However, it requires that in 40 percent of the observations shocks to the elasticity of substitution exactly offset movements in marginal cost in order to rationalize a constant price.

[18] This statistic is computed as follows. For each good we identify the modal price and cost over the three-year sample period. We then compute the fraction of weeks in which the price is equal to the modal price but the cost is not equal to the modal cost. This calculation provides a lower bound on the percentage of weeks in which the same price corresponds to different costs.

Menu cost models Standard menu cost models have three shortcomings with respect to our data. First, Table 2 documents that prices are more volatile than marginal cost, whether we work with levels or growth rates. However, calibrated versions of menu cost models imply that prices are *less* volatile than marginal cost. For example, Golosov and Lucas' (2006) model implies that the unconditional standard deviation of cost changes are 40 percent more volatile than the unconditional standard deviation of price changes. A similar pattern obtains in Burstein and Hellwig's (2007) model, which incorporates demand shocks into the Golosov-Lucas framework. The unconditional standard deviation of cost changes is twice as large as the unconditional standard deviation of price changes in the Burstein-Hellwig model.[19] Second, we need an incredible configuration of cost and demand shocks to explain why firms return often to an old (reference) price. Third, as we discuss in Section 8, it is difficult for menu cost models to match both the frequency of weekly price changes and the frequency of reference price changes.

Kehoe and Midrigan (2007) make progress on the second shortcoming by assuming that firms set two kinds of prices, 'regular' prices and 'sales' prices. Sales prices are temporary price reductions. After a sale is over the price returns to the 'regular' price. Kehoe and Midrigan assume that the menu cost associated with a sales price change is lower than the menu cost associated with a regular price change. It remains an open question whether such a model can rationalize the fact that prices, both weekly and reference, are more volatile than marginal cost.

[19] We thank Ariel Burstein for computing the volatility of prices and costs in the Golosov-Lucas model and in the Burstein-Hellwig model.

Calvo models Perhaps the most widely used pricing model in macroeconomics is the one associated with Calvo (1983).[20] An obvious failing of the standard Calvo (1983) pricing model is that it is inconsistent with the selection effects that we document in Figures 8-10. The Calvo model assumes that the probability of a price change is constant. In fact, we find that the probability of a reference price change is increasing in the deviation of the hypothetical markup from its unconditional mean. It also remains an open question whether standard Calvo pricing models are useful to understand data sets like ours in which prices are more volatile than costs.

8. Are reference prices useful for macroeconomists?

In this section we consider a simple partial-equilibrium model that accounts for the key features of the data that we document in Sections 3 and 4. In this model monetary policy shocks have important real effects even though weekly prices change very frequently. We use this model to illustrate the sense in which the frequency of reference price changes can be a useful statistic to guide macroeconomists.

In our model the firm chooses a 'price plan' which consists of a small set of prices, Ω.[21] The firm can move between prices in this set without incurring any cost, i.e. there are no menu costs of changing between prices in Ω. The key friction is that there is a fixed cost, ϕ, of changing the price plan.

The firm faces the following demand and cost functions:

$$Q_t = \mu_t P_t^{-\alpha_t},$$

$$C_t = \mu_t^{1/\alpha} c_t Q_t,$$

[20] See, for example, Rotemberg and Woodford (1997), Gali and Gertler (1999), Smets and Wouters (2003), and Christiano, Eichenbaum, and Evans (2005).

[21] See Burstein (2006) for a different formulation of price plans in which firms choose a deterministic price sequence.

where Q_t and P_t denote the quantity and price, respectively. The variable C_t denotes the cost of production. The variables α_t and c_t represent shocks to the elasticity of demand and cost, respectively.

We want to mimic the effect of a monetary shock in our simple model. We take the defining characteristic of such a shock to be that, absent pricing frictions, it has no effect on quantities. The variable μ_t, which affects both demand and cost, has this property. If prices are completely flexible, a one-percent rise in μ leads to a $1/\alpha$ percent rise in prices and has no effect on quantities sold. For this reason we refer to μ_t as a monetary policy shock.

Let s and $F(s'|s)$ denote the triplet $\{\alpha, c, \mu\}$ and the conditional density of s' given s, respectively. We denote by $V(\Omega, s)$ the value of the firm when there is no change in its price plan, Ω, and the state of the world is s. Let $W(s)$ be the value of the firm when it changes its price plan. These two value functions are given by:

$$V(\Omega, s) = \max_{P \in \Omega} \left[\mu P^{1-\alpha} - \mu^{(1+\alpha)/\alpha} c P^{-\alpha}\right] + \beta \int \{\max\left[V(\Omega, s'), W(s')\right]\} dF(s'|s),$$

and

$$W(s) = \max_{P \in \Omega', \Omega'} \left\{\mu P^{1-\alpha} - \mu^{(1+\alpha)/\alpha} c P^{-\alpha} - \phi + \beta \int \{\max\left[V(\Omega', s'), W(s')\right]\} dF(s'|s)\right\}.$$

The standard menu-cost model is a special case of this model where the set Ω is a singleton.

Model calibration The free parameters of the model are ϕ, β, and those governing the laws of motion for the three shocks, α, c, and μ. In choosing parameters values we assume that a unit of time in the model is one week. Also, we assume that Ω consists of only two prices. This choice is motivated by computational considerations and the fact that in our data the typical good spends 75 percent of the time at the two most frequently observed prices within a quarter.[22] We

[22]The probability of moving from the two most frequent prices to some other price is only one percent.

then choose the parameters of the model to match, as closely as possible, the moments of the data listed in Table 5. We compute the frequency of reference price changes using the same algorithm that we use in our empirical work. Specifically, we simulate the model and calculate the reference price as the modal price per quarter.

We set β equal to 0.999. We assume that α and μ can take on two values, while c can take on three values: $\alpha \in \{5.25, 7.5\}$, $\mu \in \{1, 1.15\}$, and $c \in \{0.85, 1.08, 1.10\}$. The three shocks are independent of each other and are governed by first-order Markov chains. We denote the transition matrix of shock i by π^i. The three transition matrices are given by:

$$\pi^{\alpha} = \begin{bmatrix} 0.99 & 0.01 \\ 0.15 & 0.85 \end{bmatrix},$$

$$\pi^{c} = \begin{bmatrix} 0.3881 & 0.4838 & 0.1281 \\ 0.2714 & 0.5472 & 0.1814 \\ 0.2116 & 0.4968 & 0.2916 \end{bmatrix},$$

and

$$\pi^{\mu} = \begin{bmatrix} 0.95 & 0.05 \\ 0.05 & 0.95 \end{bmatrix}.$$

The serial correlation of the logarithm of α, μ, and c is 0.84, 0.90, and 0.14, respectively. So, cost shocks are less persistent than the other shocks. The standard deviation of the logarithm of α, μ, and c is 0.09, 0.07, and 0.11, respectively. So, monetary policy shocks are less volatile than the other shocks.

The size of the menu cost plays a key role in determining how often the firm changes its price plan. We chose a menu cost (five percent of weekly revenue) which implies that the plan changes very infrequently (two percent of the time). This choice allows us to illustrate the point that, even when plans change infrequently, prices can change very frequently.

From Table 5 we see that a change in the reference price is an imperfect indicator of a change in the price plan. But, as we argue below, even with this calibration, focusing on the frequency of reference price changes is useful for assessing the quantitative effects of a monetary policy shock. Table 5 also indicates that the model does a reasonable job at accounting for the volatility of costs, prices and quantities, the frequency of price and cost changes, and the fraction of price changes that are not accompanied by cost changes. On this basis we conclude that we are working with a reasonable calibration.

We now turn to the effects of a monetary policy shock in the model. The top line in Figure 12 displays the response of quantities sold by the firm to a monetary policy shock of 15 percent.[23] Notice that the shock leads to a substantial, prolonged increase in quantities sold. So, even though weekly prices change very frequently in our model, a monetary policy shock has large effects. This result reflects the fact that a monetary policy shock does not induce a change in the price plan.

While our model is consistent with both the frequency of price changes and the frequency of reference price changes, it has a larger state space. As a consequence our model is harder to solve from a computational standpoint than standard menu cost models. A natural question is whether a menu cost model can provide a reasonable approximation to our model in terms of reproducing the effects of a monetary policy shock. But, if we calibrate the standard menu cost model to be consistent with the frequency of weekly price changes the answer is no.[24] If we calibrate the standard menu cost model to be consistent with the frequency of reference price changes the answer is yes.

[23] This impulse response function is computed as the average response of quantities sold after a monetary shock, expressed as percentage deviations from the unconditional average of quantities sold. We compute this impulse response function in population by combining the transition matrix of the exogenous shocks with the policy functions associated with the model.

[24] This exercise is similar in spirit to the analysis in Kehoe and Midrigan (2007).

To substantiate these claims we proceed as follows. First we specialize our model so that Ω only contains one element. Under this assumption we obtain the standard menu-cost model. We then choose a value for the menu cost so that the model is consistent with the frequency of weekly price changes observed in our data set. This exercise is the spirit of the analysis in Golosov and Lucas (2007). Because prices change so frequently we must choose a menu cost that is very small compared to the cost of changing the price plan (one percent versus five percent of weekly sales). As can be seen from Table 5, the resulting menu cost model does as well as our sticky-plan model with one important exception: it greatly overstates the frequency of reference-price changes (0.67 versus 0.27). From Figure 12 we see that this menu-cost model erroneously implies that a monetary policy shock has almost no effect on quantities sold. This property follows directly from the small size of the menu cost which induces the firm to change prices in response to almost all shocks. So, if we insist that the menu cost model reproduce the frequency of price changes, we are led to the misleading conclusion that a monetary policy shock has a very small effect on real economic activity.

Consider next the same menu cost model where the size of the menu cost is chosen so that the frequency of reference price changes is the same as in our sticky-plan model. Because reference prices change less frequently than weekly prices, we are led to a much higher value of the menu costs than in the other version of our menu cost model (46 percent versus one percent of weekly sales). This version of the model does not do as well as the other menu cost model at matching the weekly volatility of prices and quantities. But from Figure 12 we see that this version of the menu cost model does much better than the other menu cost model at reproducing the effect of a monetary policy shock. This example captures the idea that a lot of high-frequency volatility in prices and quantities has little to do with monetary policy and is perhaps best ignored by macroeconomists.

9. Conclusion

We present evidence that is consistent with the view that nominal rigidities are important. However, these rigidities do not take the form of sticky prices, i.e. prices that remain constant over time. Instead, nominal rigidities take the form of inertia in reference prices and costs. Weekly prices and costs fluctuate around reference values which tend to remain constant over extended periods of time. Reference prices are particularly inertial and have an average duration of roughly one year. So, nominal rigidities are present in our data, even though prices and cost change very frequently, roughly once every two weeks. We document the relation between prices and costs and argue that reference prices and costs are useful statistics for macroeconomic analysis.

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Table 1: Basic statistics

	Primary data set	Dominicks data set
Basic statistics		
Fraction of weeks spent at the reference price	0.62	0.77
Fraction of weeks spent at the reference cost	0.54	n.a.
Fraction of quarters in which weekly prices are constant for the whole quarter	0.11	0.19
Fraction of quarters in which weekly cost is constant for the whole quarter	0.06	n.a.
Fraction of non-reference prices that are above reference prices**	0.21	0.30
Fraction of price changes that are from a non-reference price to a reference price	0.29	0.41
Fraction of cost changes that are from a non-reference cost to a reference cost	0.25	n.a.
Fraction of quantities sold at reference prices	0.49	0.66
Fraction of revenue collected at reference prices	0.54	0.68
Probability of weekly price changing when weekly cost does not change	0.03	n.a.
Probability of reference price changing when reference cost does not change	0.15	n.a.

**Computed out of the total weeks in which the weekly price is different from the reference price.

Table 2: Volatility properties

	Primary data set	Dominicks data set
STANDARD DEVIATION OF LEVELS		
Standard deviation of quantities		
Log(weekly quantity)	0.53	0.67
Log(quantities sold at reference price)	0.42	0.41
Log(quantities sold at non-reference prices)	0.43	0.42
Standard deviation of prices		
Log(weekly price)	0.14	0.11
Log(reference price)	0.08	0.07
Log(weekly price), conditional on weekly price change	0.15	0.15
Log(reference price), conditional on reference price change	0.10	0.07
Standard deviation of costs		
Log(weekly cost)	0.12	n.a.
Log(reference cost)	0.07	n.a.
Log(weekly cost), conditional on cost change	0.13	n.a.
Log(reference cost), conditional on cost change	0.08	n.a.
Standard deviation of prices/Standard deviation of costs*		
Weekly prices/weekly costs	1.08	n.a.
Reference prices/reference costs	1.15	n.a.
Weekly prices, conditional on price changes/weekly cost conditional on cost change	1.08	n.a.
Reference price, conditional on price changes/reference cost, conditional on cost changes	1.17	n.a.
Standard deviation of markup		
Log(weekly markup)	0.11	n.a.
Log(reference markup)	0.09	n.a.
STANDARD DEVIATION OF CHANGES		
Standard deviation of prices		
Log changes in weekly prices	0.14	0.09
Log changes in reference prices	0.08	0.04
Log changes in weekly prices, conditional on price change	0.20	0.19
Log changes in reference prices, conditional on price change	0.14	0.07
Standard deviation of costs		
Log changes in weekly cost	0.11	n.a.
Log changes in reference cost	0.06	n.a.
Log changes in weekly cost, conditional on cost change	0.15	n.a.
Log changes in reference cost, conditional on cost change	0.09	n.a.
Standard deviation of prices/Standard deviation of costs*		
Weekly growth rate of prices/weekly growth rate of costs	1.10	n.a.
Reference growth rate of prices/growth rate of costs	1.13	n.a.
Weekly growth rate of price, conditional on price changes/weekly growth rate of cost, conditional on cost change	1.20	n.a.
Growth rate of reference prices conditional on price changes/growth rate of reference costs, conditional on cost changes	1.25	n.a.

*Note: the median of the ratio of standard deviations is not the ratio of the median standard deviations.

Table 3: Persistence properties

	Primary data set	Dominicks data set
Price persistence		
Probability of a weekly price change	0.43	0.24
Implied weekly price duration (in quarters)	0.18	0.32
Probability of reference price changes	0.27	0.33
Implied reference price duration (in quarters)	3.70	3.03
Cost persistence		
Probability of weekly cost changes	0.49	n.a.
Implied weekly cost duration (in quarters)	0.16	n.a.
Probability of reference cost changes	0.45	n.a.
Implied reference cost duration (in quarters)	2.22	n.a.

Table 4: Correlation properties

Correlations, primary data set

	ln(weekly price)	ln(weekly quantity)	ln(weekly cost)	ln(weekly markup)
ln(weekly price)	1	-0.47	0.71	0.51
ln(weekly quantity)		1	-0.28	-0.20
ln(weekly cost)			1	-0.34
ln(weekly markup)				1

	ln(reference price)	ln(reference quantity)	ln(reference cost)	ln(reference markup)
ln(reference price)	1	-0.17	0.44	0.70
ln(reference quantity)		1	0	-0.19
ln(reference cost)			1	-0.49
ln(reference markup)				1

Correlations, Dominicks data set

	ln(weekly price)	ln(weekly quantity)
ln(weekly price)	1	-0.37
ln(weekly quantity)		1

	ln(reference price)	ln(reference quantity)
ln(reference price)	1	-0.05
ln(reference quantity)		1

Table 5: Data and model statistics

	Data	Sticky plan model	Menu cost calibrated to the frequency of weekly price changes	Menu cost model calibrated to frequency of reference price changes
Menu cost value as percentage of steady state cash flow		0.0525	0.0100	0.4593
Weekly cost volatility	0.120	0.112	0.113	0.112
Weekly price volatility	0.140	0.111	0.113	0.075
Weekly quantity volatility	0.530	0.600	0.599	0.416
Frequency of weekly price changes	0.430	0.375	0.402	0.155
Frequency of weekly cost changes	0.490	0.577	0.574	0.576
Frequency of reference price changes	0.270	0.268	0.670	0.269
Frequency of reference costs changes	0.450	0.634	0.628	0.635
Fraction of price changes without cost changes	0.030	0.011	0.009	0.003
Frequency of plan changes		0.023		

Figure 1

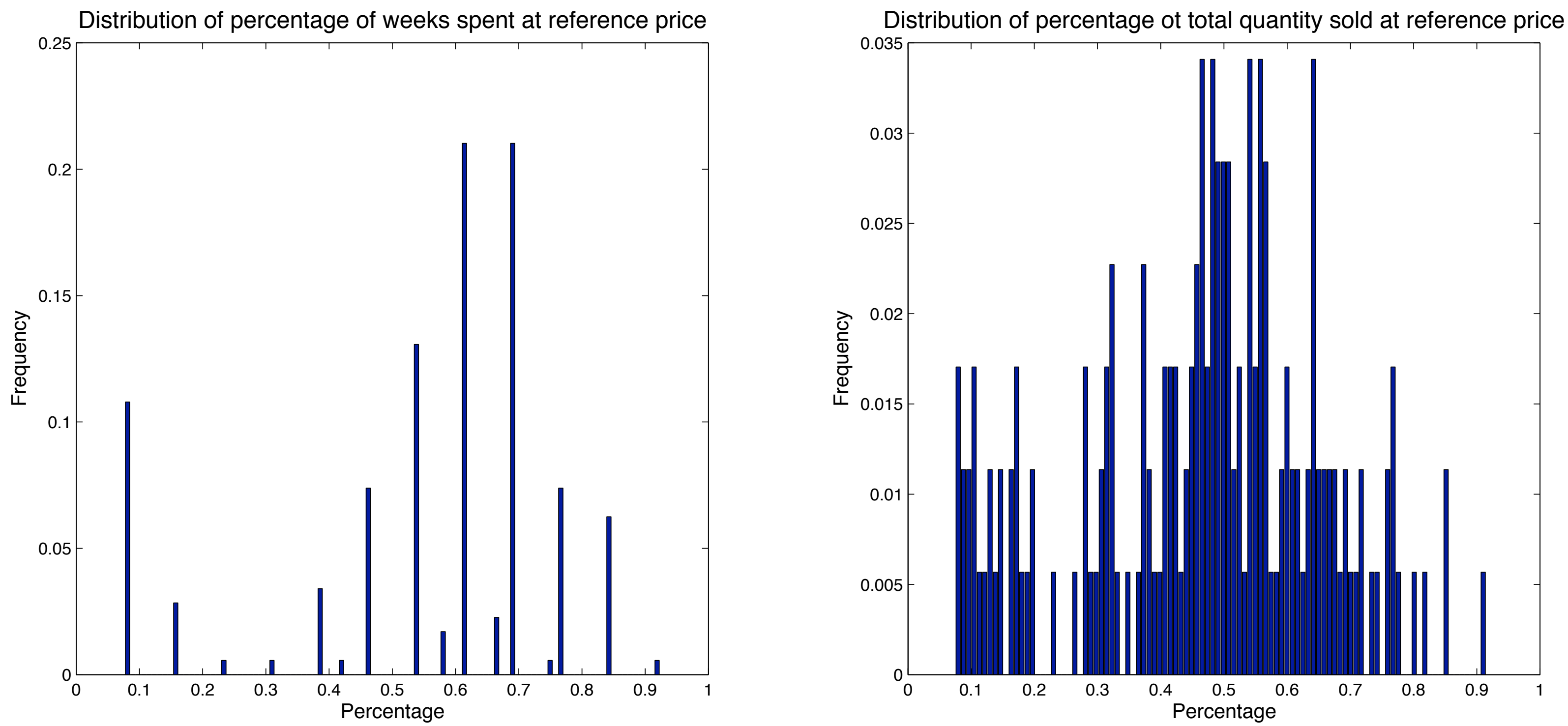
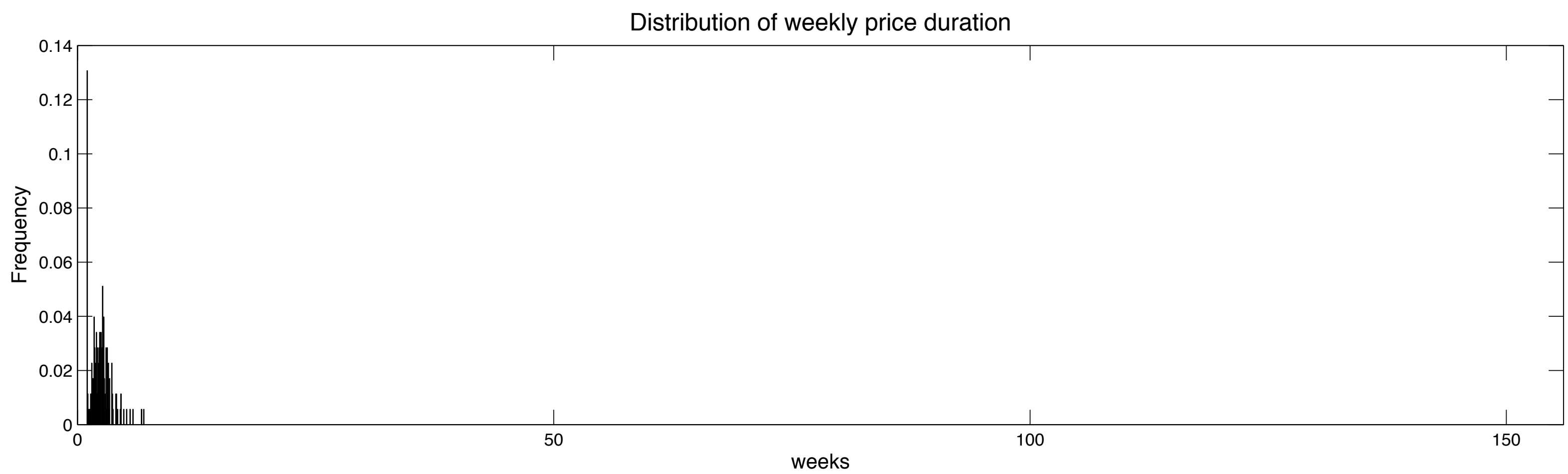
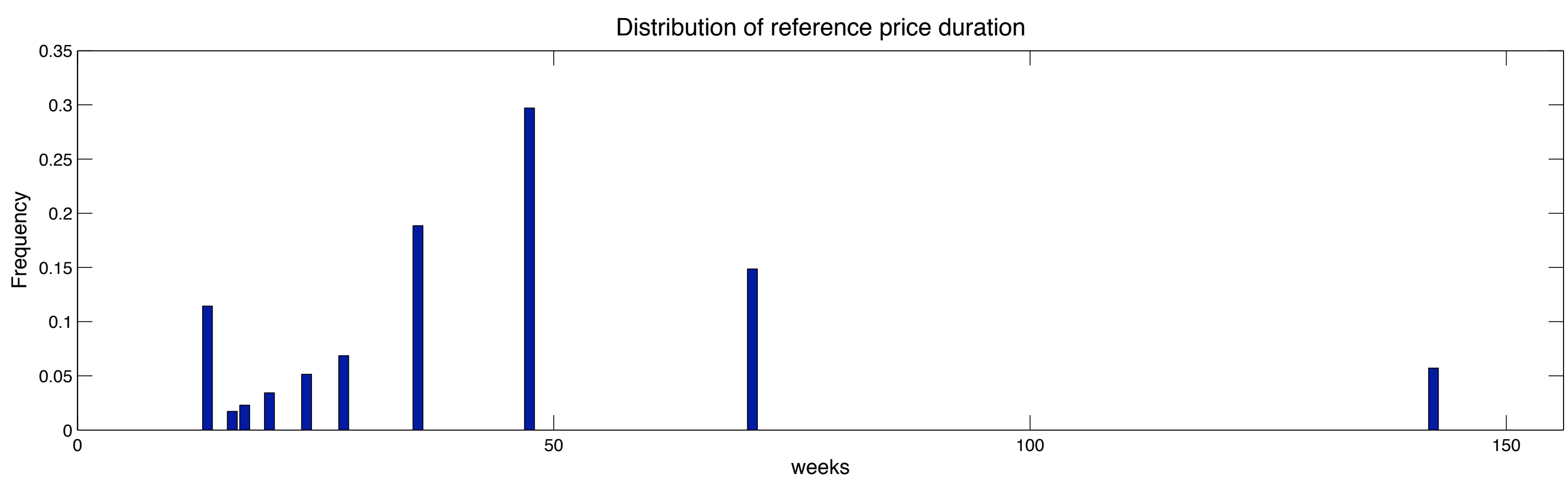

Distribution of percentage of weeks spent at reference price
Frequency
Percentage
0
0.05
0.1
0.15
0.2
0.25
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
Distribution of percentage ot total quantity sold at reference price
Frequency
Percentage
0.005
0.01
0.015
0.02
0.025
0.03
0.035

Figure 2

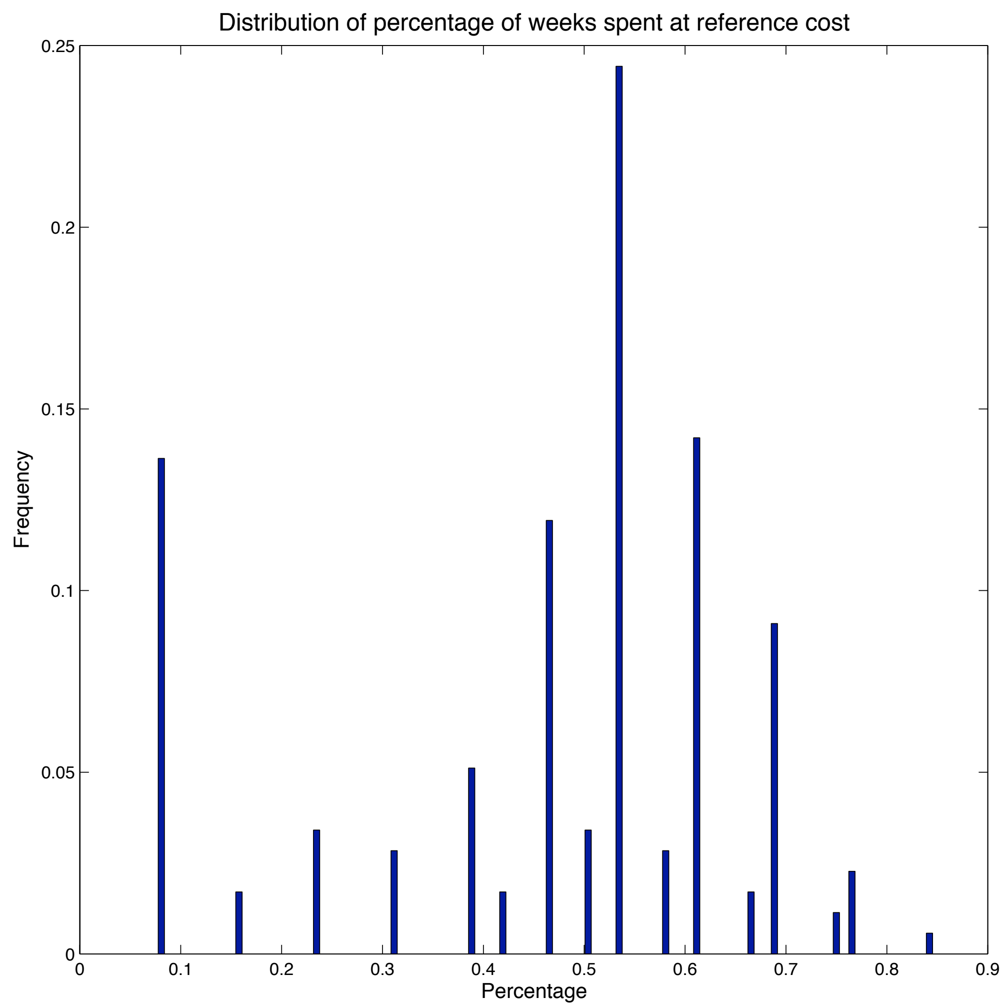


Distribution of weekly price duration
Frequency
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
0
50
100
150
weeks



Distribution of reference price duration
Frequency
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
0
50
100
150
weeks

Figure 3



Distribution of percentage of weeks spent at reference cost
0.25
0.2
0.15
0.1
0.05
0
Frequency
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
Percentage

Figure 4

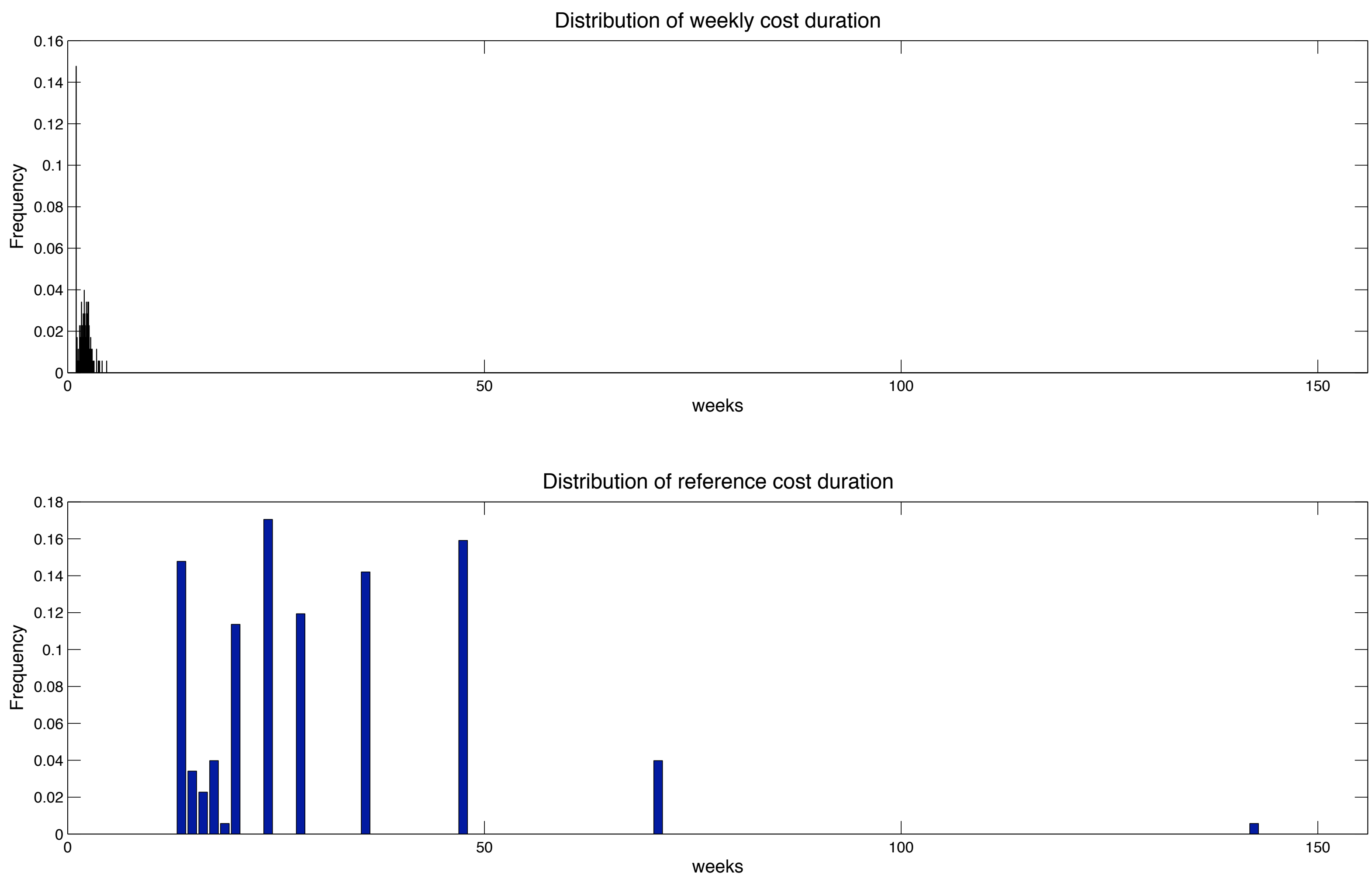
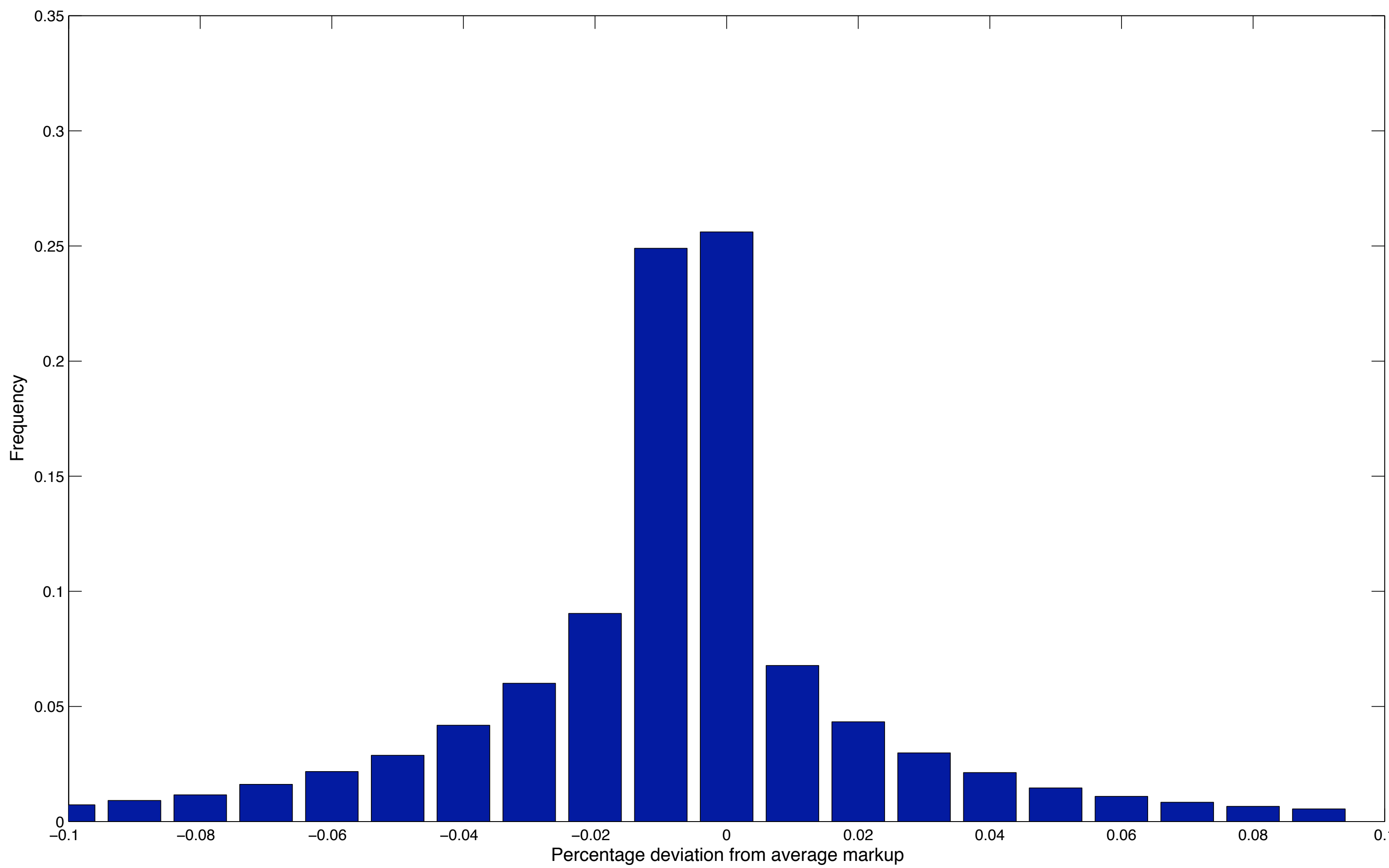

Distribution of weekly cost duration
Frequency
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
0
50
100
150
weeks
Distribution of reference cost duration
Frequency
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
0
50
100
150
weeks

Figure 5



Frequency
Percentage deviation from average markup
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
−0.1
−0.08
−0.06
−0.04
−0.02
0
0.02
0.04
0.06
0.08
0.1

Figure 6

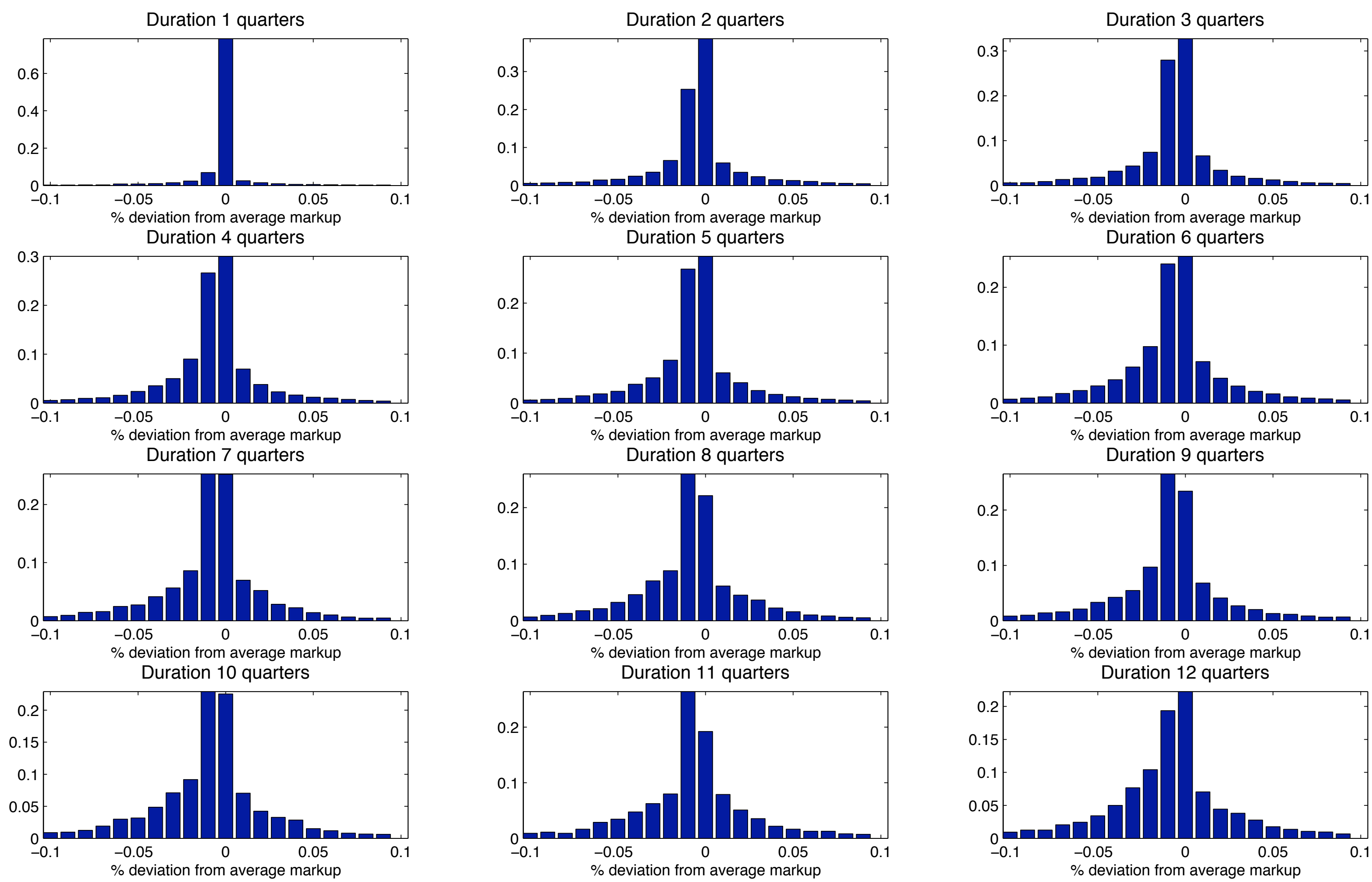
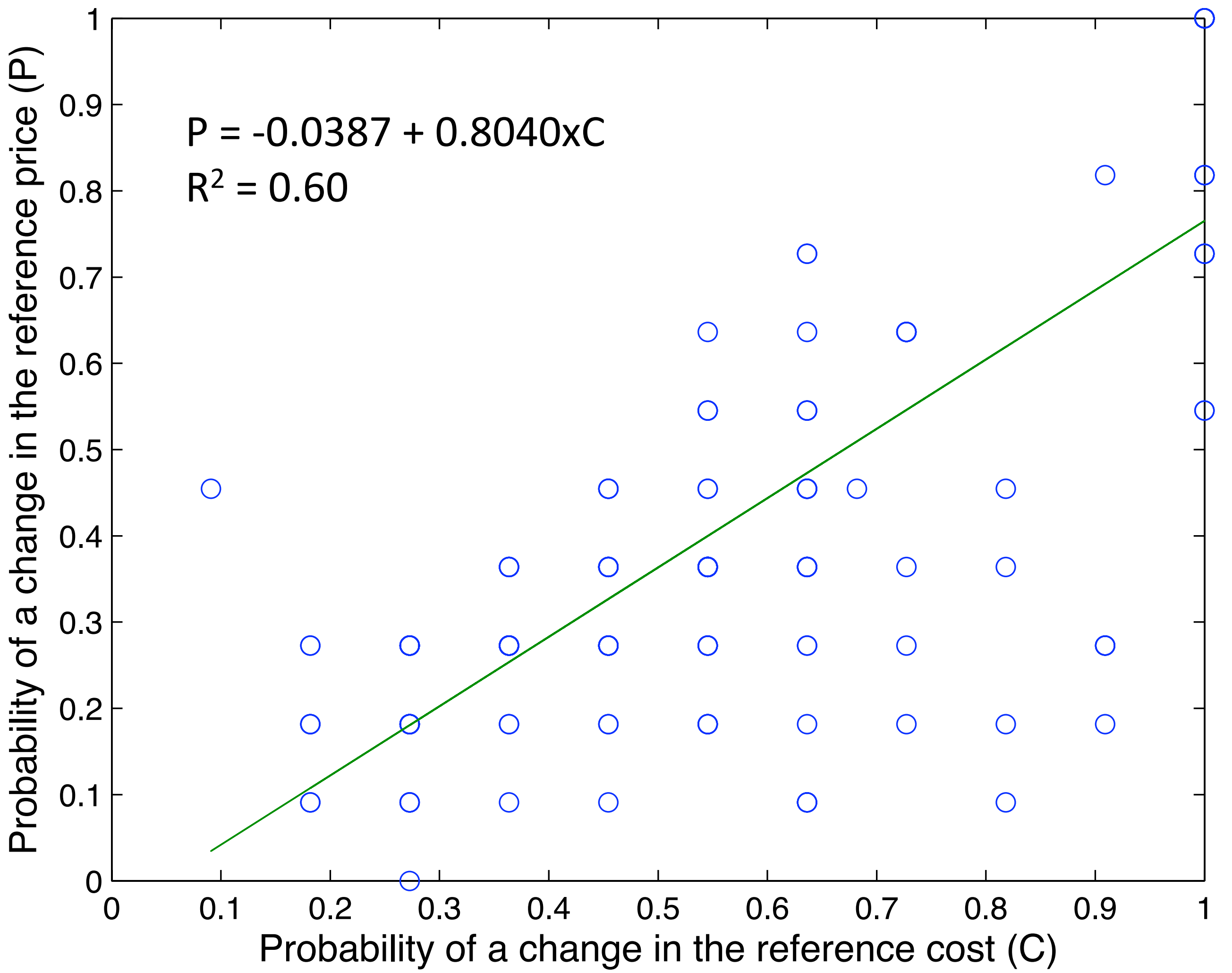
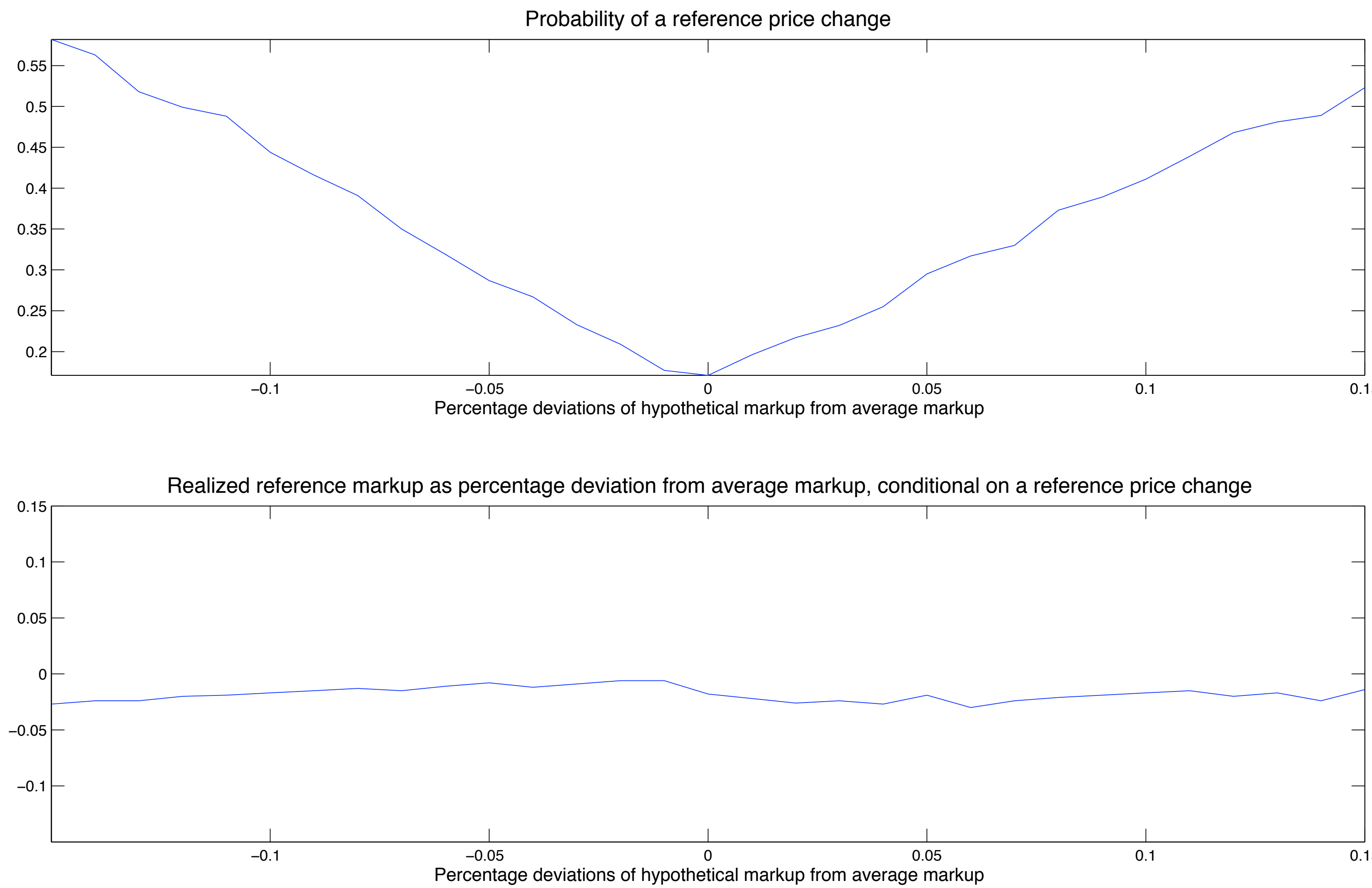

Duration 1 quarters
Duration 2 quarters
Duration 3 quarters
Duration 4 quarters
Duration 5 quarters
Duration 6 quarters
Duration 7 quarters
Duration 8 quarters
Duration 9 quarters
Duration 10 quarters
Duration 11 quarters
Duration 12 quarters
% deviation from average markup
−0.1
−0.05
0
0.05
0.1

Figure 7



P = -0.0387 + 0.8040xC
R2 = 0.60
Probability of a change in the reference price (P)
Probability of a change in the reference cost (C)
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1

Figure 8



Probability of a reference price change
0.55
0.5
0.45
0.4
0.35
0.3
0.25
0.2
−0.1
−0.05
0
0.05
0.1
0.15
Percentage deviations of hypothetical markup from average markup
Realized reference markup as percentage deviation from average markup, conditional on a reference price change
0.15
0.1
0.05
0
−0.05
−0.1
−0.1
−0.05
0
0.05
0.1
0.15
Percentage deviations of hypothetical markup from average markup

Figure 9
Probability of reference price change as a function of percentage deviation of hypothetical markup from average markup for goods with different price duration

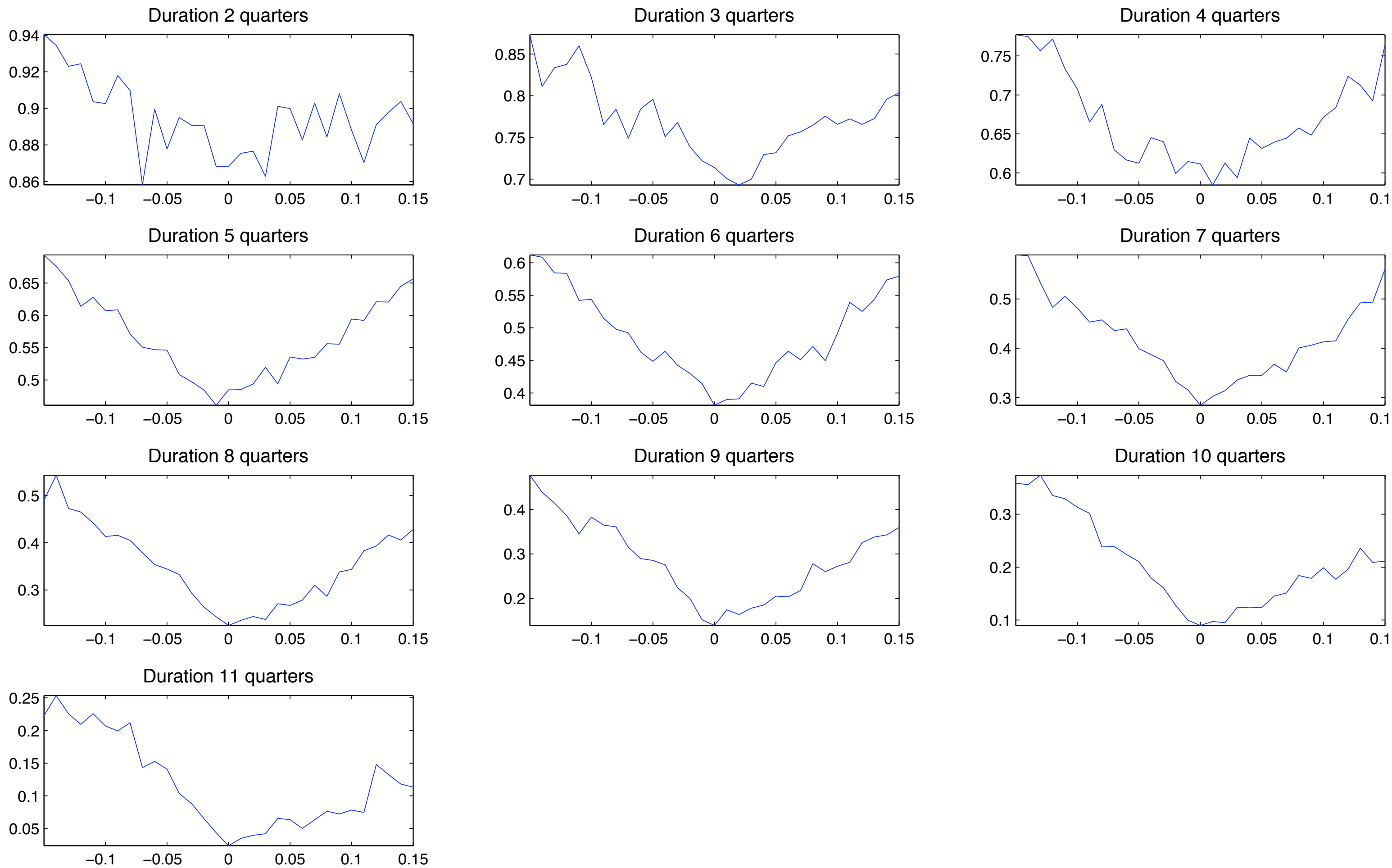


Figure 10
Probability of reference price change as a function of percentage deviation of hypothetical markup from average markup for goods with different cost volatility

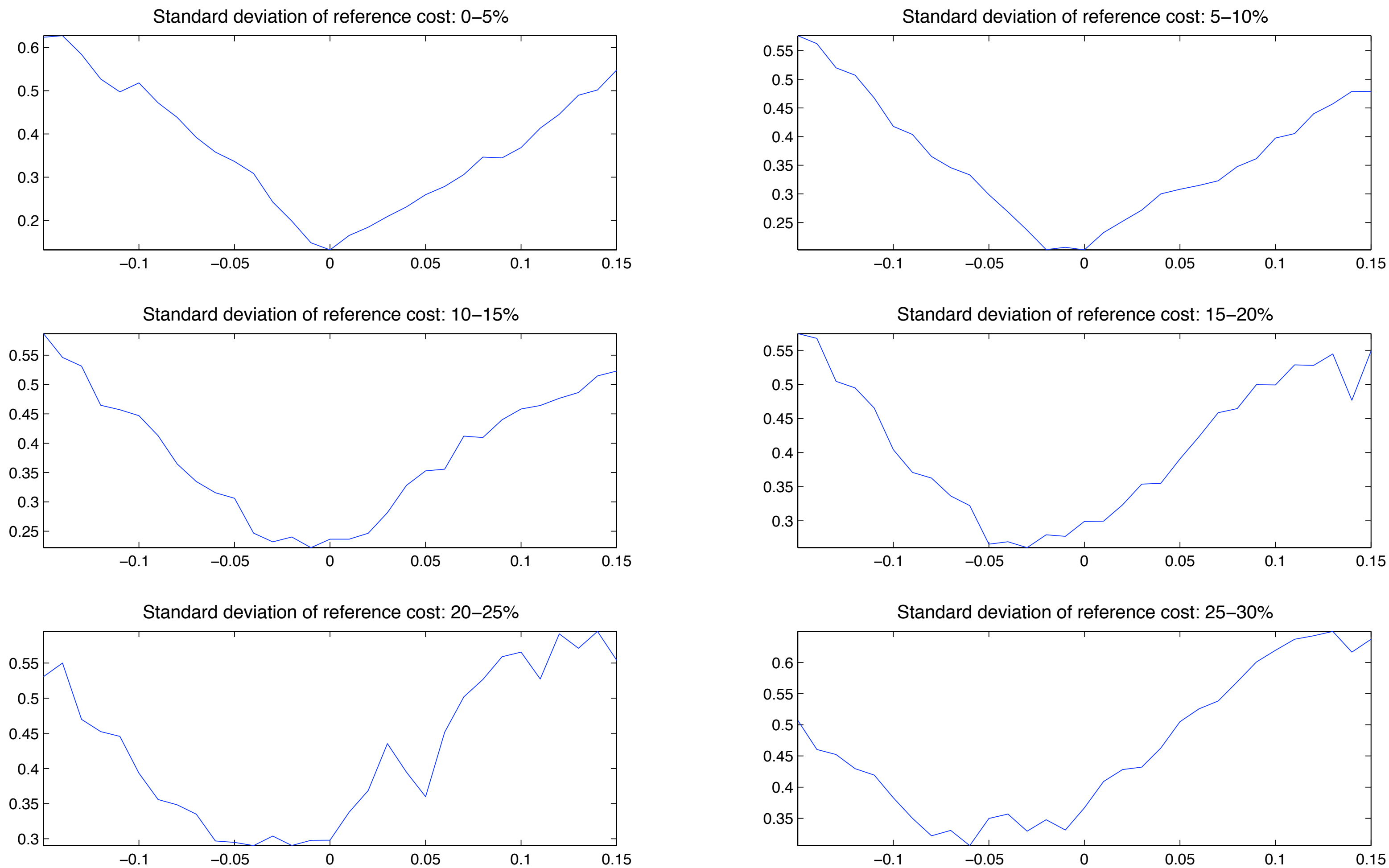
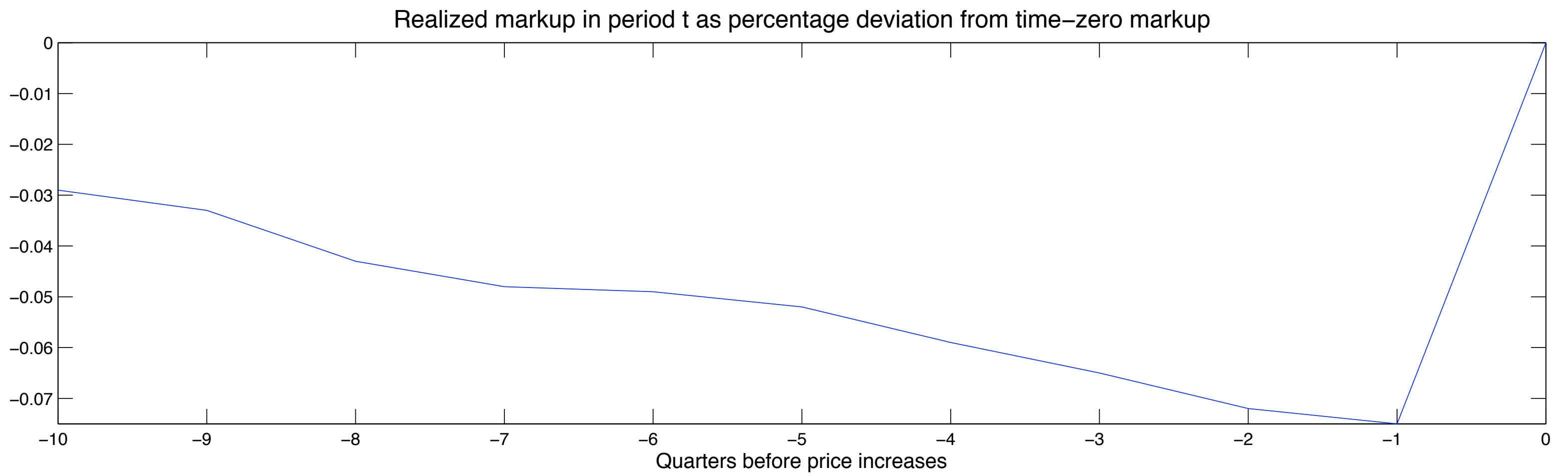
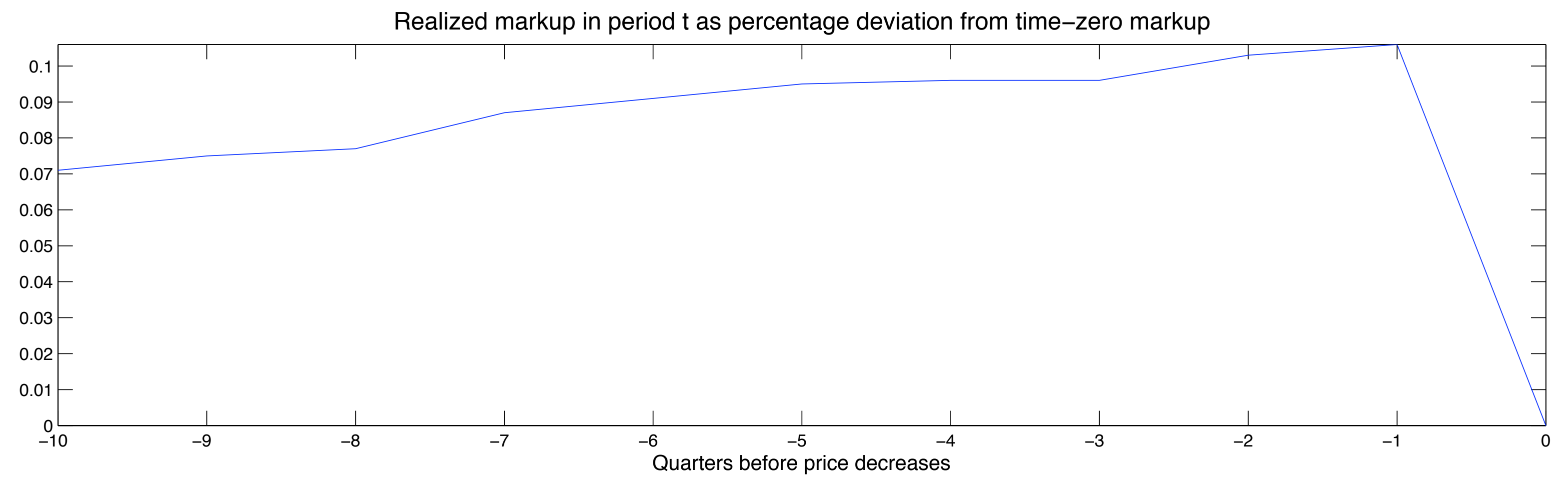


Figure 11



Realized markup in period t as percentage deviation from time−zero markup
0
−0.01
−0.02
−0.03
−0.04
−0.05
−0.06
−0.07
−10
−9
−8
−7
−6
−5
−4
−3
−2
−1
0
Quarters before price increases



Realized markup in period t as percentage deviation from time−zero markup
0.1
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
−10
−9
−8
−7
−6
−5
−4
−3
−2
−1
0
Quarters before price decreases

Figure 12: Impulse response to a monetary shock