Multiproduct Firms and Price-Setting: Theory and Evidence from U.S. Producer Prices*

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Abstract

In this paper, we establish three new facts about price-setting by multi-product firms and contribute a model that can explain our findings. On the empirical side, using micro-data on U.S. producer prices, we first show that firms selling more goods adjust their prices more frequently but on average by smaller amounts. Moreover, the higher the number of goods, the lower is the fraction of positive price changes and the more dispersed the distribution of price changes. Second, we document substantial synchronization of price changes within firms across products and show that synchronization plays a dominant role in explaining pricing dynamics. Third, we find that within-firm synchronization of price changes increases as the number of goods increases. On the theoretical side, we present a state-dependent pricing model where multi-product firms face both aggregate and idiosyncratic shocks. When we allow for firm-specific menu costs and trend inflation, the model matches the empirical findings.

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Keywords: Multi-product firms; Number of Goods; State-dependent pricing; U.S. Producer prices.

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1 Introduction

In this paper, we analyze price-setting behavior from a new angle, using the firm as the unit of analysis. We examine the micro-data underlying the U.S. Producer Price Index (PPI) and establish three new empirical facts, showing that the number of goods produced by firms, synchronization of price changes within firms, and the interaction of these two are key variables for explaining price adjustment decisions. On the theoretical side, we find that in order to match our empirical findings, we need to include firm-specific menu costs and trend inflation into a state-dependent model of multi-product firms.

Our results have important aggregate implications. First, our empirical findings are most directly related to the results of Midrigan (2010): allowing in a state-dependent DSGE model for the features which we document empirically amplifies real effects of monetary shocks.[1] Second, our results highlight that heterogeneity among firms, captured by the number of goods produced by them, plays a critical role in explaining pricing dynamics. Recent work by Carvalho (2006) and Nakamura and Steinsson (2008) has shown that heterogeneity in price dynamics magnifies non-neutrality of nominal shocks. Finally, given that approximately 98.55% of all prices in the PPI are set by firms with more than one good,[2] analyzing how the number of goods in a firm relates to pricing decisions appears to be of independent interest since it contrasts with the standard macro-economic assumption of price-setting by single-product firms. In fact, our findings directly suggest that it is necessary to model multi-product firms as distinct from an aggregate of many single-product firms.

We analyze the PPI micro data by grouping firms according to the number of goods produced by them and establish the following. First, pricing behavior is systematically related to the number of goods produced by firms. We find that as the number of goods increases, the frequency of price adjustment increases. At the same time, the average magnitude of price changes, conditional

[1] In particular, when there are complementarities in the cost of adjusting the prices of goods, price changes will always be dispersed with some very large and some very small price changes. Therefore, monetary shocks will have large real effects similar to models of time-dependent adjustment. Our empirical results, based on the entire PPI, validate the key modeling assumptions needed to produce these aggregate real effects.

[2] We define a good as a particular brand of product which is moreover identified according to certain characteristics that do not change over time, such as having the same buyer over time. The data section contains further details on the good definition.

on adjustment, decreases. This result holds for both upwards and downwards price changes. In addition, we find that small price changes are highly prevalent in the data and become more prevalent when the number of goods increases. Finally, there is substantial dispersion in the size of price changes and it increases with the number of goods. For example, the coefficient of variation of absolute price changes and the kurtosis of price changes increase as the number of goods per firm increases.

Second, we find strong evidence for substantial synchronization of individual price adjustment decisions within the firm. When we estimate a multinomial logit model to relate individual adjustment decisions to the fraction of price changes of the same sign within a firm, there is a large increase in probability that the price of another good in the firm changes in the same direction when the price of one good in a firm changes. While this result holds for both upwards and downwards adjustment decisions, the within-firm synchronization is stronger for positive than for negative price adjustment. Moreover, our results show that such synchronization within the firm is much stronger than within the industry.

Third, we document that the number of goods and the degree of within-firm synchronization strongly interact in determining individual price adjustment decisions. We find that the strength of within-firm synchronization increases monotonically as we move to firms that produce more goods. Again, this result holds both for upwards and downwards adjustment decisions. At the same time, we find that the strength of synchronization within the same industry decreases monotonically as the number of goods increases.

Next, on the theoretical side, we develop a state-dependent pricing model with idiosyncratic productivity shocks and an aggregate inflation shock that is consistent with these empirical findings. In our model of price-setting, there is a menu cost of changing prices which is firm-specific, and there are economies of scope in the menu cost technology.[3] In particular, we show how the trends in the data are critical in validating different features of the model.

The predictions of the model become clear when one compares the case of a 1-good and a 2-good firm. When a 2-good firm decides to change a particular price, it essentially gets to change the

[3]We understand this menu cost very broadly as a cost of price adjustment as Blinder et al. (1998) or Zbaracki et al. (2004) argue.

price of a second good for free. This leads, on average, to a higher frequency of price changes and a lower mean absolute, positive, and negative size of price changes. This also implies that the fraction of small price changes is higher for the 2-good firm. Moreover, with trend inflation, firms adjust downwards only when they receive substantial negative productivity shocks. Since the firm adjusts both prices when the desired price of one item is very far from its current price, a higher fraction of downward price changes becomes sustainable. Moreover, both positive and negative adjustment decisions become more synchronized within the firm. In particular, as we find in the data, due to shocks from upward trend inflation, positive adjustment decisions are more synchronized than negative adjustment decisions.

Our empirical work is directly related to the recent literature that has analyzed micro-data underlying aggregate price indices.[4] Using U.S. PPI micro-data, our paper contributes the first account of price-setting dynamics from the perspective of the firm. Two other recent papers have also used the same data to uncover interesting patterns. Nakamura and Steinsson (2008) show that there is substantial heterogeneity across sectors in the PPI in the frequency of price changes. They also match groups between the CPI and the PPI database and find that the correlation in the frequency of price changes between the groups is quite high. Goldberg and Hellerstein (2009) document that price rigidity in finished producer goods is roughly the same as consumer prices including sales and that large firms change prices more frequently and by smaller amounts compared to small firms. Our results are complementary to theirs. Neither of these papers however, contain a systematic analysis from the perspective of the firm, and in particular, how price-setting dynamics differ by the number of goods produced by them.

Our empirical results are also related to findings from papers that use retail or grocery store data to analyze pricing behavior by multi-product firms. In important contributions, Lach and Tsiddon (1996) use retail store data and Fisher and Konieczny (2000) use data from a newspaper chain to show that price changes are synchronized within a firm while staggered across firms. Moreover, Lach and Tsiddon (2007) show how small price changes are prevalent in retail store data and argue that this feature can be consistent with a model of multi-product firms where part of the cost of

[4]For a survey of this literature, see Klenow and Malin (2010). Most of this literature has focused on the U.S. or the Euro Area. For an analysis of emerging markets, see Gagnon (2009).

price adjustment is firm-specific. Midrigan (2010) uses grocery store data to show that a large fraction of price changes are small in absolute values, and that the distribution of price changes, conditional on adjustment, is leptokurtic. Our findings are significantly wider and more general compared to these studies since we use micro-data underlying the PPI with approximately 28000 firms. Importantly, given the variation in the number of goods produced by firms in our dataset, we are able to systematically uncover patterns across firms as we vary this dimension. This analysis is new to the literature.

Our model is related to theoretical work by Sheshinski and Weiss (1992), Midrigan (2010), and Alvarez and Lippi (2010). In a seminal paper, Sheshinski and Weiss (1992) show the conditions under which price-setting by multi-product firms is likely to be synchronized or staggered. They emphasize the key role played by complementarities in the menu cost technology and in the profit function. Midrigan (2010) presents a general equilibrium model where two-product firms face economies of scope in the technology of adjusting prices. The striking quantitative result of his paper is that aggregate fluctuations from monetary shocks are substantially larger than in traditional state-dependent models and almost as large as time-dependent models. Our contribution relative to the work of Sheshinski and Weiss (1992) and Midrigan (2010) is to analyze systematically price-setting trends as we vary the number of goods produced by firms, from 1 to 3 goods. In addition, by considering 2-good vs. 3-good firms, we are able to study trends in some price setting statistics, such as synchronization, that is not possible by only comparing 1-good and 2-good firms.

In a recent, independent, highly related paper, Alvarez and Lippi (2010) use stochastic control methods to characterize the price setting solution of a multi-product firm producing an arbitrary number of goods. They analytically show that given firm-specific menu costs, frequency of price change increases, absolute size decreases, and the dispersion increases as the number of goods produced increases. We show these same trends numerically. Our relative contribution is that we solve a model with trend inflation and also generate additional predictions for direction and synchronization of price changes. We then match all the empirical trends in these moments qualitatively using a calibrated model.

2 Empirics

2.1 Data

We use monthly producer price micro-data from the dataset that is normally used to compute the Producer Price Index (PPI) by the Bureau of Labor Statistics (BLS). Using producer prices makes our results comparable to other studies of price-setting behavior as well as consistent with a model where firms, and not retailers, set prices.[5]

The PPI contains a large number of monthly price quotes for individual "items", that is, particular brands of products with certain time-persistent characteristics. These items which we henceforth refer to as goods are selected to represent the entire set of goods produced in the US and are sampled according to a multi-stage design.[6] This sampling procedure takes three main steps: in a first step, the BLS compiles a sampling universe of all firms producing in the US using lists from the Unemployment Insurance System. Most firms are required to participate in this system and the BLS verifies and completes the sampling frame using additional publicly available lists, for example in the service sector. In a second step, "price-forming units" which are usually defined to be "production entities in a single location" are selected for the sample according to the total value of shipment of these units or according to their total employment. In a final series of steps called "disaggregation," a BLS agent conducts a field visit and selects the actual goods to be selected into the sample. Again, total values of shipment are used for selection.

In this last step, the BLS takes great care to obtain actual transaction prices. This emphasis on transaction prices goes back to a critique by Stigler and Kindahl (1970) when the data was based on list and not transaction prices. In addition, the BLS also uniquely identifies a good according to its "price-determining" characteristics such as the type of buyer, the type of market transaction, the method of shipment, the size and units of shipment, the freight type, and the day of the month of the transaction. Moreover, the BLS collects information on price discounts

[5] A similar analysis using CPI data is not feasible since the CPI sampling procedure does not map to the production structure of the economy, but to sales in outlets, which may sell goods from any number of firms, including imports. Moreover, it is generally also not even possible to identify the producing firms for specific CPI items. The CPI specifications data only sometimes records the item manufacturers.

[6] For a detailed description of the sampling procedures, see Chapter 14 of the BLS Handbook of Methods (US Department of Labor, 2008).

and special surcharges. Once a good has been sampled and uniquely identified according to its price-determining characteristics, the BLS collects monthly prices for that very same good and the same customer through a re-pricing form. Moreover, neither order prices nor futures prices are included in the dataset.[7]

Despite this emphasis on transaction prices, there might be some concern about the quality of the price data: respondents have the option to report on the re-pricing form that a price has not changed. This might induce a bias in the price data towards higher price stickiness if respondents are lazy. Using the episode of the 2001 anthrax scare when the BLS exclusively collected prices by phone, Nakamura and Steinsson (2008)[8] show however, that the frequency of price changes, controlling for inflation and seasonality, was the same in months when data were collected using the standard mail form as when the collection was done through personal phone calls.[9]

We supplement the BLS PPI data with the monthly inflation rate from the OECD "Main Economic Indicators (MEI)" when running our discrete choice analysis. We use both CPI inflation including food and energy prices as well as excluding food and energy prices. Since we find no qualitative difference in our results, we only report results from the inclusive CPI measure in the main part of the paper.

2.2 Identifying and Grouping Firms

The PPI data allow us to identify firms according to the number of goods produced by them. This distinction uses the firm identifiers and then counts the number of goods in the data for each firm and at any point in time. We define firms at the establishment level (for example, "Company XYZ").[10] We then group the firms into the following four good bins according to the average

[7] The PPI price then is defined as "the net revenue accruing to a specified producing establishment from a specified kind of buyer for a specified product shipped, or service provided, under specified transaction terms on a specified day of the month" (BLS, 2008).

[8] See footnote 12 in Nakamura and Steinsson (2008). This idea was first used in Gopinath and Rigobon (2008) where it is applied to export and import prices.

[9] Moreover, since the same product is priced every month, the BLS accounts for instances of product change and quality adjustments. When there is a physical change in a product, one of several quality adjustment methods are used. These include the direct adjustment method for minor physical specification changes, and either the explicit quality adjustment method or the overlap method for major changes. Hedonic regressions have also now been introduced by the BLS into these adjustment processes.

[10] Therefore, we will use the terms "firms" and "establishments" interchangeably in this paper. In the PPI dataset, they correspond to, as we have described above, what are called "price forming units."

number of goods produced by them: a) bin 1: firms with 1 to 3 goods, b) bin 2: firms with more than 3 to 5 goods, c) bin 3: firms with more than 5 to 7 goods, and d) bin 4: firms with more than 7 goods.[11] Thus, firms in higher bins sell a greater number of goods than firms in lower bins.

It is important to emphasize that the sampled data monotonically map the number of actual goods per firm.[12] On the one hand, this is due to the BLS sampling procedure. The BLS sampling design in the "disaggregation" stage is such that all the economically important products tend to be sampled with probability proportional to their sales.[13] In addition, the BLS pays special attention to cover all distinct product categories if they exist in a firm and allows some discretion in sampling when there are many products in a firm. Thus, if a firm has more products, more products will be sampled on average. On the other hand, our strategy of binning goods into the ranges given above leaves some room for potential errors of sampling into the "wrong" bin and allows us to average out such errors when we calculate our statistics of interest. Finally, as the results show, our choice of binning leads to results that our theoretical model in all cases predicts would be indeed identified with an increasing number of goods per firm.

We present in Table 1 some descriptive statistics on firms according to the groups that we construct. The mean (median) number of goods per firm across these bins is 2.2 (2.0), 4.0 (4.0), 6.1 (6.0), and 10.3 (8.0) respectively. The dispersion is higher in bin 4, with for example, a standard error of 0.11. The table also shows that while the majority of firms, around 80%, fall in bins 1 and 2, there are a substantial number of firms in bins 3 and 4 as well. In fact, since firms in bins 3 and 4 produce more goods, they account for a much larger share of prices than of firms. Firms in bins 3 and 4 set around 40% of all prices in our data.

Regarding firm size, the table reports two statistics which we compute as follows. First, after placing firms in different bins, we compute mean employment at the firm level, which is defined as employment per average number of goods per firm. Then, we take the median across different

[11] Note that we have many firms who have non-integer average numbers of goods due to the averaging of the monthly number of goods for each firm. This is one reason to have bins.

[12] We thank Alan Blinder and Chris Sims for pointing us to this important sampling concern.

[13] We know from Bernard et al. (2010) and Goldberg et al. (2008)'s Table 4 that large firms are multi-product firms with substantial value of sales concentrated in a few goods. We present an analogous table for our dataset in Appendix 3. Results suggest that sampling is likely to monotonically capture the actual number of economically important goods. Please see the appendix for details.

industries defined at the 3-digit NAICS level. Finally, we report in Table 1 as mean employment, the average of these medians across all industries in a bin, and as median employment, the median of these medians. The table shows that there is no clear trend in terms of median employment per good across these different bins.

Table 9 in Appendix 1 presents the distribution of firms across bins and industries at the 2-digit NAICS level. Table 9 shows that no particular industry substantially dominates a particular good bin and that in fact, NAICS sectors 31, 32, and 33 (durable and non-durable manufacturing) are the dominant industries for all bins, accounting for around 45-70% of all firms. Table 9 also shows that for a particular industry, typically good bins 1 and 2 contain the vast majority of firms. Notable exceptions are NAICS 22 (utilities) which contains a very high proportion of firms that fall in bin 4, and NAICS 62 (health care and social assistance) where almost half the firms are in bins 3 and 4. This broadly flat composition across industries also holds at more disaggregated levels, as we show in Appendix 1 in Tables 10 and 11.

2.3 Results

We report the results from our empirical analysis in two parts below. First, we document important aggregate statistics on price changes, such as frequency, size, direction, and dispersion of price changes, according to the good bins that we construct. Second, we show the role played by economic fundamentals in pricing decisions at the good level using a discrete choice framework.[14]

2.3.1 Basic Statistics

Frequency of price changes We compute the frequency as the mean fraction of price changes during the life of a good. We do not count the first observation as a price change and assume that

[14] In relation to recent studies of price adjustment using micro data from the BLS and retail stores, it is worth noting at the outset the following aspects of the PPI data. As documented by Nakamura and Steinsson (2008), while sale prices are important in the CPI data, they are not prevalent in the PPI data. Therefore, we do not distinguish between sale and non-sale prices, for example, by using a sales filter. Nakamura and Steinsson (2008) also show that for aggregate statistics on price changes, accounting for product substitutions can make a difference, especially in the CPI. All the baseline results we report below are excluding product substitutions. We identify product replacement by changes in the so-called "base price" which contains the price at each resampling of a good in the PPI. When this base price changes within a price time series, but the data show no change in the actual price series, we set our product substitution dummy to one. The results nevertheless remain the same while including product substitutions.

a price has not changed if a value is missing. Also, we do not explicitly take into account issues of left-censoring of price-spells. However, we verify that taking into account left-censoring leaves the resulting distribution of frequencies in the PPI essentially unchanged. For our purpose, it is most relevant that we apply our method consistently across all firms. After computing the frequency of price changes at the good level, we calculate the median frequency for all goods within the firm. Then, we report the mean, median, and standard error of frequencies across firms in a given good bin. We use the standard error to compute 95% confidence intervals through out the paper.

Figures 1 and 2 show that the monthly mean and median frequency of price changes increase with the number of goods produced by firms. The mean frequency increases from 20% in bin 1 to 29% in bin 4 while the median frequency increases from 15% to 23%. The relationship is monotonic across bins except for the mean frequency of price changes for bins 1 and 2. Inverting these frequency values, this implies that the mean duration of a price spell decreases from 5 months in bin 1 to 3.4 months in bin 4 while the median duration decreases from 6.7 months to 4.3 months. Therefore, in general, firms that produce a greater number of goods change prices more frequently.[15]

Direction and size of price changes We define the fraction of positive price changes as the number of strictly positive price changes over all zero and non-zero price changes. We compute this at the firm level and then report the mean across firms in a given good bin.[16] Figure 3 shows that the mean fraction of positive price changes decreases with the number of goods produced by firms as it goes down from 0.64 in bin 1 to 0.61 in bin 4. Firms with many goods therefore adjust prices upwards less frequently.

We next compute the size of price changes as the percentage change to last observed price. Again, we compute this at the good level, take the median across goods in a firm, and then report the mean across firms in a good bin. Figure 4 shows that the mean absolute size of price changes decreases with the number of goods produced by firms as it goes down from 8.5% in bin 1 to 6.6%

[15]Using our dataset to compute an aggregate measure of frequency and duration of price changes in the PPI, we get estimates of 0.21 and 0.16 for the mean and median frequency and 6.91 and 5.74 months for the mean and median duration. This is calculated by first computing the frequency at the good level, second by taking the median across goods in a classification group, third, by taking the median across classification groups within six-digit categories and fourth, by taking means and medians across six-digit categories.

[16]While we report only the mean across firms in a given bin for all statistics other than frequency, all our results are completely robust to whether we compute the mean or the median across firms.

in bin 4.[17]

Moreover, this relationship holds even when we separate out the price changes into positive and negative price changes. Figure 5 shows that the mean size of positive price changes decreases with the number of goods while the mean size of negative price changes increases with the number of goods. Thus, in general, firms that produce a greater number of goods adjust their prices by a smaller amount, both upwards and downwards.

An interesting statistic in this context is the fraction of small price changes where we define a small price change as: $|\Delta p_{i,t}| \leq \kappa \overline{|\Delta p_{i,t}|}$, where i is a firm and $\kappa = 0.5$. That is, a price change is small if it is less in absolute terms than a specified fraction (here 0.5) of the mean absolute price change in a firm. After computing this at the firm level, we then report the mean in a good bin. Figure 6 shows that the mean fraction of small price changes increases from 0.38 in bin 1 to 0.55 in bin 4. Therefore, small price changes are more prevalent when firms produce many goods and in fact, for bin 4, more than half the price changes are small.

Dispersion of price changes We use three measures to document the dispersion of price changes: the the coefficient of variation of absolute price changes, the kurtosis of price changes, and the 1^{st} and the 99^{th} percentiles. We report the coefficient of variation of absolute price changes that we compute as follows: we pool data at the firm level, compute the ratio of the standard deviation to the mean of absolute price changes for an item, take the mean across items in a firm, and then take means across firms in a good bin. Table 2 shows that it increases from 1.02 in bin 1 to 1.55 in bin 4.

We define the kurtosis of price changes as the ratio of the fourth moment about the mean and the variance squared:

$$K = \frac{\mu_4}{\sigma^4} \text{ where } \mu_4 = \frac{1}{T-1} \sum_{i}^{n} \sum_{t=1}^{T_i} (\Delta p_{i,t} - \overline{\Delta p})^4 \tag{1}$$

[17] Using our dataset to compute an aggregate measure of the absolute size of price changes in the PPI, we find estimates of 6.96% and 5.34% for the mean and median size. This is calculated by first computing the mean absolute price change at the good level, second by taking the median across goods in a classification group, third, by taking the median across classification groups within six-digit categories and fourth, by taking means and medians across six-digit categories.

and where in a given firm with n goods, $\Delta p_{i,t}$ denotes the price change of good i, $\overline{\Delta p}$ the mean price change and σ^4 is the square of the usual variance estimate. Figure 7 shows that the mean kurtosis of price changes increases with the number of goods produced by firms as it goes up from 5.3 in bin 1 to 16.8 in bin 4. Thus, even for bin 1, the distribution is leptokurtic.

We also document in Figure 8 that both the 1^{st} and the 99^{th} percentiles of price change take more extreme values as the number of goods increases. Thus, overall, our results show that dispersion in price changes increases with the number of goods produced by firms.

Robustness We conduct a battery of robustness tests for our aggregate results. All the results in this section can be found in Appendix 1. For conciseness, we only present results on frequency and size of price changes.

We show that our results are robust to controlling for various factors, independent of the number of goods, that might potentially lead to the trends across bins that we document. Figures 15 and 16 show that the trends hold while controlling linearly for the size of the firm, using the total number of employees in the firm as a measure of firm size, while Figures 17 and 18 document the same trends while controlling at 2-, 3-, and 4-digit NAICS sectoral levels. As we document above, a majority of the firms are in 2-digit sectors 31, 32, and 33, and so it is natural to wonder if our results are valid only for these sectors. We show in Figures 19 - 22 that this is not the case. The trends in frequency and size remain whether we take out sectors 31, 32, and 33, or if we compute these statistics separately for these sectors.

While we show that our results do not change when we add controls for sectors, one might still worry that the trends across bins are due to varying elasticities of demand or degrees of substitution. To verify that this is not the case, we conduct the following detailed test. First, we pick firms that sell goods in a narrow product code provided by the BLS at the 6-digit level.[18] Second, we compute the median frequency of price changes, the absolute size of price changes, and the number of goods sold by the firms at a point in time. Third, we run two regressions: first, the frequency of price changes on the number of goods and second, the absolute size of price changes on the number

[18]The relevant product code is the PPI product code. We exclude firms which sell in multiple product codes to simplify the analysis and avoid having to "split up" firms.

of goods. We take the median of the estimated coefficients across all product codes, and then report summary statistics on these medians over time. Tables 12 and 13 present the results and show clearly that the estimates go in the right direction. Thus, the positive relationship between frequency of price changes and number of goods, and the negative relationship between size of price changes and number of goods continues to hold, even when we tightly control for varying elasticities of demand or substitution.

We also verify that our results on small price changes are robust to various alternate definitions. Recall that in our baseline results, we defined small price change as $|\Delta p_{i,t}| \leq \kappa \overline{|\Delta p_{i,t}|}$ where i is a firm and $\kappa = 0.5$. In Table 14 we show that our results continue to hold for $\kappa = 0.10,\ 0.25,$ and 0.33. Table 14 also shows that the results are robust if we define small price changes in terms of absolute values. That is, price changes that are less than 0.25%, or 0.5%, or 1%. In Table 15 we show that the trends across bins also persist if we measure small price changes relative to the mean in the industry. That is, a small price change is now defined as $|\Delta p_{i,j,t}| \leq \kappa \overline{|\Delta p_{j,t}|}$ where i is a firm, j is the industry defined at the 4-, 6-, and 8-digit NAICS levels, and $\kappa = 0.5$. Finally, the results also do not change if we define small price changes at the level of the good and relative to the mean price change of that good, and only then aggregate up to the level of the firm. Table 16 shows the results for $\kappa = 0.5$. Again, results show that there is a substantial fraction of small price changes. This fraction increases monotonically with the number of goods. Thus, our finding of substantial fraction of small price changes is not a mechanical result due to computation of this fraction at the firm-level.[19]

While we have conducted exhaustive checks to confirm that it is the number of goods produced by firms that is responsible for the variation across the good bins, one might still wonder if the trends are due to other sources of permanent heterogeneity across firms or sectors. To control for such spurious effects, we have filtered out month-, product-, and firm-level fixed effects, with product-level fixed effects defined at the 4-, 6- and 8-digit PPI product codes. We show in Table

[19] Additionally, there is a third way to compute a fraction of small price changes for a firm by computing the fraction of small price changes for a good but relative to the mean absolute size of price changes at the firm level and then aggregating across goods. We have also computed the fraction of small price changes this way and obtain very similar results.

17 that the variation in price changes explained by these fixed effects is at most 29%.[20]

Finally, since we have panel data, another potential check on our results would be to consider time-series variation in the number of goods for a given firm and compute the various statistics. Unfortunately, in our dataset, there is very little variation in the number of goods over time for a given firm, and hence we do not investigate this further.[21]

2.3.2 Regression Analysis

Here, we go beyond providing aggregate statistics and estimate a discrete choice model to analyze what economic fundamentals determine pricing dynamics at the good level. In particular, we estimate a multinomial logit model for the decision to change prices. This allows us to separately examine the relationship of upwards and downwards adjustment decisions with the explanators.[22]

We impose a multinomial logit link function with 3 categories: $m = 0$ for no price change, $m = 1$ for a price increase, and $m = -1$ for a price decrease. The multinomial logit model is described in detail for example, by Agresti (2007). Denoting by $\Pi_{i,m}$ the probability that decision m is taken for good i, the probability under the multinomial logit link is given by:

$$\Pi_{i,m,t} = \frac{e^{X_{i,t}\alpha_m}}{\sum_m e^{X_{i,t}\alpha_m}}. \tag{3}$$

Since $\sum_m \Pi_{m,t} = 1$, the three sets of parameters are not unique. Therefore, we follow standard

[20]For example, we estimate the following specification regarding variation in $|\Delta p|$, the absolute size of price changes:

$$|\Delta p|_{i,f,p,t} = \alpha_0 \{D^{Month\ m}_{i,f,p,t}\}_{m=1}^{m=12} + \alpha_1 D^{Product}_{i,f,p,t} + \alpha_2 D^{Firm}_{i,f,p,t} + \epsilon_{i,f,p,t} \tag{2}$$

where i denotes an item, f a firm, p a product at the 4-, 6-, and 8-digit level, and t time. Dummies are for months, products, and firms. This is a standard decomposition similar to the one performed in Midrigan (2010).

[21]The median change in the number of goods during our 1998 to 2005 sampling period is 0. Even when there is change in the number of goods, it is small so that firms generally do not fall into a different bin. The median increase in the number of goods, given an increase in the number of goods, is 1 good and the median decrease is 1 good. The lack of time series variation is not surprising for several reasons. First, resampling usually takes place only every 5 years so that the number of goods remains constant in the meantime. Second, the relative importance of firms according to the BLS does not change as drastically such as as to lead to a different number of goods being sampled for a given firm when the survey sampling design fixes how many goods to sample in total due to a budget constraint.

[22]Instead of the multinomial logit model, we could also estimate an ordered probit model, as in Midrigan (2010) and Neiman (2010). This would assume that there is a "ranking" of outcomes in terms of how the latent underlying variable cutoffs relate to the right-hand side variables. The latent variable in our case could be interpreted as deviation from the desired optimal price. This might indeed result in some ordering – for example, high inflation means one is likely below the desired optimal price and hence, 1 is the adjustment decision preferred to 0 and -1. For other right-hand side variables, however, this relationship is unclear, for example for the fraction of price changes within the firm or even month dummies. Hence, we estimate conservatively using the multinomial logit model.

practice and choose category $m = 0$ as a baseline category:

$$\Pi_{i,0,t} = \frac{1}{1 + \sum_{m \in (-1,1)} e^{X_{i,t}\alpha_m}}. \tag{4}$$

We estimate the two remaining logit equations simultaneously. The logit model has the convenient property that the estimated coefficients take on the natural interpretation of the effect of the explanators on the probability of adjusting prices up or down over taking no action.

We include as controls in X the fraction of price changes at the same firm and the same six-digit NAICS sector, excluding the price change of the good we are trying to explain. These variables are meant to capture the extent of synchronization in price setting at the firm and the sectoral level. Moreover, to control for a measure of marginal costs, we also include in X the average price change of goods in the same firm and six-digit NAICS sector. We also include a dummy for product replacement where we can identify it: so-called "base prices" in the PPI contain the first price at each resampling. When this base price changes within a price time series but the data show no change in the actual price series, we set the product replacement dummy to one. As an important fundamental factor, we include energy and food inclusive CPIs in X. Finally, we control for the total number of employees in the firm, industry fixed effects, month fixed effects, and time trends in the data.

We are not aware of any other similar broad-based analysis of U.S. producer micro prices. Since the results for the PPI as a whole are likely to be of independent interest, we first estimate the model on pooled data across all good bins. Then, we focus on estimation separately by good bins.

Pooled Data Table 18 in Appendix 1 shows the detailed results from this multinomial logit model for the pooled data across all good bins. There, we report what are called the relative risk ratios, equivalently the odds ratios, for the different independent variables. Therefore, a coefficient value greater than 1 indicates that a change in the independent variable increases the odds of the dependent category compared with the base category. In the following, we focus on the marginal effect at the mean and the effect when the dependent variable changes from mean $-1/2$ standard deviation to mean $+1/2$ standard deviation. Our main findings are as follows:

Synchronization of price changes We find robust evidence for synchronization of price setting both within the industry and the firm, as documented in Table 3.[23] First, we find that adjustment decisions are synchronized within the industry: the probability of adjusting the price of a good in a firm is higher when the fraction of price changes of the same sign in the industry, excluding that good, increases. This holds for both negative and positive price changes. The effects are both statistically and economically significant. When evaluated at the mean, a 1 percentage point increase in the fraction of negative price changes of other goods in the industry leads to a 0.06 percentage point increase in probability of a negative price change of a good. Similarly, a 1 percentage point increase in the fraction of positive price changes of other goods in the industry leads to a 0.1 percentage point increase in probability of a positive price change of a good. The economic significance can also be discerned from the effects when at the mean the fraction of price changes of the same sign changes by one standard deviation: for negative price changes, the probability of a downward price change of a good increases by 1.32 percentage points, while for positive price changes, the probability of an upward price change of a good increases by 2.27 percentage points.

Second, the results also show that there is substantial synchronization of adjustment decisions within the firm. When the fraction of price changes of the same sign of other goods within the firm increases, then the likelihood of a price change of a given good increases. Again, this holds for both negative and positive price changes. When evaluated at the mean, a 1 percentage point increase in the fraction of negative price changes of other goods in the firm leads to a 0.32 percentage point increase in probability of a negative price change of a good. Similarly, a 1 percentage point increase in the fraction of positive price changes of other goods in the firm leads to a 0.53 percentage point increase in probability of a positive price change of a good. These effects are therefore not only statistically, but also highly economically, significant. The economic significance can also be discerned from the effects when at the mean, the fraction of price changes of the same sign changes by one standard deviation: for negative price changes, the probability of a downward price change of a good increases by 8.81 percentage points, while for positive price changes, the probability

[23] To avoid cluttering, we do not report the p-values, but all the results we report are statistically significant.

of an upward price change of a good increases by 14.7 percentage points. Finally, the coefficient on the fraction of same-signed price changes is larger for positive adjustment decisions than for negative adjustment decisions. In fact, the marginal effect is about twice as large for positive price adjustment decisions.

State-dependent response to inflation The results in table 3 also show evidence for the fundamental role played by inflation, an important aggregate shock, in pricing decisions. In particular, the likelihood of a price decrease decreases with higher CPI inflation while the likelihood of a price increase increases. This is as one would expect from a model where firms adjust prices in a state-dependent fashion. The effects are both statistically and economically significant. When evaluated at the mean, a 1 percentage point increase in CPI inflation decreases the probability of a negative price change of a good by 0.61 percentage points, while increasing the probability of a positive price change by 0.48 percentage points. Similarly, when at the mean, CPI inflation changes by one standard deviation, the probability of a negative price change of a good decreases by 0.21 percentage points, while the probability of a positive price change increases by 0.17 percentage points.

Critical role of within-firm variables The inclusion of within-firm variables, which is unique to our analysis, plays a critical role in explaining price setting behavior. Notice from above that the within-firm effects are much stronger than the within industry effects. To isolate the key role of the within-firm variables more clearly, we run the same regressions as above but exclude from X the fraction of price changes in the same firm and the average price change of goods in the same firm. Tables 4 shows that while the evidence on synchronization of price changes within the industry and the fundamental role of inflation remain intact, the explanatory power of the model drops significantly. The R^2 goes down from 48% to 30%.[24]

By Bins Next, we run the multinominal logit regression for the four good bins separately to investigate differences due to the number of goods produced by firms. Tables 5 and 6 show the

[24]The R^2 measure we report denotes the usual pseudo-R^2. This statistic is based on the likelihood and measures improvements of the model fit.

results for the marginal effect at the mean and the effect when the dependent variable changes from mean $-$ 1/2 standard deviation to mean + 1/2 standard deviation. Our main results, as we move from bin 1 to bin 4, are as follows:

Decreasing within-industry synchronization It is clear that the coefficient on the fraction of price changes in the industry decreases as the number of goods produced by firms increases. When evaluated at the mean, the effect of a 1 percentage point increase in the fraction of negative price changes of other goods in the industry on the probability of a negative price change of the good goes down from 0.11 percentage points in bin 1 to -0.06 percentage points in bin 4. Similarly, the effect of a 1 percentage point increase in the fraction of positive price changes of other goods in the industry on the probability of a positive price change of the good goes down from 0.16 percentage points in bin 1 to 0 percentage points in bin 4. Finally, the effect when at the mean, the fraction of price changes of the same sign changes by one standard deviation goes down from 2.10 percentage points to -1.51 percentage points for negative price changes and from 3.07 percentage points to 0.21 percentage points for positive price changes.

Increasing within-firm synchronization The tables also show that the coefficients on the fraction of price changes on goods within the same firm increases as the number of goods produced by firms increases. When evaluated at the mean, the effect of a 1 percentage point increase in the fraction of negative price changes of other goods in the firm on the probability of a negative price change of the good goes up substantially from 0.25 percentage points in bin 1 to 0.51 percentage points in bin 4. Similarly, the effect of a 1 percentage point increase in the fraction of positive price changes of other goods in the firm on the probability of a positive price change of the good goes up from 0.44 percentage points in bin 1 to 0.78 percentage points in bin 4. Finally, the effect when at the mean, the fraction of price changes of the same sign changes by one standard deviation, increases from 5.38 percentage points to 15.8 percentage points for negative price changes and from 9.61 percentage points to 24.24 percentage points for positive price changes. Importantly, the marginal effects of a change in the fraction of price adjustment within the firm on individual adjustment decisions is systematically larger across all bins for positive adjustment decisions compared to negative adjustment decisions. Thus, we find that there is evidence for greater synchronization of price changes within the firm as the number of goods produced by the firm increases. Moreover, synchronization is always stronger for positive than for negative price changes.

Robustness We conduct a battery of robustness tests for our good-level regressions. First, we consider different levels of aggregation for our definition of the industry variable. In conducting this extension, in addition to checking for robustness, we are motivated by the theoretical results in Bhaskar (2002) that synchronization is likely to be higher within groups with higher elasticity of substitution among goods, that is, at a more disaggregated industry level. Table 20 in Appendix 1 presents results using an industry classification at the 2-digit NAICS level. It shows that at this higher level of aggregation, prices in the pooled data specification are much less synchronized at the industry level, compared with Table 3. Table 20 also shows results for the four good bins separately. The general result of higher firm level synchronization and lower industry level synchronization as we move to higher good bins is robust to this alternate definition of industry.[25] Compared to Table 6 and as predicted by Bhaskar (2002), however, we see the significant extent to which the industry level synchronization has decreased across all bins.

Second, we check that clustering standard errors at the industry level do not affect out findings. Third, we use a polynomial function for the size of firms to control for non-linear size effects in the regressions. Our results do not change due to this modification. Fourth, we use a CPI measure that excludes food and energy prices. Finally, we estimate the multinomial logit model only for the adjustment decisions for the largest sales-value item of each firm. Again, our results do not change due to this modification, in particular with respect to synchronization.[26]

[25] This result is similar to that of Cornille and Dossche (2008) and Dhyne and Konieczny (2007) who use the Belgian PPI and the CPI respectively. They use the Fisher-Konieczny measure of synchronization and find that prices tend to be more synchronized at a more disaggregated industry level. Neither of these papers look at the level of the firm, however, which is the focus of our paper, and also the factor that matters most quantitatively in our data.

[26] The results mentioned in the second robustness paragraph are available upon request from the authors.

3 Theory

Compared to the literature, our main challenge here is to theoretically explain the various trends we observe in price setting as we vary the number of goods produced by firms, an analysis that has not been undertaken before. We turn to this task next. Since the mapping from the good bins that we construct in the empirical section to the number of goods in the model is not clear and direct, we view our exercise in this section as qualitative in nature. At the same time, however, the results from model simulations will play a key role in validating features that are needed to explain the empirical trends.

3.1 Model

We use a partial equilibrium setting of a firm that decides each period whether to update the prices of its n goods indexed by $i \in (1, 2, 3)$, and what prices to charge if it updates. Our model is similar to the ones in Sheshinski and Weiss (1992), Midrigan (2010), and Alvarez and Lippi (2010). The main difference is that compared to Sheshinski and Weiss (1992) and Alvarez and Lippi (2010) we allow for a stochastic aggregate shock, while compared to Midrigan (2010), we solve for equilibrium as we vary n. In particular, the latter variation allows us to make two contributions. First, we can solve for trends in price-setting behavior with respect to how many goods firms produce. Second, we can compute trends in synchronization of price-setting by comparing 2-good and 3-good firms. Since no measures of synchronization can be computed in the one-good case, the comparison of 2-good and 3-good firms is necessary to model trends in synchronization of adjustment decisions.

In our model, the firm produces output of good i using a technology that is linear in labor:

$$c_{i,t} = A_{i,t}\ l_{i,t}$$

where $A_{i,t}$ is a good-specific productivity shock that follows an exogenous process:

$$\ln A_{i,t} = \rho_A^i \ln A_{i,t-1} + \epsilon_{A,t}^i$$

where $\mathbf{E}[\epsilon^i_{A,t}] = 0$ and $var(A_{i,t}) = (\sigma^i_A)^2$. We assume that there is no correlation between good-specific shocks. We do this in order to isolate the effect of multi-product firms on the decision to synchronize price adjustment when the underlying idiosyncratic shocks are uncorrelated, while controlling for the common inflationary shock.

The firm's product i is subject to the following demand:

$$c_{i,t} = \left(\frac{p_{i,t}}{P_t}\right)^{-\theta} C_t \qquad i = 1, 2, ..., n$$

where C_t is aggregate consumption, P_t is the aggregate price level, $p_{i,t}$ is the price of good i, and θ is the elasticity of substitution across goods. In this partial equilibrium setting, we normalize $C_t = \bar{C}$. We also assume that the price level P_t exogenously follows a random walk with a drift:

$$\ln P_t = \mu_P + \ln P_{t-1} + \epsilon_{P,t}$$

where $\mathbf{E}[\epsilon_{P,t}] = 0$ and $var(\epsilon_{P,t}) = (\sigma_P)^2$. Given our assumption about technology, the real marginal cost of the firm for good i, $MC_{i,t}$, is therefore given by: $MC_{i,t} = \frac{W_t}{A_{i,t}P_t}$, where W_t is the nominal wage. We normalize $\frac{W_t}{P_t} = \bar{w}$.

Whenever the firm adjusts one or more than one of its prices, it has to pay a constant, firm-specific "menu cost", $K(n) > 0$.[27] We understand this "menu cost" very broadly as a general cost of price adjustment, not the literal cost of relabeling the price tags of goods. Blinder et al. (1998) and Zbaracki et al. (2004) provide some evidence for such a broader interpretation of "menu costs." The cost of changing prices may depend on the number of goods produced by the firm and in particular, we assume that:

$$\frac{\partial K(n)}{\partial n} > 0 \text{ and } \frac{K(n+1)}{K(n)} < \frac{n+1}{n}. \tag{5}$$

These assumptions mean that the cost of changing prices increases monotonically with the number

[27] This assumption implies that the firm will either adjust all the prices at the same time or adjust none. In our dataset, this is a good first-order assumption: conditional on observing at least one adjustment per firm, the total fraction of goods adjusting in a firm is 0.75.

of goods produced, and that there are increasing cost savings as more and more goods are subject to price adjustment. Therefore, there are economies of scope in the cost of changing prices.[28]

Given this setup, the firm maximizes the expected discounted sum of profits from selling all of its goods. Total period gross profits, before paying the menu costs, are given by:

$$\pi_t = \sum_i^n \left(\frac{p_{i,t}}{P_t} - \frac{\overline{w}}{A_{i,t}} \right) \left(\frac{p_{i,t}}{P_t} \right)^{-\theta} \bar{C}.$$

The problem of the firm is to choose whether to update all prices in a given period, and if so, by how much. Whenever it updates prices, it has to pay the menu cost K.

3.2 Results

3.2.1 Computation

We solve this problem for a firm that produces $n = 1$, $n = 2$, and $n = 3$ goods. First, we employ collocation methods to find the policy functions of the firm. Second, given the policy functions, we simulate time series of shocks and corresponding adjustment decisions for many periods. Finally, we compute statistics of interest for each simulation and good, and across simulations. We also estimate a multi-nomial logit model of adjustment decisions using the simulated data to compare our theoretical results with the empirical findings. Appendix 2 provides further details about computation and analysis.

We present our choice of parameters in Table 7. Since our model is monthly, we choose a discount rate β of $(0.96)^{\frac{1}{12}}$. We use a value of K such that menu costs are a 0.35% of steady-state revenues for the 1-good firm, 0.65% for a 2-good firm, and 0.75% for a 3-good firm.[29] We choose θ to be 4, which implies a markup of 33%. To parametrize the exogenous processes, we set the trend in aggregate inflation to be a monthly increase of 0.21%. We use persistent idiosyncratic productivity shocks, where the $AR(1)$ parameter is 0.96. We choose 0.37% and 2% respectively for

[28] While we do not model this adjustment process in detail, one can for example think about the adjustment technology as a fixed cost of hiring a manager to change prices: it is costly to hire him in the first place, but much less costly to have him adjust the price of each additional good.

[29] We will need to have menu cost increasing as we increase the number of goods, since otherwise we will not be able to generate large price changes.

the standard deviations of the aggregate inflation and the idiosyncratic productivity shock. For the firms with 2 and 3 goods, we use the same values for the persistence and variance of the all idiosyncratic productivity shocks.[30] All of our parameters are standard in the literature.

3.2.2 Findings

We present the main results from the simulations in Table 8 and illustrate them graphically in Figures 9-14. As we increase the number of goods from 1 to 3, the model predicts clear and systematic trends in the key price-setting statistics which align, qualitatively, with our empirical findings.

First, we find that the frequency of price changes goes up from 15.22% to 19.72% while the mean absolute size of price changes goes down from 5.21% to 3.96% as we increase the number of goods. Second, the decrease in the absolute size of price changes also holds for both positive and negative prices changes: they go down from 5.34% to 4.23% and from −5.02% to −3.57% respectively. Third, the fraction of small price changes increases from 1.33%, barely none, to 23.59%. Thus, while firms with more goods change prices more frequently, they does so by smaller amounts on average. Fourth, we also see that the fraction of positive price changes decreases from 61.68% to 59.38%. Thus, as in the data, firms with more goods adjust downwards more frequently. Finally, the model predicts that kurtosis increases from 1.38 to 1.97, again consistent with our empirical findings.

What is the mechanism behind our results? For simplicity, compare a 1-good firm with a 2-good firm. For the case of a 2-good firm, when the firm decides to pay the firm-specific menu cost to adjust one of the prices, it also changes the price of the other good because it gets to change it basically for free. This leads, on average, to a higher frequency of price changes. At the same time, for the 2-good firm, since a lot of price changes happen even when the desired price is not very different from the current price of the good, the mean absolute size of price changes is lower. This smaller mean also implies that the fraction of "small" price changes is much higher for the 2-good firm. In fact, for the 1-good firm, which is the standard menu cost model, the fraction of small

[30] As emphasized before, in the baseline case, we assume that there is no correlation among the idiosyncratic productivity shocks within the firm.

price changes is negligible because in that case, the firm adjusts prices only when the desired price is very different from the current price.

What causes the decrease in the fraction of positive price changes? With trend inflation, firms adjust downwards only when they receive very big negative productivity shocks. With firm-specific menu costs, since the firm adjusts both prices when the desired price of one good is very far from its current price, it is now more sustainable to have a higher fraction of downward price changes. Finally, kurtosis increases as we go from one good to two goods because of a higher fraction of price changes in the middle of the distribution.

Next, we address trend in synchronization of individual good-level price changes. Using simulated data, we run the same multinominal logit regression as in the empirical section to investigate if price changes become more synchronized as the number of goods produced by firms increases. We thus estimate the following equation, with no price changes as the base category:

$$\{\Delta p_t \neq 0\}_{-1,0,+1} = \beta_0 + \beta_1 f_t + \beta_2 \Pi_t + \epsilon_t \tag{6}$$

where f_t is the fraction of same-signed adjustment decisions at time t within the firm and Π_t is the inflation rate at time t.

It is important to emphasize here the need to go beyond a 2-good case and consider a 3-good case, because we otherwise cannot check if the model predicts trends in synchronization of price changes that are consistent with the empirical findings. Table 8 shows that the strength of synchronization, that is the coefficient estimate in the multinominal logit regressions for the fraction of other goods of the firm changing in the same direction, increases as we go from a 2-good firm to a 3-good firm. Importantly, as is the case empirically, this is the case with both upwards and downwards price changes.

In addition, Table 8 also makes clear that the simulations predict that positive price adjustment decisions are more synchronized than negative adjustment decisions. That is, the synchronization coefficient for upwards price adjustment decisions is always higher than the coefficient for downwards adjustment decisions. This difference in synchronization probabilities is due to positive trend inflation. Without positive trend inflation, the difference disappears. The model thus matches our findings on synchronization established in the empirical section.

3.2.3 Robustness

In this section, we discuss several extensions of our baseline model. The key objective in this section is to investigate if there are alternative ways to generate the trends that we find in the data. In particular, we will mainly shut down the economies of scope in menu cost channel that we have proposed above, while computing results under other modeling assumptions. Appendix 2 contains the tables summarizing results from these simulations.

First, we investigate the possibility that perhaps our empirical results are driven by the fact that firms that produce more goods also produce more substitutable goods. We simulate a specification of 2 and 3 good firms with no economies of scope in the cost of adjusting prices but with an elasticity of substitution among goods that is higher than that compared to the 1 good firm. As Table 21 shows, while matching the trends in frequency, size, and fraction of positive price changes, this specification fails to match trends in the fraction of small price changes, kurtosis, and synchronization as we increase the number of goods.

Second, we allow for correlation among the productivity shocks. In our main setup, we had not allowed for correlation of productivity shocks at the firm-level in order to isolate the predictions of the model arising solely due to economies of scope in menu costs. Table 22 shows that allowing for such correlation does yield a higher synchronization of price changes within the firm, but at the same time, fails to match trends in frequency and size of price changes.

Third, there might be concern that our synchronization results could be due to purely mechanical, statistical reasons. To investigate this possibility, we perform two tests. In the first, we run a Monte-Carlo exercise based on a simple statistical model of price changes. We model price changes as i.i.d. Bernoulli trials with a fixed probability of success. Using simulated time series for an arbitrary number of goods, we estimate our synchronization equation. We find no mechanical trend in synchronization as the number of goods increases. In the second test, we use the same parametrized model of a single-good firm from our simulation exercise and model a multi-product firm as a collection of multiple, independent single-product firms. That is, a 2-good firm now is simply a collection of two single-good firms, with no economies of scope in cost of adjusting prices. Similarly, a 3-good firm is a collection of three single-good firms, with no economies of scope in cost of adjusting prices. When we run our synchronization test with simulated data from these specifications, we find that the model cannot produce synchronization results that are consistent with the empirical findings. For example, the synchronization coefficient estimated using simulated data on negative price changes is negative, as opposed to positive in the data. Incidentally, this specification of multiproduct firms as multiple single-good firms fails to match any of our aggregate trends in price-setting as shown in Table 23. These results therefore highlight the need to model a multi-product firm as distinctly different from an aggregate of multiple single-product firms.

Fourth, we allow for a menu of menu costs instead of the firm-specific menu cost structure that we use. For example, in the 2-good case, the firm now has a choice of adjusting 0, 1, or 2 goods. There are different menu costs for adjusting the price of 1 good and 2 goods, but some savings in the cost when adjusting the prices of both goods. Our results are robust to this possible extension. In fact, as shown in Table 24, this specification cannot account for the extent of synchronization in price changes observed in the data.

Fifth, we consider two alternative demand specifications. In the first specification, we allow for non-zero cross-elasticities of demand among the goods produced by the firm, which is precluded in our baseline model with CES demand. As Table 25 shows, while this case generates a higher fraction of small price changes and greater kurtosis, it cannot account for the trend in the size of price changes. In the second specification, we allow for idiosyncratic demand shocks as an alternative to productivity shocks. We present the results in Table 26. We find that demand shocks are unable to generate the fraction of negative price changes that we observe in the data.

4 Discussion

Our empirical results have a direct bearing on modeling price-setting by firms, as already reflected in our choice of the model in Section 3. The significant fraction of negative price changes that we document implies, as Golosov and Lucas Jr. (2007) and Nakamura and Steinsson (2008) also argue, that models that rely on only aggregate shocks, and hence predict predominantly positive price changes with modest inflation, are inconsistent with micro data. We have also shown that the absolute size of price changes are large, which again suggests the need for idiosyncratic firm-level shocks, as emphasized by Golosov and Lucas Jr. (2007) and Klenow and Kryvtsov (2008). At the same time however, there is a substantial fraction of small price changes in the data and the distribution of price changes is highly leptokurtic. This observation implies that simple menu cost models are inconsistent with micro data since they do not predict enough small price changes, which Klenow and Kryvtsov (2008) and Midrigan (2010) similarly point out. Using a discrete choice model for changes of producer prices, we have documented new broad based evidence for synchronization of producer price changes within industries and firms. This suggests a model with industry and firm level strategic complementaries. We also show that inflation plays a fundamental role in pricing decisions by increasing the likelihood of a price increase while decreasing the likelihood of a price decrease. This suggests that a model with simple time-dependent pricing rules will be unable to match the findings.

More importantly, the central empirical focus of this paper, an analysis according to the number of goods produced by firms, has substantial aggregate implications related to real effects of monetary shocks. We have documented that heterogeneity, captured by the number of goods produced by firms, matters critically for price dynamics. We know from recent work of Carvalho (2006) and Nakamura and Steinsson (2008), which take a sectoral perspective, that heterogeneity in price dynamics magnifies non-neutrality of nominal shocks. Translating this insight to heterogeneity at the firm level similarly implies non-neutrality of nominal shocks. Moreover, most directly related to our empirical findings are the aggregate implications of Midrigan (2010). He shows that if one includes firm-specific menu costs, then a state-dependent model produces substantial real effects of monetary shocks, almost as much as a time-dependent model. Our empirical results, based on the entire PPI, validate that modeling assumption, in particular, by matching trends for firms with different numbers of goods.

5 Conclusion

In this paper, we have established three new facts regarding multi-product price-setting in the U.S. Producer Price Index. First, we show that as the number of goods produced by firms increases, price changes are more frequent, the size price changes is lower, the fraction of positive price changes decreases, and price changes become more dispersed. Second, we find evidence for substantial synchronization of price adjustment decisions within the firm. Third, we find that the number of goods and the degree of synchronization within firms strongly interact in determining price adjustment decisions: as the number of goods increases, synchronization within firms increases.

Motivated by these findings, we present a model with firm-specific menu costs where firms are subject to both idiosyncratic and aggregate shocks. We show that as we change the number of goods produced by the firms, the patterns predicted by the model regarding frequency, size, direction, dispersion, and synchronization of price changes are consistent with the empirical findings.

While beyond the scope of this paper, an immediate question for future research will be to look into reasons why firms produce different numbers of goods. We also hope to investigate in future work the implications of our findings for business cycle dynamics, real exchange rate behavior, and optimal monetary policy.

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6 Tables

Table 1: Summary Statistics by Bin

	Number of Goods			
	1-3	3-5	5-7	>7
Mean Employment	2996	1427	1132	1016
Median Employment	427	155	195	296
% of Prices	17.15	43.53	18.16	21.16
Mean # of Goods	2.21	4.05	6.06	10.26
Std. Error # Goods	0.01	0.00	0.01	0.11
Std. Dev. # Goods	0.77	0.34	0.40	4.88
Minimum # of Goods	1	3.01	5.01	7.02
Maximum # of Goods	3	5	7	77
25% Percentile # Goods	1.78	3.94	5.91	7.98
Median # Goods	2	4	6	8
75% Percentile # Goods	3	4	6	11.77
Number of Firms	9111	13577	3532	2160

We group firms in the PPI by the number of goods. Bin 1 groups firms with 1 to 3, bin 2 firms with 3 to 5, bin 3 firms with 5 to 7 and bin 4 firms with more than 7 goods. We calculate mean and median employment by taking means and medians of the number of employees per good across firms in a category. % of Prices denotes the fraction of prices in the PPI set by firms in each bin.

Table 2: Coefficient of Variation of Price Changes

	Firm-Based	Good-Based
1-3 Goods	1.02	0.96
	(0.01)	(0.01)
3-5 Goods	1.15	1.00
	(0.01)	(0.01)
5-7 Goods	1.30	1.10
	(0.02)	(0.02)
$>$ 7 Goods	1.55	1.24
	(0.02)	(0.02)

For the first column, we compute the coefficient of variation at the level of the firm pooling all price changes. Then, we take medians across firms, bin by bin. For the second column, we compute the coefficient of variation for each good, take the median across goods within the firm and then medians across firms.

Table 3: Marginal Effects, Multinomial Logit

	Marginal Effects		$\pm$ 1/2 Std. Dev.	
	-	+	-	+
Fraction Industry	0.06%	0.10%	1.32%	2.27%
Fraction Firm	0.32%	0.53%	8.82%	14.73%
π_{CPI}	-0.61%	0.48%	-0.21%	0.17%
R^2	47.56%			

Based on the regression results in Table 18, the table shows two marginal effects associated with changes in key explanatory variables for upwards (+) and downwards (-) adjustment. The first is the change in percentage points in the probability of adjusting upwards or downwards given a unit change in the explanatory variable at the mean. The second ($\pm$ 1/2 Std. Dev.) is the change in percentage points in probability associated with a change from half a standard deviation below to half a standard deviation above the mean of the explanator. All effects are statistically significantly different from zero.

Table 4: Marginal Effects, Multinomial Logit

	Marginal Effects		$\pm$ 1/2 Std. Dev.	
	-	+	-	+
Fraction Industry	0.27%	0.47%	6.00%	10.29%
π_{CPI}	-0.73%	0.47%	-0.25%	0.16%
R^2	29.33%			

Based on the regression results in Table 19, the table shows two marginal effects associated with changes in key explanatory variables for upwards (+) and downwards (-) adjustment. The first is the change in percentage points in the probability of adjusting upwards or downwards given a unit change in the explanatory variable at the mean. The second ($\pm$ 1/2 Std. Dev.) is the change in percentage points in probability associated with a change from half a standard deviation below to half a standard deviation above the mean of the explanator. All effects are statistically significantly different from zero.

Table 5: Marginal Effects by Bin

	Bin 1	Bin 2	Bin 3	Bin 4
Negative Change				
Fraction Industry	0.11%	0.07%	0.04%	-0.06%
Fraction Firm	0.25%	0.26%	0.35%	0.51%
π_{CPI}	-0.24%	-0.39%	-0.50%	-1.55%
Positive Change				
Fraction Industry	0.16%	0.10%	0.07%	0.01%
Fraction Firm	0.45%	0.45%	0.56%	0.78%
π_{CPI}	0.49%	0.28%	0.41%	1.02%
R^2	42.85%	47.93%	48.33%	49.10%

The table shows the bin-specific marginal effects in percentage points of a unit change in the explanators around the mean on the probability of adjusting prices upwards or downwards. Marginal effects are calculated for the model estimated as for Table 18 but for each bin separately. All reported effects are statistically significantly different from zero.

Table 6: Marginal Effects by Bin, ± 1/2 Std. Dev.

	Bin 1	Bin 2	Bin 3	Bin 4
Negative Change				
Fraction Industry	2.10%	1.41%	0.89%	-1.51%
Fraction Firm	5.38%	6.52%	9.92%	15.78%
π_{CPI}	-0.08%	-0.14%	-0.17%	-0.54%
Positive Change				
Fraction Industry	3.07%	2.12%	1.55%	0.21%
Fraction Firm	9.61%	11.46%	15.94%	24.24%
π_{CPI}	0.17%	0.10%	0.14%	0.35%
R^2	42.85%	47.93%	48.33%	49.10%

The table shows the bin-specific marginal effects in percentage points of a one-standard deviation change in the explanators around the mean on the probability of adjusting prices upwards or downwards. Marginal effects are calculated for the model estimated as for Table 18 but for each bin separately. All reported effects are statistically significantly different from zero.

Table 7: Parameters in Simulation

β	$(0.96)^{\frac{1}{12}}$
μ_P	0.21%
θ	4
ρ	0.96
σ_A	2%
σ_P	.37%

The table shows our choice of parameter values used in the simulation exercise.

Table 8: Results of Simulation

	1 Good	2 Goods	3 Goods
Frequency of price changes	15.22%	18.05%	19.72%
Absolute size of price changes	5.21%	4.29%	3.96%
Size of positive price changes	5.34%	4.46%	4.23%
Size of negative price changes	-5.02%	-4.04%	-3.57%
Fraction of positive price changes	61.68%	61.28%	59.38%
Fraction of small price changes	1.33%	20.97%	23.59%
Kurtosis	1.38	1.76	1.97
First Percentile	-6.84%	-7.60%	-8.06%
99th Percentile	7.09%	8.07%	8.63%
Synchronization measures:			
Fraction, Upwards Adjustments	-	30.25	38.11
Fraction, Downwards Adjustments	-	29.39	37.19
Correlation coefficient	-	0	0
Menu costs	0.35%	0.65%	0.75%

We perform stochastic simulation of our model in the 1-good, 2-good and 3-good cases and record price adjustment decisions in each case. Then, we calculate statistics for each case as described in the text. In the 2-good and the 3-good cases, we report the mean of the good-specific statistics. We obtain the synchronization measure from a multinomial logit regression analogous to the empirical multinomial logit regression. We control for inflation. Menu costs are given as a percentage of steady state revenues.

7 Graphs Based on Empirical Analysis

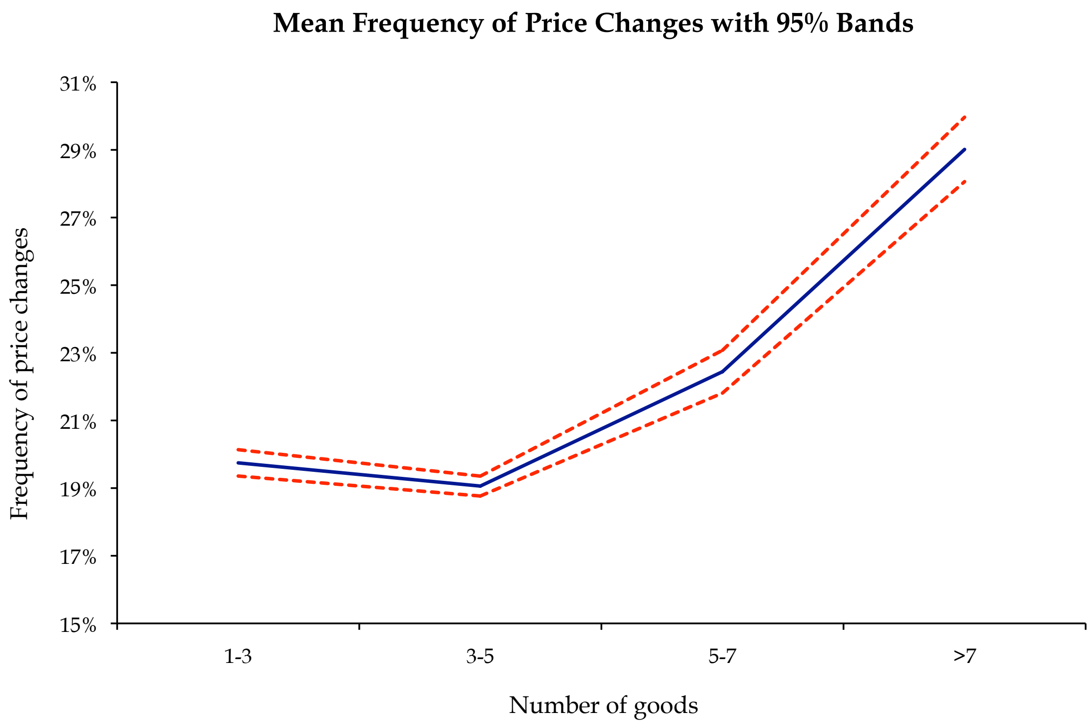

Figure 1: Mean Frequency of Price Changes with 95% Bands

Based on the PPI data we group firms by the number of goods they produce. We compute the mean frequency of price changes in these groups in the following way. First, we compute the frequency of price change at the good level. Then, we compute the median frequency of price changes across goods at the firm level. Finally, we report the mean across firms in a given group.

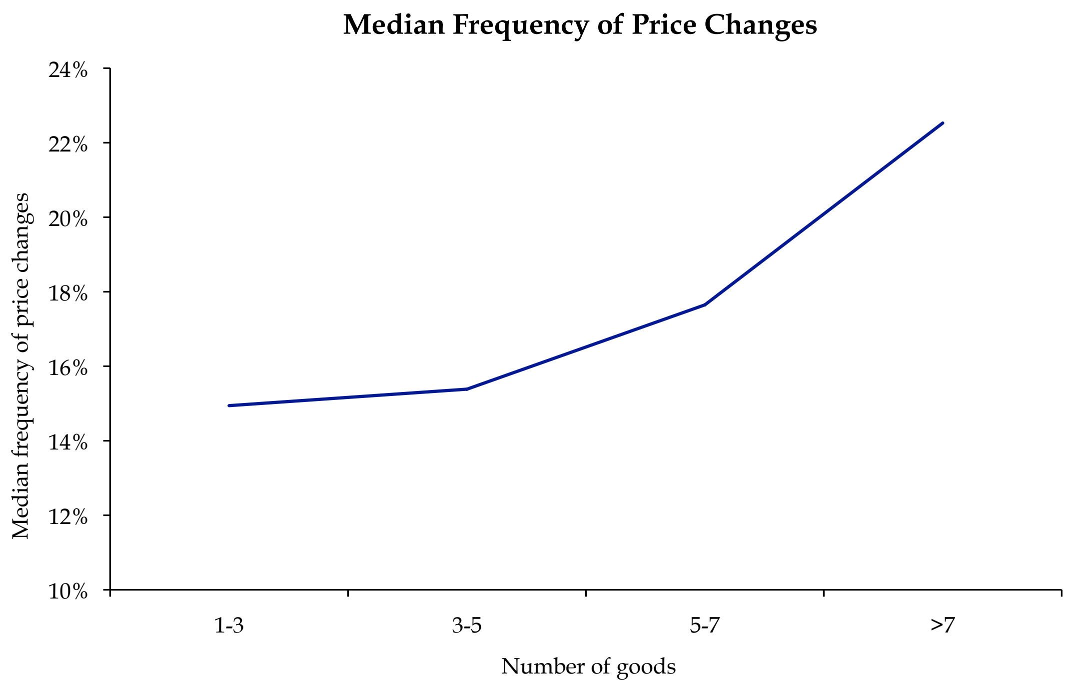

Figure 2: Median Frequency of Price Changes

Based on the PPI data we group firms by the number of goods they produce. We compute the median frequency of price changes in these groups in the following way. First, we compute the frequency of price change at the good level. Then, we compute the median frequency of price changes across goods at the firm level. Finally, we report the median across firms in a given group.

Figure 3: Mean Fraction of Positive Price Changes with 95% Bands

Based on the PPI data we group firms by the number of goods they produce. We compute the mean fraction of positive price changes in these groups in the following way. First, we compute the number of strictly positive good level price changes over all zero and non-zero price changes for a given firm. Then, we report the mean across firms in a given group.

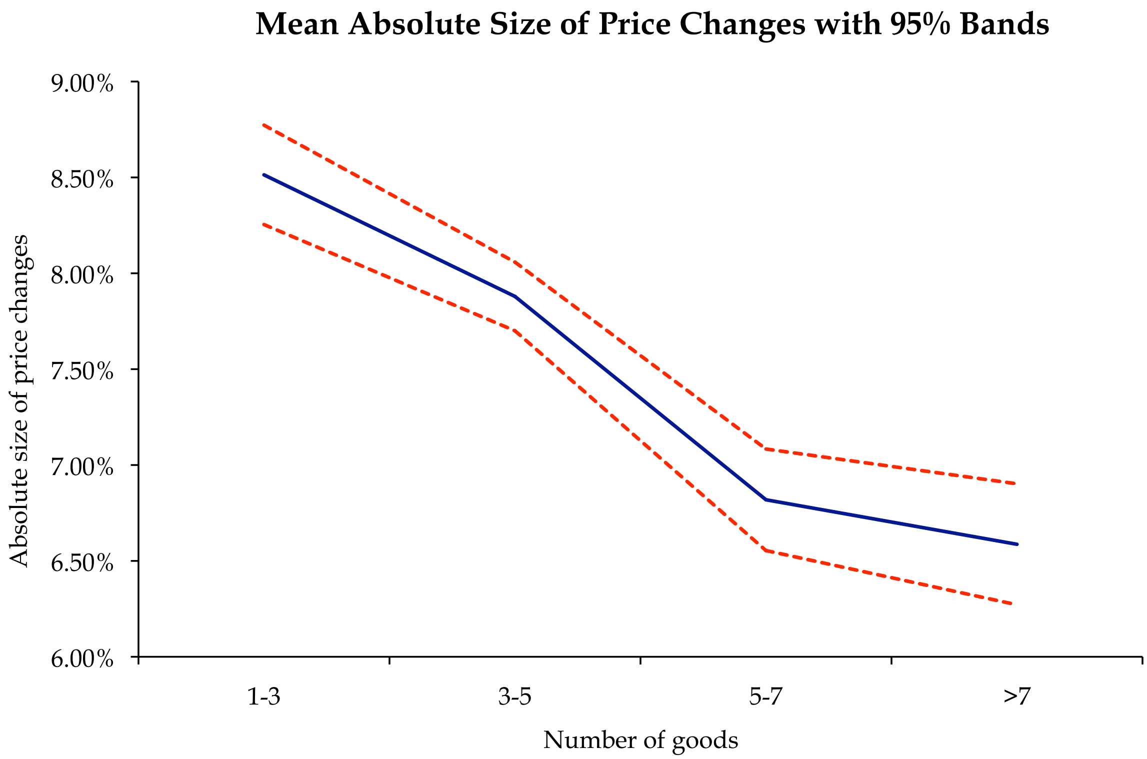

Figure 4: Mean Absolute Size of Price Changes with 95% Bands

Based on the PPI data we group firms by the number of goods they produce. We compute the mean absolute size of price changes in these groups in the following way. First, we compute the percentage change to last observed price at the good level. Then, we compute the median size of price changes across goods at the firm level. Then, we report the mean across firms in a given group.

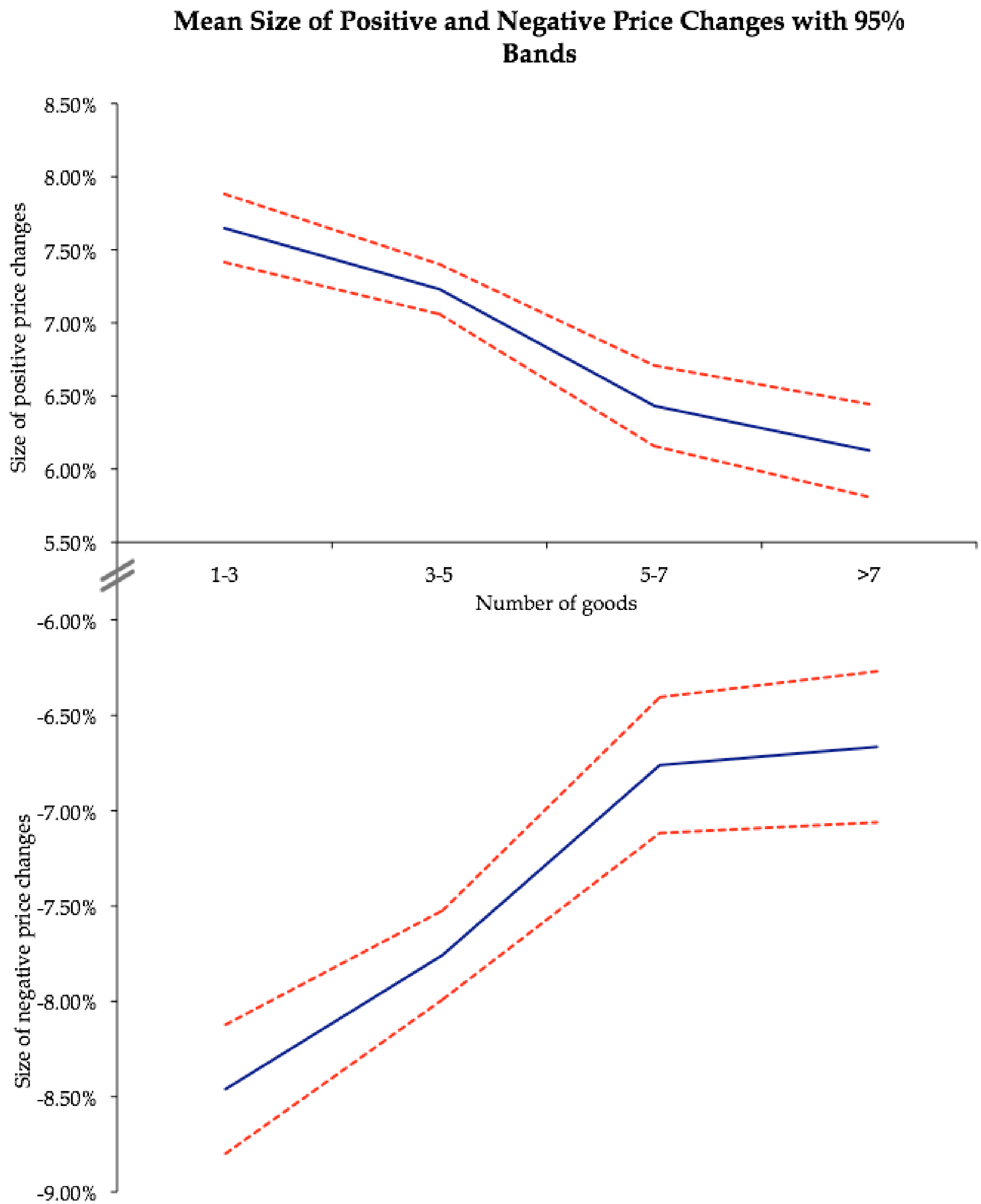

Figure 5: Mean Size of Positive and Negative Price Changes with 95% Bands

Based on the PPI data we group firms by the number of goods they produce. We compute the mean size of positive price changes in these groups in the following way. First, we compute the percentage change to last observed price at the good level. Then, we compute the median size of price changes across goods at the firm level. Then, we report the mean across firms in a given group.

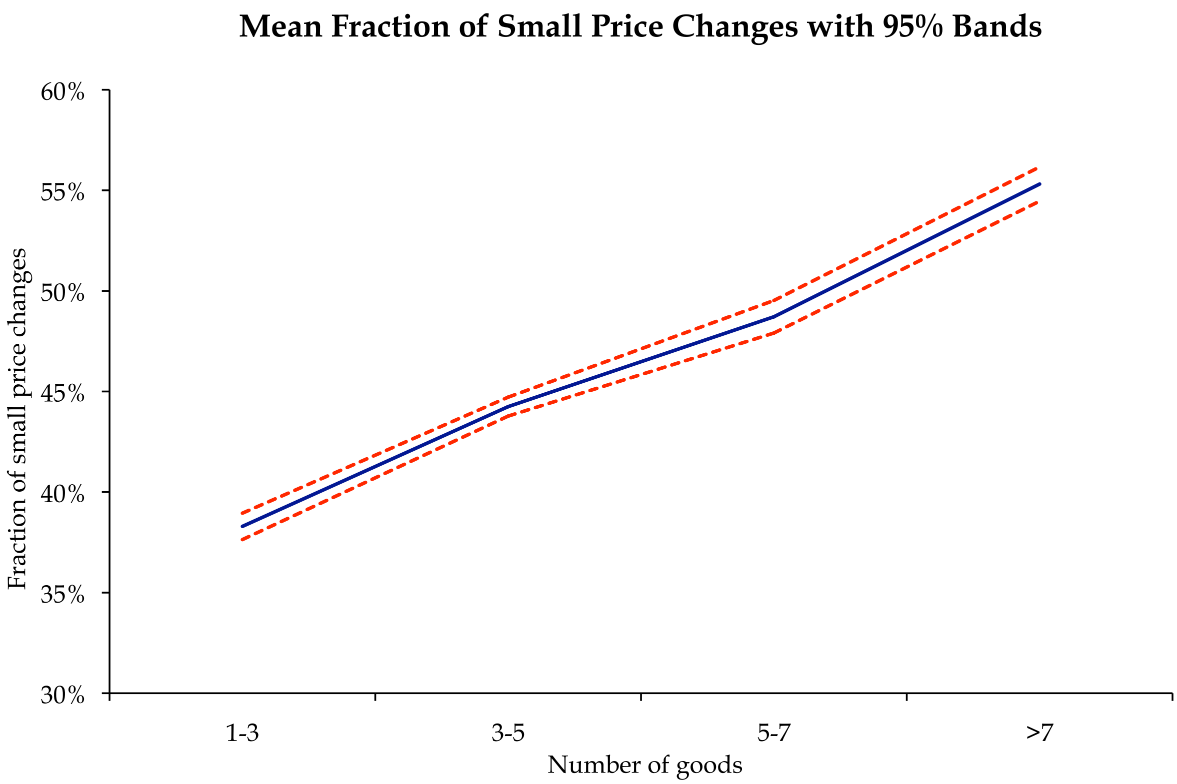

Figure 6: Mean Fraction of Small Price Changes with 95% Bands

Based on the PPI data we group firms by the number of goods they produce. We compute the mean fraction of small price changes in these groups in the following way. First, we compute the fraction of price changes that are smaller than 0.5 times the mean absolute percentage size of price changes across all goods in a firm. Then, we report the mean across firms in a given group.

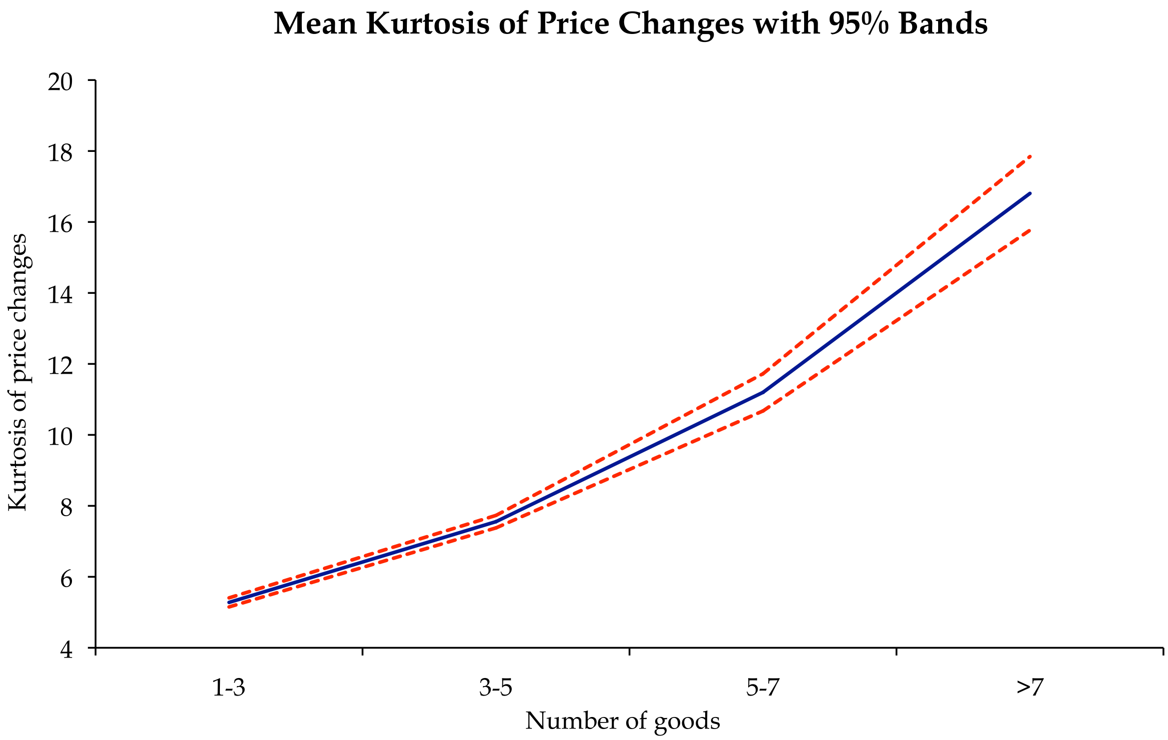

Figure 7: Mean Kurtosis of Price Changes with 95% Bands

Based on the PPI data we group firms by the number of goods they produce. We compute the mean kurtosis of price changes in these groups in the following way. First, we compute the kurtosis of price changes at the firm level, defined as the ratio of the fourth moment about the mean and the variance squared of percentage price changes. Then, we report the mean across firms in a given group.

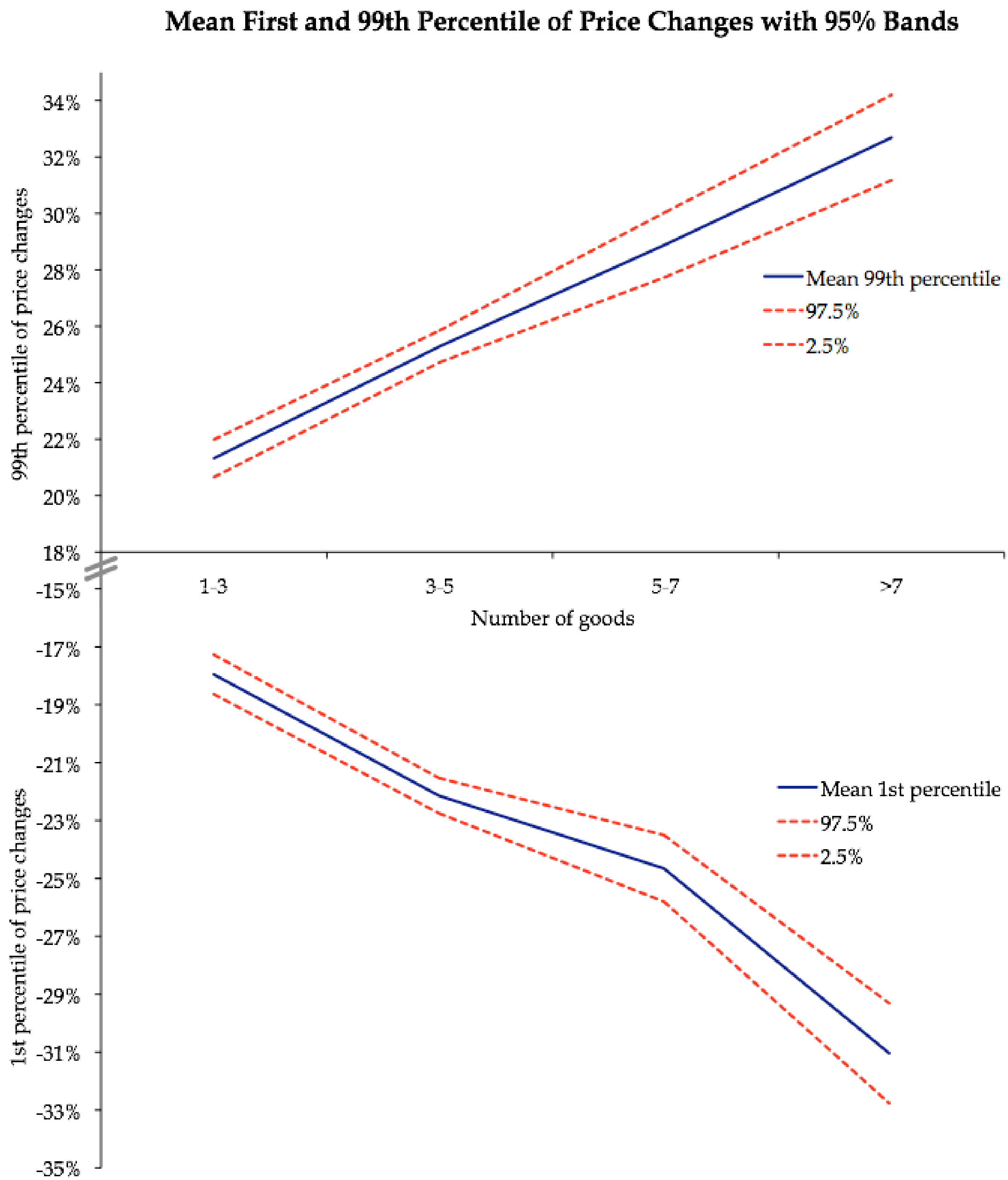

Figure 8: Mean First and 99th Percentile of Price Changes with 95% Bands

Based on the PPI data we group firms by the number of goods they produce. We compute the mean size of positive price changes in these groups in the following way. First, we compute the percentage change to last observed price at the good level. Then, we compute the median size of price changes across goods at the firm level. Then, we report the mean across firms in a given group.

7.1 Graphs Based on Simulation

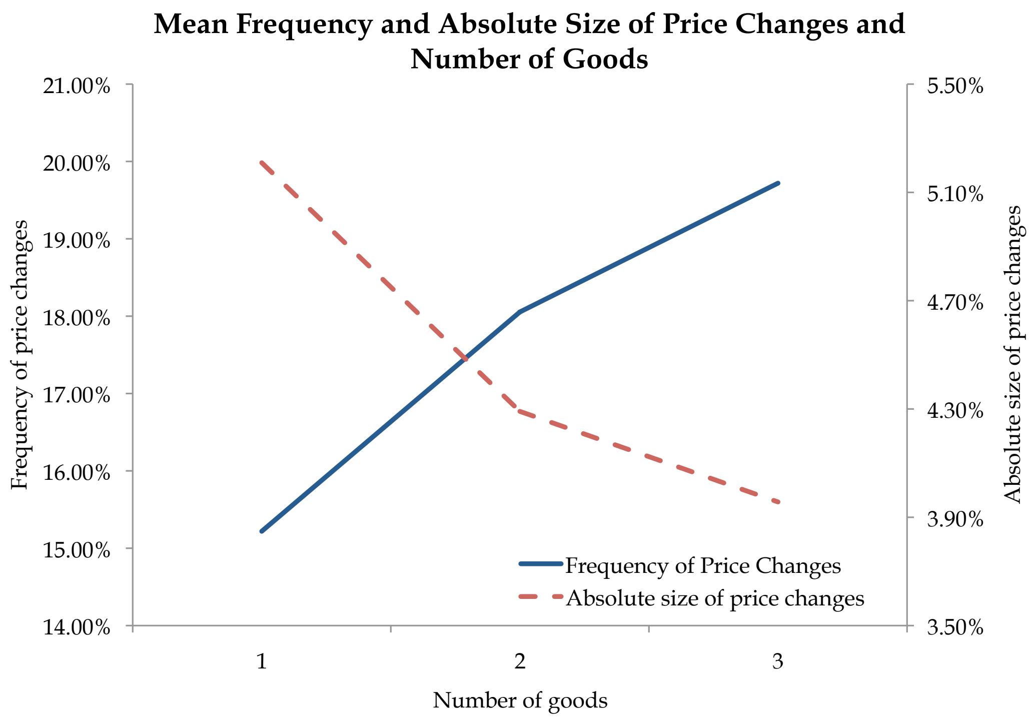

Figure 9: Mean Frequency, Absolute Size of Price Changes and Number of Goods

We simulate our model for 1, 2, and 3 goods and compute the frequency and size of price changes exactly as in the computations for Figure 1.

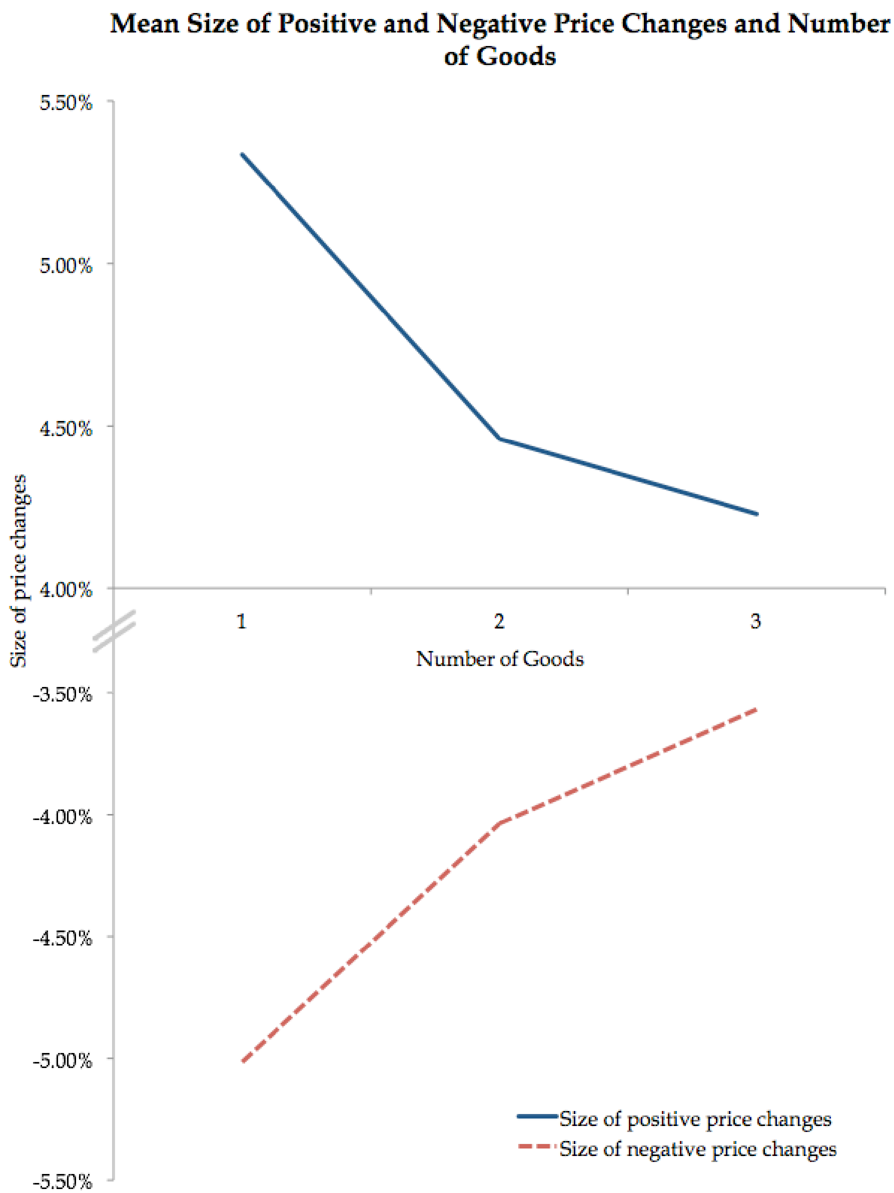

Figure 10: Mean Size of Positive and Negative Price Changes and Number of Goods

We simulate our model for 1, 2, and 3 goods and compute the size of positive and negative price changes exactly as in the computations for Figure 5.

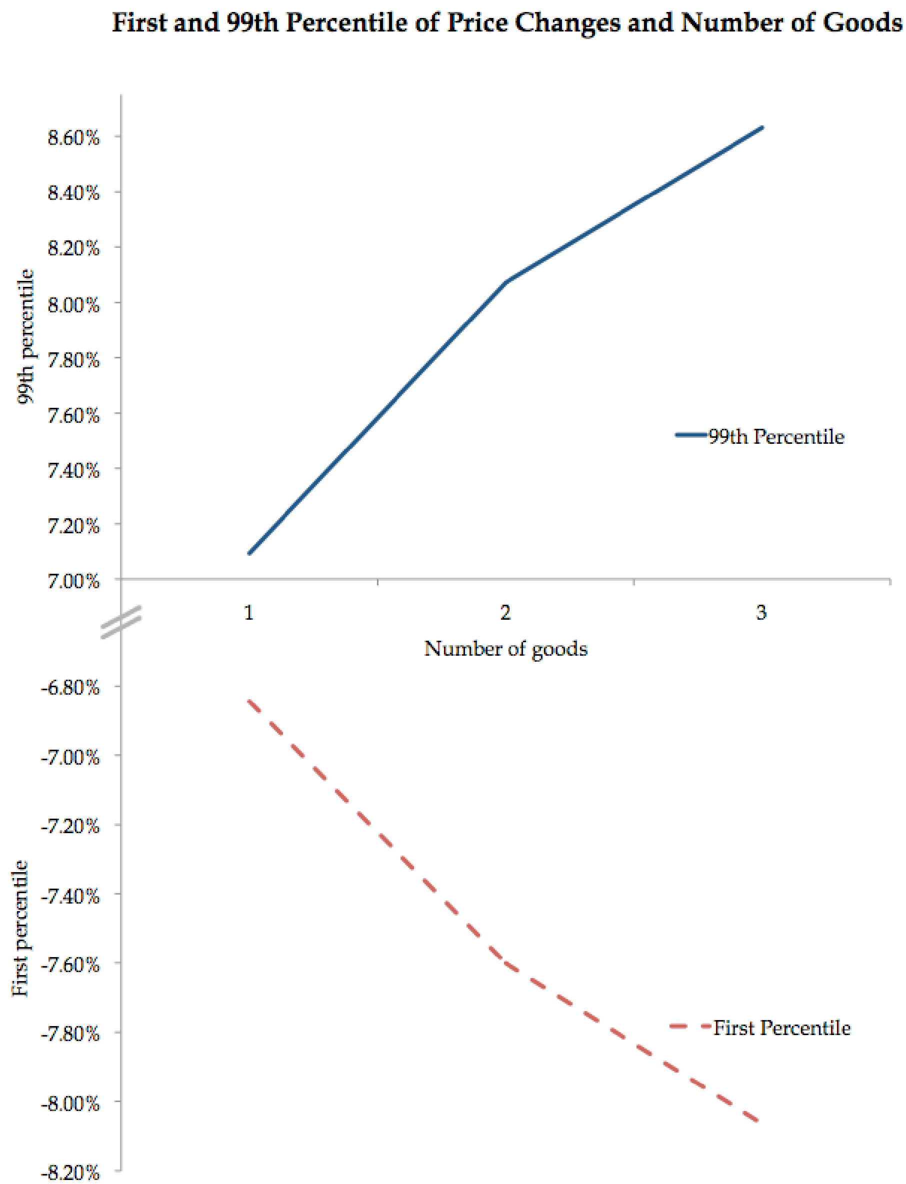

Figure 11: First and 99th Percentile of Price Changes and Number of Goods

We simulate our model for 1, 2, and 3 goods and compute the first and 99th percentiles of price changes exactly as in the computations for Figure 8.

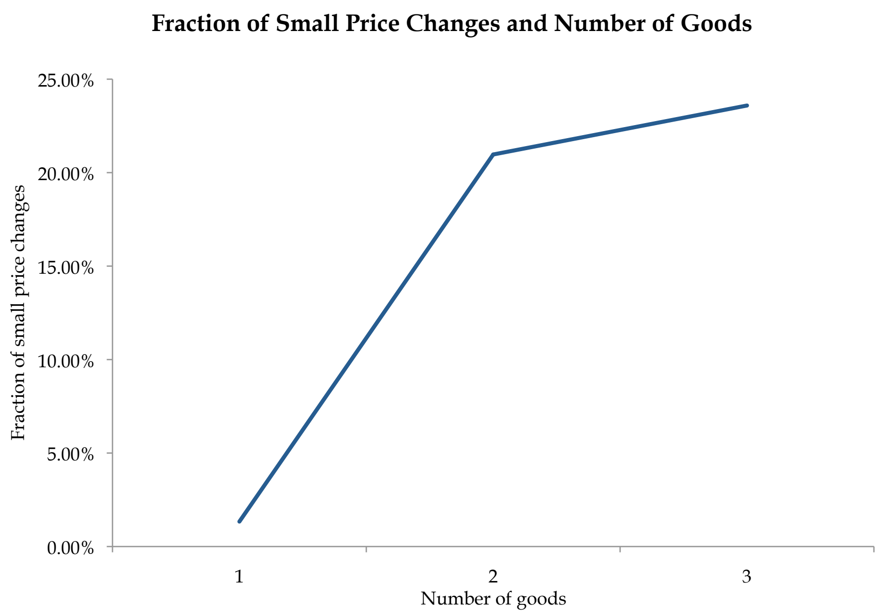

Figure 12: Fraction of Small Price Changes and Number of Goods

We simulate our model for 1, 2, and 3 goods and compute the fraction of small price changes exactly as in the computations for Figure 6.

Figure 13: Kurtosis of Price Changes and Number of Goods

We simulate our model for 1, 2, and 3 goods and compute the kurtosis of price changes exactly as in the computations for Figure 7.

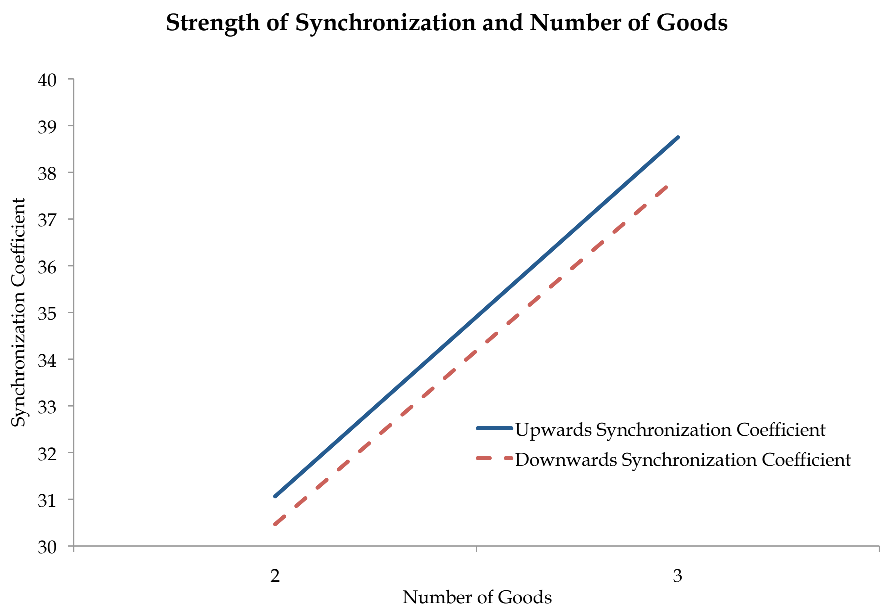

Figure 14: Strength of Synchronization and Number of Goods

We simulate our model for 2 and 3 goods and use the simulated data to estimate the following equation, with no price changes as the base category: $\{\Delta p_t \neq 0\}_{-1,0,+1} = \beta_0 + \beta_1 f_t + \beta_2 \Pi_t + \epsilon_t$ where f_t is the fraction of same-signed adjustment decisions at time t within the firm and Π_t is the inflation rate at time t.

APPENDIX 1

This appendix contains empirical robustness results to which we make reference in the text.

Table 9: Distribution of Firms across Sectors and Bins

Sector	Bin 1	Bin 2	Bin 3	Bin 4	Total
11	58.1%	30.95%	5.24%	5.71%	100%
	1.36%	0.5%	0.32%	0.58%	0.77%
21	74.48%	19.84%	3.6%	2.09%	100%
	7.17%	1.32%	0.91%	0.87%	3.15%
22	19.11%	9.95%	10.73%	60.21%	100%
	0.82%	0.29%	1.21%	11.16%	1.4%
23	48.25%	51.75%	0%	0%	100%
	3.08%	2.29%	0%	0%	2.09%
31	28.01%	49.92%	15.05%	7.02%	100%
	12%	14.79%	16.96%	13.05%	14.02%
32	34.17%	47.73%	13.33%	4.77%	100%
	18.82%	18.17%	19.31%	11.4%	18.01%
33	28.72%	52.85%	13.32%	5.11%	100%
	28.76%	36.59%	35.1%	22.22%	32.76%
42	27.23%	61.95%	7.33%	3.49%	100%
	1.74%	2.74%	1.23%	0.97%	2.09%
44	35.28%	47.18%	7.93%	9.6%	100%
	3.78%	3.49%	2.23%	4.46%	3.5%
45	28.12%	50.94%	7.5%	13.44%	100%
	1.01%	1.26%	0.71%	2.09%	1.17%
48	36.74%	48.17%	6.55%	8.54%	100%
	2.69%	2.44%	1.26%	2.72%	2.4%
49	45.03%	38.6%	8.19%	8.19%	100%
	0.86%	0.51%	0.41%	0.68%	0.63%
51	30.79%	48.31%	8.85%	12.05%	100%
	3.65%	3.96%	2.76%	6.21%	3.88%
52	28.07%	31.65%	20.45%	19.83%	100%
	4.03%	3.14%	7.73%	12.37%	4.7%
53	59.56%	33.81%	2.37%	4.27%	100%
	4.21%	1.65%	0.44%	1.31%	2.31%
54	37.34%	53.32%	8.51%	0.83%	100%
	2.01%	1.99%	1.21%	0.19%	1.76%
56	29.81%	35.82%	29.09%	5.29%	100%
	1.39%	1.15%	3.56%	1.07%	1.52%
62	21.06%	38.89%	17.44%	22.61%	100%
	1.82%	2.33%	3.97%	8.49%	2.83%
71	26.87%	62.69%	10.45%	0%	100%

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Table 9 – continued from previous page

Sector	Bin 1	Bin 2	Bin 3	Bin 4	Total
	0.2%	0.32%	0.21%	0%	0.24%
72	25%	65.87%	7.69%	1.44%	100%
	0.58%	1.06%	0.47%	0.15%	0.76%
Total	32.71%	47.32%	12.44%	7.53%	100%
	100%	100%	100%	100%	100

The table shows the percentage of firms in the PPI that belong to a bin in a given two-digit NAICS category (each first line per industry) and the percentage in an industry given a bin (each second line). Bin 1 groups firms with 1 to 3 goods, bin 2 firms with 3 to 5 goods, bin 3 firms with 5 to 7 goods and bin 4 firms with more than 7 goods

Table 10: Distribution of Firms across Sectors and Bins

Sector	Bin 1	Bin 2	Bin 3	Bin 4	Total
111	72.73%	19.32%	3.41%	4.55%	100%
	0.72%	0.13%	0.09%	0.19%	0.32%
112	30%	35%	15%	20%	100%
	0.07%	0.05%	0.09%	0.19%	0.07%
113	50%	45.45%	4.55%	0%	100%
	0.49%	0.31%	0.12%	0%	0.32%
114	57.14%	7.14%	7.14%	28.57%	100%
	0.09%	0.01%	0.03%	0.19%	0.05%
211	25.3%	45.78%	15.66%	13.25%	100%
	0.23%	0.29%	0.38%	0.53%	0.3%
212	81.33%	15.59%	2.16%	0.93%	100%
	5.89%	0.78%	0.41%	0.29%	2.37%
213	71.76%	24.43%	3.05%	0.76%	100%
	1.05%	0.25%	0.12%	0.05%	0.48%
221	19.11%	9.95%	10.73%	60.21%	100%
	0.82%	0.29%	1.21%	11.16%	1.4%
236	48.25%	51.75%	0%	0%	100%
	3.08%	2.29%	0%	0%	2.09%
311	24.47%	46.58%	18.93%	10.02%	100%
	5.43%	7.15%	11.05%	9.66%	7.26%
312	31.62%	38.14%	21.65%	8.59%	100%
	1.03%	0.86%	1.85%	1.21%	1.06%
313	27.15%	62.37%	8.06%	2.42%	100%
	1.13%	1.79%	0.88%	0.44%	1.36%
314	25.53%	65.77%	5.71%	3%	100%
	0.95%	1.69%	0.56%	0.49%	1.22%
315	34.63%	52.03%	9.92%	3.41%	100%

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Table 10 – continued from previous page

Sector	Bin 1	Bin 2	Bin 3	Bin 4	Total
	2.38%	2.47%	1.79%	1.02%	2.25%
316	40.93%	45.15%	11.81%	2.11%	100%
	1.08%	0.83%	0.82%	0.24%	0.87%
321	36.64%	53.75%	7.21%	2.4%	100%
	2.73%	2.77%	1.41%	0.78%	2.43%
322	29.45%	57.45%	10%	3.09%	100%
	1.81%	2.44%	1.62%	0.82%	2.01%
323	24.08%	47.35%	27.55%	1.02%	100%
	1.32%	1.79%	3.97%	0.24%	1.79%
324	63.48%	30%	0.87%	5.65%	100%
	1.63%	0.53%	0.06%	0.63%	0.84%
325	29.09%	41.82%	20.78%	8.31%	100%
	3.75%	3.73%	7.05%	4.66%	4.22%
326	24.11%	54.1%	11.75%	10.05%	100%
	1.74%	2.7%	2.23%	3.15%	2.37%
327	43.87%	45.71%	8.49%	1.93%	100%
	5.83%	4.2%	2.97%	1.12%	4.35%
331	35.74%	46.55%	13.79%	3.92%	100%
	3.77%	3.39%	3.82%	1.8%	3.45%
332	32.08%	54.82%	9.69%	3.4%	100%
	6.21%	7.34%	4.94%	2.86%	6.33%
333	24.21%	52.86%	17.26%	5.67%	100%
	5.25%	7.93%	9.85%	5.34%	7.1%
334	29.14%	52.04%	12.88%	5.93%	100%
	3.18%	3.93%	3.7%	2.81%	3.58%
335	27.93%	50.27%	13.56%	8.24%	100%
	2.35%	2.92%	3%	3.01%	2.75%
336	30.99%	51.15%	13.24%	4.61%	100%
	3.45%	3.94%	3.88%	2.23%	3.64%
337	21.9%	57.14%	16.82%	4.14%	100%
	1.83%	3.31%	3.7%	1.5%	2.74%
339	27.96%	57.08%	8.63%	6.33%	100%
	2.72%	3.83%	2.2%	2.67%	3.18%
421	36.97%	54.62%	5.04%	3.36%	100%
	0.49%	0.5%	0.18%	0.19%	0.44%
423	24.9%	64.66%	8.03%	2.41%	100%
	0.69%	1.24%	0.59%	0.29%	0.91%
424	25.29%	60%	8.82%	5.88%	100%
	0.48%	0.79%	0.44%	0.49%	0.62%
425	20%	77.14%	2.86%	0%	100%
	0.08%	0.21%	0.03%	0%	0.13%
441	41.24%	41.24%	5.15%	12.37%	100%
	0.45%	0.31%	0.15%	0.58%	0.35%

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Table 10 – continued from previous page

Sector	Bin 1	Bin 2	Bin 3	Bin 4	Total
442	79.07%	19.77%	1.16%	0%	100%
	0.76%	0.13%	0.03%	0%	0.31%
443	67.39%	28.26%	3.26%	1.09%	100%
	0.69%	0.2%	0.09%	0.05%	0.34%
444	27.03%	67.57%	4.73%	0.68%	100%
	0.45%	0.77%	0.21%	0.05%	0.54%
445	13.41%	60.15%	12.64%	13.79%	100%
	0.39%	1.21%	0.97%	1.75%	0.95%
446	7.25%	62.32%	5.8%	24.64%	100%
	0.06%	0.33%	0.12%	0.82%	0.25%
447	41.67%	45.24%	3.57%	9.52%	100%
	0.39%	0.29%	0.09%	0.39%	0.31%
448	43.8%	25.62%	16.53%	14.05%	100%
	0.59%	0.24%	0.59%	0.82%	0.44%
451	33.33%	34.85%	7.58%	24.24%	100%
	0.25%	0.18%	0.15%	0.78%	0.24%
452	50.7%	22.54%	7.04%	19.72%	100%
	0.4%	0.12%	0.15%	0.68%	0.26%
453	14.49%	65.22%	5.8%	14.49%	100%
	0.11%	0.35%	0.12%	0.49%	0.25%
454	19.3%	69.3%	8.77%	2.63%	100%
	0.25%	0.61%	0.29%	0.15%	0.42%
481	44.44%	20.83%	9.72%	25%	100%
	0.36%	0.12%	0.21%	0.87%	0.26%
482	15.15%	21.21%	27.27%	36.36%	100%
	0.06%	0.05%	0.26%	0.58%	0.12%
483	47.14%	32.86%	12.86%	7.14%	100%
	0.37%	0.18%	0.26%	0.24%	0.26%
484	28.39%	61.44%	3.39%	6.78%	100%
	0.75%	1.12%	0.24%	0.78%	0.86%
486	12.77%	82.98%	4.26%	0%	100%
	0.07%	0.3%	0.06%	0%	0.17%
488	49.49%	43.94%	4.04%	2.53%	100%
	1.1%	0.67%	0.24%	0.24%	0.72%
491	0%	0%	0%	100%	100%
	0%	0%	0%	0.05%	0%
492	21.67%	51.67%	5%	21.67%	100%
	0.15%	0.24%	0.09%	0.63%	0.22%
493	58.18%	31.82%	10%	0%	100%
	0.72%	0.27%	0.32%	0%	0.4%
511	31.49%	55.25%	6.14%	7.13%	100%
	1.78%	2.16%	0.91%	1.75%	1.85%
515	30.05%	62.3%	7.65%	0%	100%

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Table 10 – continued from previous page

Sector	Bin 1	Bin 2	Bin 3	Bin 4	Total
	0.61%	0.88%	0.41%	0%	0.67%
517	14.48%	23.53%	20.36%	41.63%	100%
	0.36%	0.4%	1.32%	4.46%	0.81%
518	52.94%	44.44%	2.61%	0%	100%
	0.91%	0.53%	0.12%	0%	0.56%
522	54.48%	36.94%	6.34%	2.24%	100%
	1.63%	0.76%	0.5%	0.29%	0.98%
523	42.86%	43.88%	4.08%	9.18%	100%
	0.94%	0.66%	0.24%	0.87%	0.72%
524	15.94%	27.01%	28.95%	28.1%	100%
	1.46%	1.72%	7%	11.21%	3%
531	71.55%	25.1%	1.67%	1.67%	100%
	3.82%	0.93%	0.24%	0.39%	1.75%
532	22.58%	60.65%	4.52%	12.26%	100%
	0.39%	0.73%	0.21%	0.92%	0.57%
541	37.34%	53.32%	8.51%	0.83%	100%
	2.01%	1.99%	1.21%	0.19%	1.76%
561	29.8%	34.98%	29.8%	5.42%	100%
	1.35%	1.1%	3.56%	1.07%	1.48%
562	30%	70%	0%	0%	100%
	0.03%	0.05%	0%	0%	0.04%
621	22.49%	60.55%	8.65%	8.3%	100%
	0.73%	1.35%	0.73%	1.16%	1.06%
622	7.21%	11.91%	34.48%	46.39%	100%
	0.26%	0.29%	3.23%	7.18%	1.17%
623	45.18%	53.01%	0%	1.81%	100%
	0.84%	0.68%	0%	0.15%	0.61%
713	26.87%	62.69%	10.45%	0%	100%
	0.2%	0.32%	0.21%	0%	0.24%
721	25%	65.87%	7.69%	1.44%	100%
	0.58%	1.06%	0.47%	0.15%	0.76%
Total	32.71%	47.32%	12.44%	7.53%	100%
	100%	100%	100%	100%	100%

The table shows the percentage of firms in the PPI that belong to a bin in a given three-digit NAICS category (each first line per industry) and the percentage in an industry given a bin (each second line). Bin 1 groups firms with 1 to 3 goods, bin 2 firms with 3 to 5 goods, bin 3 firms with 5 to 7 goods and bin 4 firms with more than 7 goods.

Table 11: Distribution of Firms across Sectors and Bins

Sector	Bin 1	Bin 2	Bin 3	Bin 4	Total
1111	66.67%	19.05%	9.52%	4.76%	100
	0.16%	0.03%	0.06%	0.05%	0.08
1112	70.97%	22.58%	0%	6.45%	100
	0.25%	0.05%	0%	0.1%	0.11
1113	77.42%	16.13%	3.23%	3.23%	100
	0.27%	0.04%	0.03%	0.05%	0.11
1119	80%	20%	0%	0%	100
	0.04%	0.01%	0%	0%	0.02
1121	60%	0%	0%	40%	100
	0.03%	0%	0%	0.1%	0.02
1122	50%	0%	50%	0%	100
	0.01%	0%	0.03%	0%	0.01
1123	18.18%	54.55%	9.09%	18.18%	100
	0.02%	0.05%	0.03%	0.1%	0.04
1124	0%	50%	50%	0%	100
	0%	0.01%	0.03%	0%	0.01
1133	50%	45.45%	4.55%	0%	100
	0.49%	0.31%	0.12%	0%	0.32
1141	57.14%	7.14%	7.14%	28.57%	100
	0.09%	0.01%	0.03%	0.19%	0.05
2111	25.3%	45.78%	15.66%	13.25%	100
	0.23%	0.29%	0.38%	0.53%	0.3
2121	74.19%	21.77%	4.03%	0%	100
	1.03%	0.21%	0.15%	0%	0.45
2122	93.94%	6.06%	0%	0%	100
	0.35%	0.02%	0%	0%	0.12
2123	82.28%	14.66%	1.83%	1.22%	100
	4.51%	0.56%	0.26%	0.29%	1.79
2131	71.76%	24.43%	3.05%	0.76%	100
	1.05%	0.25%	0.12%	0.05%	0.48
2211	22.56%	12.78%	12.41%	52.26%	100
	0.67%	0.26%	0.97%	6.74%	0.97
2212	11.21%	3.45%	6.9%	78.45%	100
	0.15%	0.03%	0.24%	4.42%	0.42
2362	48.25%	51.75%	0%	0%	100
	3.08%	2.29%	0%	0%	2.09
3111	20.57%	49.28%	16.75%	13.4%	100
	0.48%	0.8%	1.03%	1.36%	0.76
3112	23.03%	44.94%	19.1%	12.92%	100
	0.46%	0.62%	1%	1.12%	0.65
3113	45.76%	19.49%	27.97%	6.78%	100

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Table 11 – continued from previous page

Sector	Bin 1	Bin 2	Bin 3	Bin 4	Total
	0.6%	0.18%	0.97%	0.39%	0.43
3114	29.15%	46.86%	13.65%	10.33%	100
	0.88%	0.98%	1.09%	1.36%	0.99
3115	16.12%	38.79%	31.23%	13.85%	100
	0.72%	1.19%	3.64%	2.67%	1.45
3116	19.72%	55.63%	18.66%	5.99%	100
	0.63%	1.22%	1.56%	0.82%	1.04
3117	65.71%	20%	10.48%	3.81%	100
	0.77%	0.16%	0.32%	0.19%	0.38
3118	17.73%	54.09%	14.09%	14.09%	100
	0.44%	0.92%	0.91%	1.5%	0.8
3119	20.1%	68.63%	8.82%	2.45%	100
	0.46%	1.08%	0.53%	0.24%	0.75
3121	27.32%	40.49%	22.44%	9.76%	100
	0.63%	0.64%	1.35%	0.97%	0.75
3122	41.86%	32.56%	19.77%	5.81%	100
	0.4%	0.22%	0.5%	0.24%	0.31
3131	29.23%	56.92%	10.77%	3.08%	100
	0.21%	0.29%	0.21%	0.1%	0.24
3132	31.22%	59.92%	6.75%	2.11%	100
	0.83%	1.1%	0.47%	0.24%	0.87
3133	11.43%	75.71%	10%	2.86%	100
	0.09%	0.41%	0.21%	0.1%	0.26
3141	23.33%	61.33%	9.33%	6%	100
	0.39%	0.71%	0.41%	0.44%	0.55
3149	27.32%	69.4%	2.73%	0.55%	100
	0.56%	0.98%	0.15%	0.05%	0.67
3151	17.7%	53.98%	23.01%	5.31%	100
	0.22%	0.47%	0.76%	0.29%	0.41
3152	44.3%	45.57%	7.09%	3.04%	100
	1.96%	1.39%	0.82%	0.58%	1.44
3159	16.82%	73.83%	6.54%	2.8%	100
	0.2%	0.61%	0.21%	0.15%	0.39
3161	30.88%	57.35%	4.41%	7.35%	100
	0.23%	0.3%	0.09%	0.24%	0.25
3162	27.78%	44.44%	27.78%	0%	100
	0.17%	0.19%	0.44%	0%	0.2
3169	53.04%	38.26%	8.7%	0%	100
	0.68%	0.34%	0.29%	0%	0.42
3211	13.41%	67.07%	13.41%	6.1%	100
	0.25%	0.85%	0.65%	0.49%	0.6
3212	61.61%	28.91%	6.64%	2.84%	100
	1.45%	0.47%	0.41%	0.29%	0.77

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Table 11 – continued from previous page

Sector	Bin 1	Bin 2	Bin 3	Bin 4	Total
3219	31.62%	64.26%	4.12%	0%	100
	1.03%	1.44%	0.35%	0%	1.06
3221	37.5%	28.12%	25%	9.38%	100
	0.27%	0.14%	0.47%	0.29%	0.23
3222	28.4%	61.32%	8.02%	2.26%	100
	1.54%	2.3%	1.15%	0.53%	1.78
3231	24.08%	47.35%	27.55%	1.02%	100
	1.32%	1.79%	3.97%	0.24%	1.79
3241	63.48%	30%	0.87%	5.65%	100
	1.63%	0.53%	0.06%	0.63%	0.84
3251	35.05%	45.33%	16.36%	3.27%	100
	0.84%	0.75%	1.03%	0.34%	0.78
3252	33.08%	34.59%	22.56%	9.77%	100
	0.49%	0.36%	0.88%	0.63%	0.49
3253	31.4%	53.49%	12.79%	2.33%	100
	0.3%	0.36%	0.32%	0.1%	0.31
3254	38.12%	25.25%	18.32%	18.32%	100
	0.86%	0.39%	1.09%	1.8%	0.74
3255	16.37%	51.46%	25.15%	7.02%	100
	0.31%	0.68%	1.26%	0.58%	0.63
3256	17.9%	31.48%	40.74%	9.88%	100
	0.32%	0.39%	1.94%	0.78%	0.59
3259	29.95%	55.61%	9.63%	4.81%	100
	0.63%	0.8%	0.53%	0.44%	0.68
3261	27.2%	60.2%	7.05%	5.54%	100
	1.21%	1.85%	0.82%	1.07%	1.45
3262	19.2%	44.4%	19.2%	17.2%	100
	0.54%	0.86%	1.41%	2.09%	0.91
3271	29.59%	57.53%	10.41%	2.47%	100
	1.21%	1.62%	1.12%	0.44%	1.33
3272	34.36%	52.86%	10.13%	2.64%	100
	0.87%	0.93%	0.68%	0.29%	0.83
3273	56.84%	37%	4.83%	1.34%	100
	2.37%	1.07%	0.53%	0.24%	1.36
3274	38%	50%	12%	0%	100
	0.21%	0.19%	0.18%	0%	0.18
3279	60%	29.14%	9.14%	1.71%	100
	1.17%	0.39%	0.47%	0.15%	0.64
3311	25.74%	23.76%	36.63%	13.86%	100
	0.29%	0.19%	1.09%	0.68%	0.37
3312	30.23%	49.42%	18.6%	1.74%	100
	0.58%	0.66%	0.94%	0.15%	0.63
3313	41.27%	42.06%	9.52%	7.14%	100

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Table 11 – continued from previous page

Sector	Bin 1	Bin 2	Bin 3	Bin 4	Total
	0.58%	0.41%	0.35%	0.44%	0.46
3314	49.74%	39.49%	8.21%	2.56%	100
	1.08%	0.59%	0.47%	0.24%	0.71
3315	31.52%	57.31%	9.46%	1.72%	100
	1.23%	1.55%	0.97%	0.29%	1.28
3321	50.79%	46.03%	1.59%	1.59%	100
	0.72%	0.45%	0.06%	0.1%	0.46
3322	23.85%	43.85%	31.54%	0.77%	100
	0.35%	0.44%	1.21%	0.05%	0.48
3323	34.84%	60.37%	3.19%	1.6%	100
	1.46%	1.75%	0.35%	0.29%	1.37
3324	30.95%	49.21%	13.49%	6.35%	100
	0.44%	0.48%	0.5%	0.39%	0.46
3325	25%	47.5%	25%	2.5%	100
	0.22%	0.29%	0.59%	0.1%	0.29
3326	32.17%	66.09%	1.74%	0%	100
	0.41%	0.59%	0.06%	0%	0.42
3327	25.95%	70.89%	3.16%	0%	100
	0.46%	0.87%	0.15%	0%	0.58
3328	36.07%	61.2%	2.73%	0%	100
	0.74%	0.87%	0.15%	0%	0.67
3329	28.93%	47.38%	14.58%	9.11%	100
	1.42%	1.61%	1.88%	1.94%	1.6
3331	15.51%	46.12%	22.86%	15.51%	100
	0.42%	0.87%	1.65%	1.84%	0.9
3332	33.82%	53.06%	11.08%	2.04%	100
	1.3%	1.41%	1.12%	0.34%	1.25
3333	23.74%	57.55%	15.83%	2.88%	100
	0.37%	0.62%	0.65%	0.19%	0.51
3334	20.32%	60.43%	18.18%	1.07%	100
	0.42%	0.87%	1%	0.1%	0.68
3335	29.89%	62.36%	5.54%	2.21%	100
	0.91%	1.31%	0.44%	0.29%	0.99
3336	22.16%	52.1%	18.56%	7.19%	100
	0.41%	0.67%	0.91%	0.58%	0.61
3339	21.56%	47.88%	23.6%	6.96%	100
	1.42%	2.18%	4.09%	1.99%	2.15
3341	42.48%	37.17%	12.39%	7.96%	100
	0.54%	0.32%	0.41%	0.44%	0.41
3342	22.73%	62.5%	11.36%	3.41%	100
	0.22%	0.42%	0.29%	0.15%	0.32
3343	35%	55%	10%	0%	100
	0.08%	0.08%	0.06%	0%	0.07

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Table 11 – continued from previous page

Sector	Bin 1	Bin 2	Bin 3	Bin 4	Total
3344	25.86%	52.02%	14.33%	7.79%	100
	0.93%	1.29%	1.35%	1.21%	1.17
3345	28.35%	53.92%	13.16%	4.56%	100
	1.25%	1.65%	1.53%	0.87%	1.44
3346	36.59%	51.22%	4.88%	7.32%	100
	0.17%	0.16%	0.06%	0.15%	0.15
3351	46.28%	40.43%	11.17%	2.13%	100
	0.97%	0.59%	0.62%	0.19%	0.69
3352	20.55%	45.21%	26.03%	8.22%	100
	0.17%	0.25%	0.56%	0.29%	0.27
3353	24.37%	56.3%	10.92%	8.4%	100
	0.65%	1.04%	0.76%	0.97%	0.87
3359	19.76%	53.36%	14.23%	12.65%	100
	0.56%	1.04%	1.06%	1.55%	0.92
3361	25%	53.12%	9.38%	12.5%	100
	0.09%	0.13%	0.09%	0.19%	0.12
3362	36.9%	50.8%	10.7%	1.6%	100
	0.77%	0.73%	0.59%	0.15%	0.68
3363	16.32%	60.14%	17.48%	6.06%	100
	0.78%	1.99%	2.2%	1.26%	1.57
3364	38.97%	50%	6.62%	4.41%	100
	0.59%	0.53%	0.26%	0.29%	0.5
3365	24.32%	64.86%	10.81%	0%	100
	0.1%	0.19%	0.12%	0%	0.14
3366	62.59%	25.9%	7.91%	3.6%	100
	0.97%	0.28%	0.32%	0.24%	0.51
3369	35.14%	32.43%	27.03%	5.41%	100
	0.15%	0.09%	0.29%	0.1%	0.14
3371	22.66%	59.05%	15.31%	2.98%	100
	1.27%	2.29%	2.26%	0.73%	1.84
3372	20%	58.18%	12.12%	9.7%	100
	0.37%	0.74%	0.59%	0.78%	0.6
3379	20.99%	43.21%	35.8%	0%	100
	0.19%	0.27%	0.85%	0%	0.3
3391	22.53%	55.97%	11.6%	9.9%	100
	0.74%	1.27%	1%	1.41%	1.07
3399	30.73%	57.64%	7.12%	4.51%	100
	1.98%	2.56%	1.21%	1.26%	2.11
4219	36.97%	54.62%	5.04%	3.36%	100
	0.49%	0.5%	0.18%	0.19%	0.44
4230	24.9%	64.66%	8.03%	2.41%	100
	0.69%	1.24%	0.59%	0.29%	0.91
4240	25.29%	60%	8.82%	5.88%	100

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Table 11 – continued from previous page

Sector	Bin 1	Bin 2	Bin 3	Bin 4	Total
	0.48%	0.79%	0.44%	0.49%	0.62
4251	20%	77.14%	2.86%	0%	100
	0.08%	0.21%	0.03%	0%	0.13
4411	52.38%	4.76%	14.29%	28.57%	100
	0.12%	0.01%	0.09%	0.29%	0.08
4412	47.92%	47.92%	0%	4.17%	100
	0.26%	0.18%	0%	0.1%	0.18
4413	21.43%	57.14%	7.14%	14.29%	100
	0.07%	0.12%	0.06%	0.19%	0.1
4421	84.75%	13.56%	1.69%	0%	100
	0.56%	0.06%	0.03%	0%	0.22
4422	66.67%	33.33%	0%	0%	100
	0.2%	0.07%	0%	0%	0.1
4431	67.39%	28.26%	3.26%	1.09%	100
	0.69%	0.2%	0.09%	0.05%	0.34
4441	26.89%	68.07%	4.2%	0.84%	100
	0.36%	0.63%	0.15%	0.05%	0.44
4442	27.59%	65.52%	6.9%	0%	100
	0.09%	0.15%	0.06%	0%	0.11
4451	4.72%	44.34%	25.47%	25.47%	100
	0.06%	0.36%	0.79%	1.31%	0.39
4452	21.21%	68.94%	4.55%	5.3%	100
	0.31%	0.7%	0.18%	0.34%	0.48
4453	8.7%	82.61%	0%	8.7%	100
	0.02%	0.15%	0%	0.1%	0.08
4461	7.25%	62.32%	5.8%	24.64%	100
	0.06%	0.33%	0.12%	0.82%	0.25
4471	41.67%	45.24%	3.57%	9.52%	100
	0.39%	0.29%	0.09%	0.39%	0.31
4481	55.07%	20.29%	18.84%	5.8%	100
	0.42%	0.11%	0.38%	0.19%	0.25
4482	60%	15%	5%	20%	100
	0.13%	0.02%	0.03%	0.19%	0.07
4483	9.38%	43.75%	18.75%	28.12%	100
	0.03%	0.11%	0.18%	0.44%	0.12
4511	12.2%	43.9%	12.2%	31.71%	100
	0.06%	0.14%	0.15%	0.63%	0.15
4512	68%	20%	0%	12%	100
	0.19%	0.04%	0%	0.15%	0.09
4521	50%	25%	10%	15%	100
	0.22%	0.08%	0.12%	0.29%	0.15
4529	51.61%	19.35%	3.23%	25.81%	100
	0.18%	0.05%	0.03%	0.39%	0.11

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Sector	Bin 1	Bin 2	Bin 3	Bin 4	Total
4531	11.11%	88.89%	0%	0%	100
	0.02%	0.12%	0%	0%	0.07
4532	3.03%	54.55%	12.12%	30.3%	100
	0.01%	0.14%	0.12%	0.49%	0.12
4539	38.89%	61.11%	0%	0%	100
	0.08%	0.08%	0%	0%	0.07
4541	13.51%	75.68%	6.76%	4.05%	100
	0.11%	0.43%	0.15%	0.15%	0.27
4542	16.67%	72.22%	11.11%	0%	100
	0.03%	0.1%	0.06%	0%	0.07
4543	40.91%	45.45%	13.64%	0%	100
	0.1%	0.08%	0.09%	0%	0.08
4811	16.28%	25.58%	16.28%	41.86%	100
	0.08%	0.08%	0.21%	0.87%	0.16
4812	86.21%	13.79%	0%	0%	100
	0.28%	0.03%	0%	0%	0.11
4821	15.15%	21.21%	27.27%	36.36%	100
	0.06%	0.05%	0.26%	0.58%	0.12
4831	31.43%	42.86%	11.43%	14.29%	100
	0.12%	0.12%	0.12%	0.24%	0.13
4832	62.86%	22.86%	14.29%	0%	100
	0.25%	0.06%	0.15%	0%	0.13
4841	20.83%	62.5%	5%	11.67%	100
	0.28%	0.58%	0.18%	0.68%	0.44
4842	36.21%	60.34%	1.72%	1.72%	100
	0.47%	0.54%	0.06%	0.1%	0.42
4861	28.57%	66.67%	4.76%	0%	100
	0.07%	0.11%	0.03%	0%	0.08
4869	0%	96.15%	3.85%	0%	100
	0%	0.19%	0.03%	0%	0.1
4881	53.33%	28.33%	10%	8.33%	100
	0.36%	0.13%	0.18%	0.24%	0.22
4883	48.15%	50%	1.85%	0%	100
	0.58%	0.42%	0.06%	0%	0.39
4885	46.67%	53.33%	0%	0%	100
	0.16%	0.12%	0%	0%	0.11
4911	0%	0%	0%	100%	100
	0%	0%	0%	0.05%	0
4921	21.21%	33.33%	9.09%	36.36%	100
	0.08%	0.08%	0.09%	0.58%	0.12
4922	22.22%	74.07%	0%	3.7%	100
	0.07%	0.15%	0%	0.05%	0.1
4931	58.18%	31.82%	10%	0%	100

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Sector	Bin 1	Bin 2	Bin 3	Bin 4	Total
	0.72%	0.27%	0.32%	0%	0.4
5111	24.01%	60.64%	6.93%	8.42%	100
	1.08%	1.89%	0.82%	1.65%	1.48
5112	61.39%	33.66%	2.97%	1.98%	100
	0.69%	0.26%	0.09%	0.1%	0.37
5151	30.06%	62.58%	7.36%	0%	100
	0.55%	0.79%	0.35%	0%	0.6
5152	30%	60%	10%	0%	100
	0.07%	0.09%	0.06%	0%	0.07
5171	0%	3.37%	13.48%	83.15%	100
	0%	0.02%	0.35%	3.59%	0.33
5172	55%	5%	10%	30%	100
	0.12%	0.01%	0.06%	0.29%	0.07
5175	18.75%	42.86%	27.68%	10.71%	100
	0.23%	0.37%	0.91%	0.58%	0.41
5181	52.44%	42.68%	4.88%	0%	100
	0.48%	0.27%	0.12%	0%	0.3
5182	53.52%	46.48%	0%	0%	100
	0.42%	0.25%	0%	0%	0.26
5221	54.48%	36.94%	6.34%	2.24%	100
	1.63%	0.76%	0.5%	0.29%	0.98
5231	45.71%	40.95%	4.76%	8.57%	100
	0.54%	0.33%	0.15%	0.44%	0.38
5239	39.56%	47.25%	3.3%	9.89%	100
	0.4%	0.33%	0.09%	0.44%	0.33
5241	13.77%	21.81%	31.56%	32.86%	100
	1.07%	1.17%	6.47%	11.11%	2.55
5242	28%	56%	14.4%	1.6%	100
	0.39%	0.54%	0.53%	0.1%	0.46
5311	94.6%	5.04%	0%	0.36%	100
	2.94%	0.11%	0%	0.05%	1.02
5312	38.24%	51.96%	5.88%	3.92%	100
	0.44%	0.41%	0.18%	0.19%	0.37
5313	40.82%	54.08%	2.04%	3.06%	100
	0.45%	0.41%	0.06%	0.15%	0.36
5321	28.95%	43.42%	2.63%	25%	100
	0.25%	0.25%	0.06%	0.92%	0.28
5324	16.46%	77.22%	6.33%	0%	100
	0.15%	0.47%	0.15%	0%	0.29
5411	28.43%	59.31%	10.29%	1.96%	100
	0.65%	0.93%	0.62%	0.19%	0.75
5412	48.67%	46.02%	5.31%	0%	100
	0.61%	0.4%	0.18%	0%	0.41

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Sector	Bin 1	Bin 2	Bin 3	Bin 4	Total
5413	52.63%	33.33%	14.04%	0%	100
	0.34%	0.15%	0.24%	0%	0.21
5416	33.87%	61.29%	4.84%	0%	100
	0.23%	0.29%	0.09%	0%	0.23
5418	34.78%	58.7%	6.52%	0%	100
	0.18%	0.21%	0.09%	0%	0.17
5613	23.38%	44.81%	24.68%	7.14%	100
	0.4%	0.53%	1.12%	0.53%	0.56
5615	24.07%	25.93%	48.15%	1.85%	100
	0.15%	0.11%	0.76%	0.05%	0.2
5616	35.53%	18.42%	42.11%	3.95%	100
	0.3%	0.11%	0.94%	0.15%	0.28
5617	36.89%	36.89%	20.49%	5.74%	100
	0.5%	0.35%	0.73%	0.34%	0.45
5621	30%	70%	0%	0%	100
	0.03%	0.05%	0%	0%	0.04
6211	20.13%	54.55%	13.64%	11.69%	100
	0.35%	0.65%	0.62%	0.87%	0.56
6216	25.19%	67.41%	2.96%	4.44%	100
	0.38%	0.7%	0.12%	0.29%	0.49
6221	7.38%	11.07%	27.31%	54.24%	100
	0.22%	0.23%	2.18%	7.13%	0.99
6222	7.32%	19.51%	73.17%	0%	100
	0.03%	0.06%	0.88%	0%	0.15
6223	0%	0%	85.71%	14.29%	100
	0%	0%	0.18%	0.05%	0.03
6231	43.31%	54.78%	0%	1.91%	100
	0.76%	0.66%	0%	0.15%	0.57
6232	77.78%	22.22%	0%	0%	100
	0.08%	0.02%	0%	0%	0.03
7131	0%	88.89%	11.11%	0%	100
	0%	0.06%	0.03%	0%	0.03
7139	31.03%	58.62%	10.34%	0%	100
	0.2%	0.26%	0.18%	0%	0.21
7211	25%	65.87%	7.69%	1.44%	100
	0.58%	1.06%	0.47%	0.15%	0.76
Total	32.71%	47.32%	12.44%	7.53%	100
	100%	100%	100%	100%	100

The table shows the percentage of firms in the PPI that belong to a bin in a given four-digit NAICS category (each first line per industry) and the percentage in an industry given a bin (each second line). Bin 1 groups firms with 1 to 3 goods, bin 2 firms with 3 to 5 goods, bin 3 firms with 5 to 7 goods and bin 4 firms with more than 7 goods.

Table 12: Relation of Frequency and Number of Goods, Six-Digit Level

	Estimated Coefficient
Mean	1.22
	(0.12)
Median	1.32
25% Percentile	0.59
75% Percentile	1.80

We estimate the following specification: $f_{j,p} = \beta_{0,p} + \beta_{1,p} n_{j,p} + \epsilon_{j,p}$, where $f_{j,p}$ denotes the frequency of firm j in a six-digit product category p and $n_{j,p}$ the number of goods of that firm. We estimate the specification at each date, take the median of $\beta_{1,p}$ across all products at that date and report the mean, median and quartiles of median $\beta_{1,p}$ over time.

Table 13: Relation of Absolute Size of Price Changes and Number of Goods, Six-Digit Level

	Estimated Coefficient
Mean	-0.38
	(0.026)
Median	-0.358
25% Percentile	-0.521
75% Percentile	-0.0315

We estimate the following specification: $|\Delta p|_{j,p} = \beta_{0,p} + \beta_{1,p} n_{j,p} + \epsilon_{j,p}$, where $|\Delta p|_{j,p}$ denotes the mean absolute size of price changes of firm j in a six-digit product category p and $n_{j,p}$ the number of goods of that firm. We estimate the specification at each date, take the mean of $\beta_{1,p}$ across all products at that date and report the mean, median and quartiles of median $\beta_{1,p}$ over time.

Table 14: Fraction of Small Price Changes According to Different Definitions

Number of Goods	$\lvert dp\rvert < \frac{1}{2}\overline{\lvert dp\rvert}$	$\lvert dp\rvert < \frac{1}{3}\overline{\lvert dp\rvert}$	$\lvert dp\rvert < \frac{1}{4}\overline{\lvert dp\rvert}$	$\lvert dp\rvert < \frac{1}{10}\overline{\lvert dp\rvert}$	$\lvert dp\rvert < 1\%$	$\lvert dp\rvert < 0.5\%$	$\lvert dp\rvert < 0.25\%$
1-3	39.46%	31.70%	27.28%	17.95%	32.74%	25.78%	20.19%
	(0.32%)	(0.32%)	(0.31%)	(0.29%)	(0.39%)	(0.37%)	(0.34%)
3-5	44.61%	36.52%	31.74%	21.53%	35.98%	28.81%	22.86%
	(0.31%)	(0.32%)	(0.32%)	(0.31%)	(0.4%)	(0.38%)	(0.36%)
5-7	47.45%	39.20%	34.80%	23.69%	37.53%	30.15%	23.75%
	(0.54%)	(0.58%)	(0.59%)	(0.58%)	(0.73%)	(0.71%)	(0.66%)
> 7	50.22%	42.41%	37.56%	26.41%	40.97%	33.40%	26.77%
	(0.61%)	(0.69%)	(0.73%)	(0.76%)	(0.94%)	(0.94%)	(0.89%)
Pooled	42.93%	34.98%	30.40%	20.44%	34.98%	27.86%	21.98%
	(0.2%)	(0.2%)	(0.2%)	(0.19%)	(0.25%)	(0.24%)	(0.23%)

The fraction of small price changes is computed in the following way: First, we compute a cut-off that defines a small price change. This is either a fraction of the mean absolute size of price changes $\overline{\lvert dp\rvert}$ for a given firm, as indicated in the columns, or an absolute percentage number. Second, we compute the fraction of absolute price changes falling below the cut-off. Third, we summarize means across firms within each bin.

Table 15: Fraction of Small Price Changes, Defined Relative to Industry

	Fraction Small, Relative Measure Aggregated at		
	Four Digits	Six Digits	Eight Digits
	4d	6d	8d
1-3 Goods	65.90%	65.46%	64.96%
	(0.0038%)	(0.0038%)	(0.0038%)
3-5 Goods	69.46%	69.18%	68.80%
	(0.0038%)	(0.0037%)	(0.0037%)
5-7 Goods	70.50%	70.15%	70.20%
	(0.0067%)	(0.0066%)	(0.0065%)
> 7 Goods	72.41%	72.23%	72.00%
	(0.0075%)	(0.0073%)	(0.0073%)

The fraction of small price changes is computed in the following way: First, we compute the fraction of absolute log price changes in a given firm smaller than the mean absolute size of log price changes in a given 4-digit, 6-digit, or 8-digit industry. Second, we take means across firms in a given bin.

Table 16: Fraction of Small Price Changes According to Different Definitions, Item-Level Based

Number of Goods	$\lvert dp\rvert < \frac{1}{2}\overline{\lvert dp\rvert}$	$\lvert dp\rvert < \frac{1}{3}\overline{\lvert dp\rvert}$	$\lvert dp\rvert < \frac{1}{4}\overline{\lvert dp\rvert}$	$\lvert dp\rvert < \frac{1}{10}\overline{\lvert dp\rvert}$	$\lvert dp\rvert < 1\%$	$\lvert dp\rvert < 0.5\%$	$\lvert dp\rvert < 0.25\%$
1-3	32.18%	25.43%	21.79%	14.15%	31.00%	23.91%	18.78%
	0.30%	0.28%	0.27%	0.24%	0.29%	0.29%	0.29%
3-5	31.34%	25.22%	21.88%	14.51%	34.68%	27.46%	21.55%
	0.24%	0.23%	0.22%	0.20%	0.31%	0.31%	0.31%
5-7	35.97%	29.74%	26.23%	17.88%	40.51%	33.25%	26.45%
	0.47%	0.46%	0.45%	0.43%	0.58%	0.58%	0.58%
> 7	43.83%	37.53%	33.73%	24.77%	47.13%	40.43%	33.64%
	0.57%	0.59%	0.60%	0.61%	0.76%	0.76%	0.76%
Pooled	33.19%	26.84%	23.35%	15.64%	35.25%	28.11%	22.26%
	0.17%	0.16%	0.16%	0.14%	0.22%	0.21%	0.20%

The fraction of small price changes is computed in the following way: First, we compute a cut-off that defines a small price change. This is either a fraction of the mean absolute size of price changes $\overline{\lvert dp\rvert}$ for a given good, as indicated in the columns, or an absolute percentage number. Second, we compute the fraction of absolute price changes of the good that fall below the cut-off. Third, we take medians across goods within a firm. Finally, we take means across firms within each bin.

Table 17: Variation Explained by Fixed-Effects

	Products at four-digit level			Products at six-digit level			Products at eight-digit level		
R^2	3.20%	10.39%	26.95%	3.20%	13.56%	27.64%	3.20%	15.68%	28.54%
Adjusted R^2	3.20%	10.39%	25.31%	3.20%	13.47%	25.80%	3.20%	15.48%	26.41%
Month FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product FEs	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Firm FEs	No	No	Yes	No	No	Yes	No	No	Yes

We estimate the following specification regarding variation in $\lvert\Delta p\rvert$, the absolute size of price changes: $\lvert\Delta p\rvert_{i,f,p,t} = \alpha_0\{D^{Month\ m}_{i,f,p,t}\}^{m=12}_{m=1} + \alpha_1 D^{Product}_{i,f,p,t} + \alpha_2 D^{Firm}_{i,f,p,t} + \epsilon_{i,f,p,t}$ where i denotes a good, f a firm, p a product at the 4-, 6-, and 8-digit level, and t time. Dummies are for months, products, and firms.

Table 18: Multinomial Logit

	Negative Change				Positive Change			
	RRR	Std. Err.	z	$P > \|z\|$	RRR	Std. Err.	z	$P > \|z\|$
Fraction industry	1.0129	0.0001	92.85	0	1.0141	0.0001	109.37	0
Fraction firm	1.0710	0.0001	705.44	0	1.0750	0.0001	842.91	0
$\overline{\Delta p}$ industry	1	5.03E-09	-1.74	0.082	1	4.75E-09	11.42	0
$\overline{\Delta p}$ firm	1	2.66E-09	-4.86	0	1	2.40E-09	7.03	0
Change in product code	48.1927	3.5692	52.32	0	46.9592	3.290421	54.93	0
π_{CPI}	0.8936	0.0078	-12.88	0	1.0556	0.0081	7.07	0
Employees	1+4E-06	1.50E-07	26.57	0	1+3E-06	1.41E-07	24.5	0
Month 1	1.0060	0.0122	0.49	0.624	1.3367	0.0142	27.41	0
Month 2	0.5562	0.0073	-44.9	0	1.5790	0.0171	42.15	0
Month 3	10.8005	0.1297	198.22	0	0.8005	0.0103	-17.38	0
Month 4	1.0102	0.0122	0.84	0.4	1.0517	0.0115	4.63	0
Month 5	0.9786	0.0113	-1.88	0.06	0.9493	0.0100	-4.94	0
Month 6	0.9542	0.0112	-4.01	0	0.9484	0.0101	-4.99	0
Month 7	0.2765	0.0035	-101.95	0	1.6793	0.0172	50.69	0
Month 8	1.0547	0.0123	4.56	0	1.0129	0.0108	1.2	0.229
Month 9	1.0338	0.0129	2.67	0.008	1.0352	0.0117	3.06	0.002
Month 10	1.0699	0.0119	6.1	0	1.0773	0.0109	7.37	0
Month 11	1.0470	0.0112	4.3	0	1.0192	0.0101	1.93	0.053
R^2	47.56%							

The table reports results from the estimation of a multinomial logit model for positive and negative price changes. The base category is no price change. Coefficients show the estimated relative risk ratios, where values bigger (smaller) than 1 mean that the decision to adjust upwards or downwards is more (less) likely due to a change in the explanator and relative to the base category. The z-ratio is for the test that $RRR = 1$. Among the variables, Fraction industry and Fraction firm denote the monthly fractions of price changes within the industry or firm that have the same sign as the good under consideration which is excluded from the calculation. $\overline{\Delta p}$ industry and $\overline{\Delta p}$ firm denote the average monthly size of log price changes of all goods in the industry or firm, excluding the price of the good under consideration. We also control for two-digit industry fixed effects which we omit from the table. Change in product code is an indicator variable that takes on the value of 1 if the underlying base price has changes but the price in the data has not. Employees refers to the average number of employees per good in a firm, π_{CPI} to monthly CPI inflation, Month 1 to 11 to month dummies for January through December and Item bin 2 through 4 to dummies for the bin of each good. Bin 1 groups firms with 1 to 3 goods, bin 2 firms with 3 to 5 goods, bin 3 firms with 5 to 7 goods and bin 4 firms with more than 7 goods.

Table 19: Multinomial Logit, No Firm Variables

	Negative Change				Positive Change			
	RRR	Std. Err.	z	$P > \|z\|$	RRR	Std. Err.	z	$P > \|z\|$
Fraction Industry	1.0538	0.0001	503.87	0	1.0540	0.0001	556.89	0
$\overline{\Delta p}$ industry	1.0000	3.98E-09	-4.87	0	1.0000	3.65E-09	12.97	0
Change in product code	53.9963	3.6933	58.32	0	51.3618	3.2870	61.55	0
π_{CPI}	0.8876	0.0068	-15.5	0	1.0417	0.0065	6.58	0
Employees	1+6E-06	1.24E-07	44.68	0	1+5E-06	1.08E-07	46.99	0
Month 1	1.0707	0.0114	6.39	0	1.4681	0.0126	44.62	0
Month 2	0.6114	0.0071	-42.55	0	1.8924	0.0164	73.47	0
Month 3	11.1243	0.1158	231.34	0	0.9541	0.0103	-4.36	0
Month 4	0.9870	0.0106	-1.22	0.224	1.0414	0.0094	4.5	0
Month 5	0.9648	0.0099	-3.5	0	0.9317	0.0082	-8.01	0
Month 6	0.9445	0.0098	-5.5	0	0.9306	0.0083	-8.1	0
Month 7	0.3209	0.0036	-101.86	0	2.2186	0.0181	97.65	0
Month 8	1.0479	0.0108	4.53	0	1.0117	0.0090	1.32	0.187
Month 9	1.0216	0.0113	1.93	0.053	1.0355	0.0097	3.74	0
Month 10	1.0761	0.0106	7.48	0	1.0955	0.0092	10.89	0
Month 11	1.0496	0.0099	5.14	0	1.0244	0.0084	2.94	0.003
R^2	29.93%							

The table reports results from the estimation of a multinomial logit model for positive and negative price changes. The base category is no price change. Coefficients show the estimated relative risk ratios, where values bigger (smaller) than 1 mean that the decision to adjust upwards or downwards is more (less) likely due to a change in the explanator and relative to the base category. The z-ratio is for the test that $RRR = 1$. Among the variables, Fraction industry denotes the monthly fractions of price changes within the industry that have the same sign as the good under consideration which is excluded from the calculation. $\overline{\Delta p}$ industry denotes the average monthly size of log price changes of all goods in the firm, excluding the price of the good under consideration. We also control for two-digit industry fixed effects which we omit from the table. Change in product code is an indicator variable that takes on the value of 1 if the underlying base price has changes but the price in the data has not. Employees refers to the average number of employees per good in a firm, π_{CPI} to monthly CPI inflation, Month 1 to 11 to month dummies for January through December and Item bin 2 through 4 to dummies for the bin of each good. Bin 1 groups firms with 1 to 3 goods, bin 2 firms with 3 to 5 goods, bin 3 firms with 5 to 7 goods and bin 4 firms with more than 7 goods.

Table 20: Marginal Effects for Two-Digit Industries, ± 1/2 Std. Dev., Multinomial Logit

	Pooled	1-3 Goods	3-5 Goods	5-7 Goods	>7 Goods
Negative Changes					
Fraction Industry	-0.30%	1.11%	0.68%	-0.58%	-3.59%
Fraction Firm	9.83%	8.13%	8.02%	11.53%	16.22%
Positive Changes					
Fraction Industry	0.01%	0.97%	0.25%	-1.10%	-3.09%
Fraction Firm	15.84%	13.57%	13.61%	17.79%	25.73%

The table shows the marginal effects in percentage points of a one-standard deviation change in the explanators around the mean on the probability of adjusting prices upwards or downwards. Marginal effects are calculated for the model estimated as for Table 18 but for each bin separately and with a fraction of same-signed industry-level price changes defined at the two-digit level. Estimation, given by the separate columns, is for the pooled data and each bin separately. All reported effects are statistically significantly different from zero.

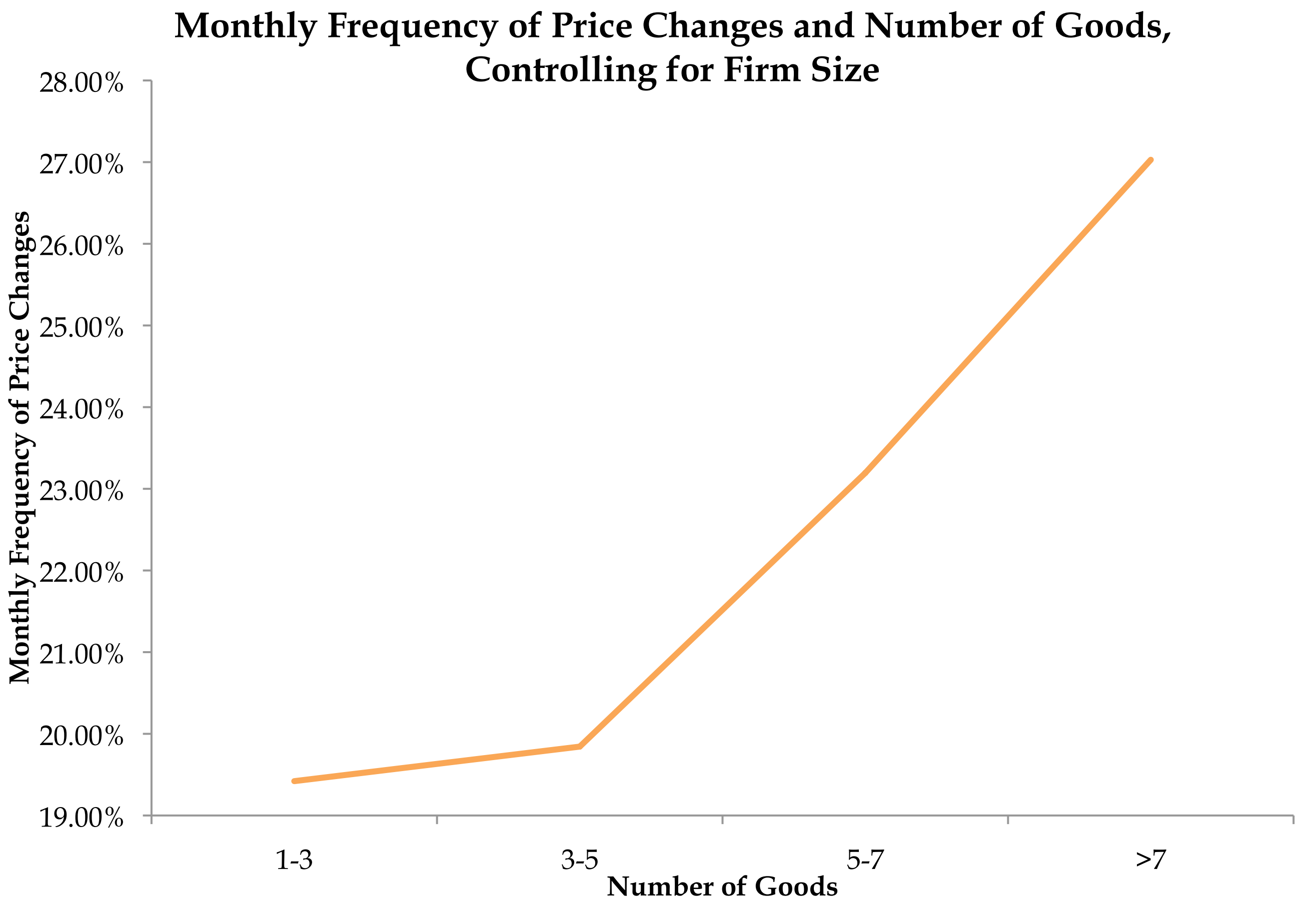


Figure 15: Mean Frequency Size of Price Changes and Number of Goods, Controlling for Size

To obtain the frequency value shown, we estimate the following specification: $f_i = \beta_0 employment_i + \sum_k \beta_k D_{k,i} + \epsilon_i$ where f_i is the median frequency of price adjustment for a firm i, *employment* the number of employees of the firm and $D_{k,i}$ a dummy for bin k that the firm is in. We then graph β_k.

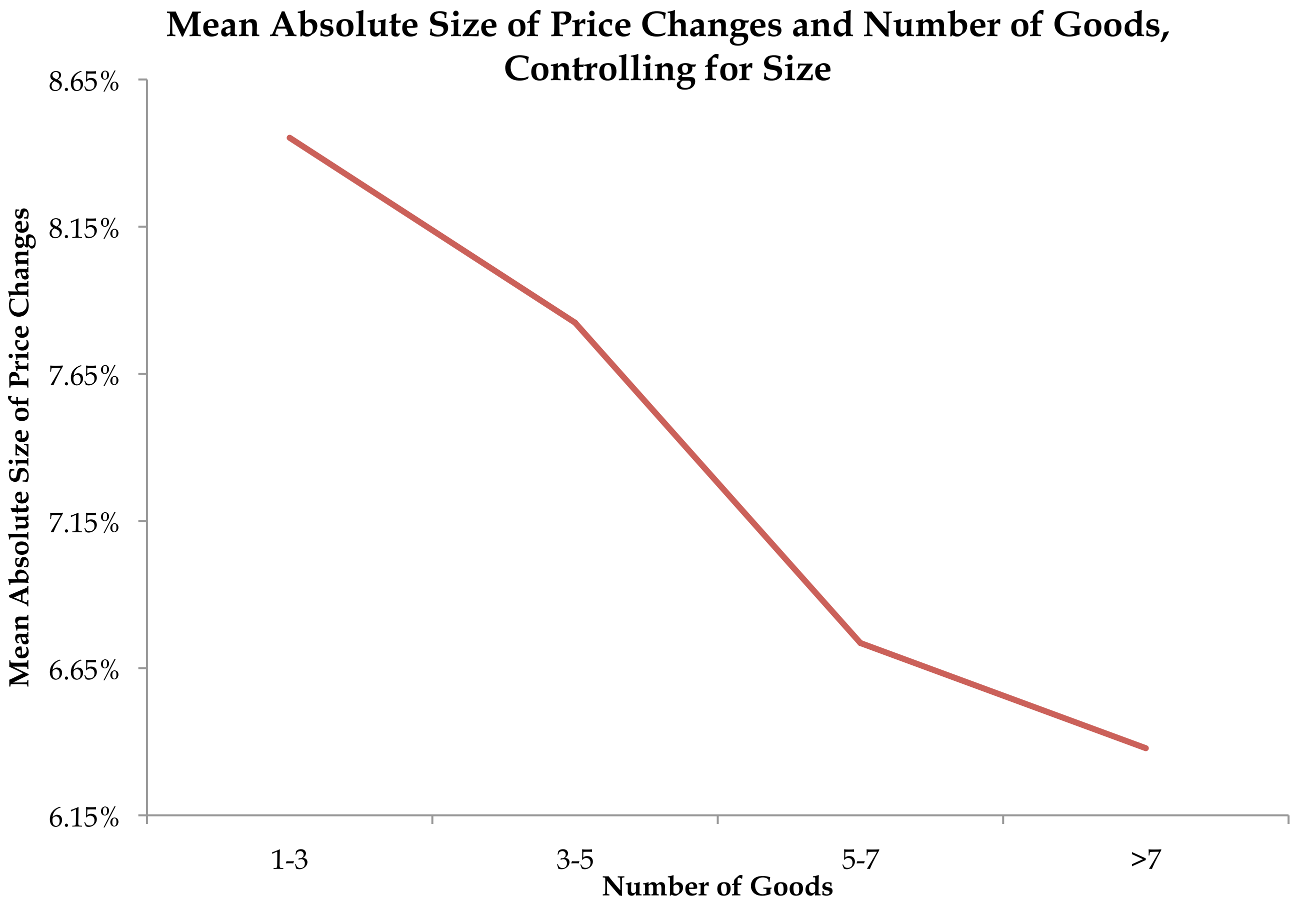


Figure 16: Mean Absolute Size of Price Changes and Number of Goods, Controlling for Size

To obtain the mean absolute size of price change values shown, we estimate the following specification: $|\Delta p_i| = \beta_0 employment_i + \sum_k \beta_k D_{k,i} + \epsilon_i$ where $|\Delta p_i|$ is the median absolute size of price changes for a firm i, *employment* the number of employees of the firm and $D_{k,i}$ a dummy for bin k that the firm is in. We then show β_k.

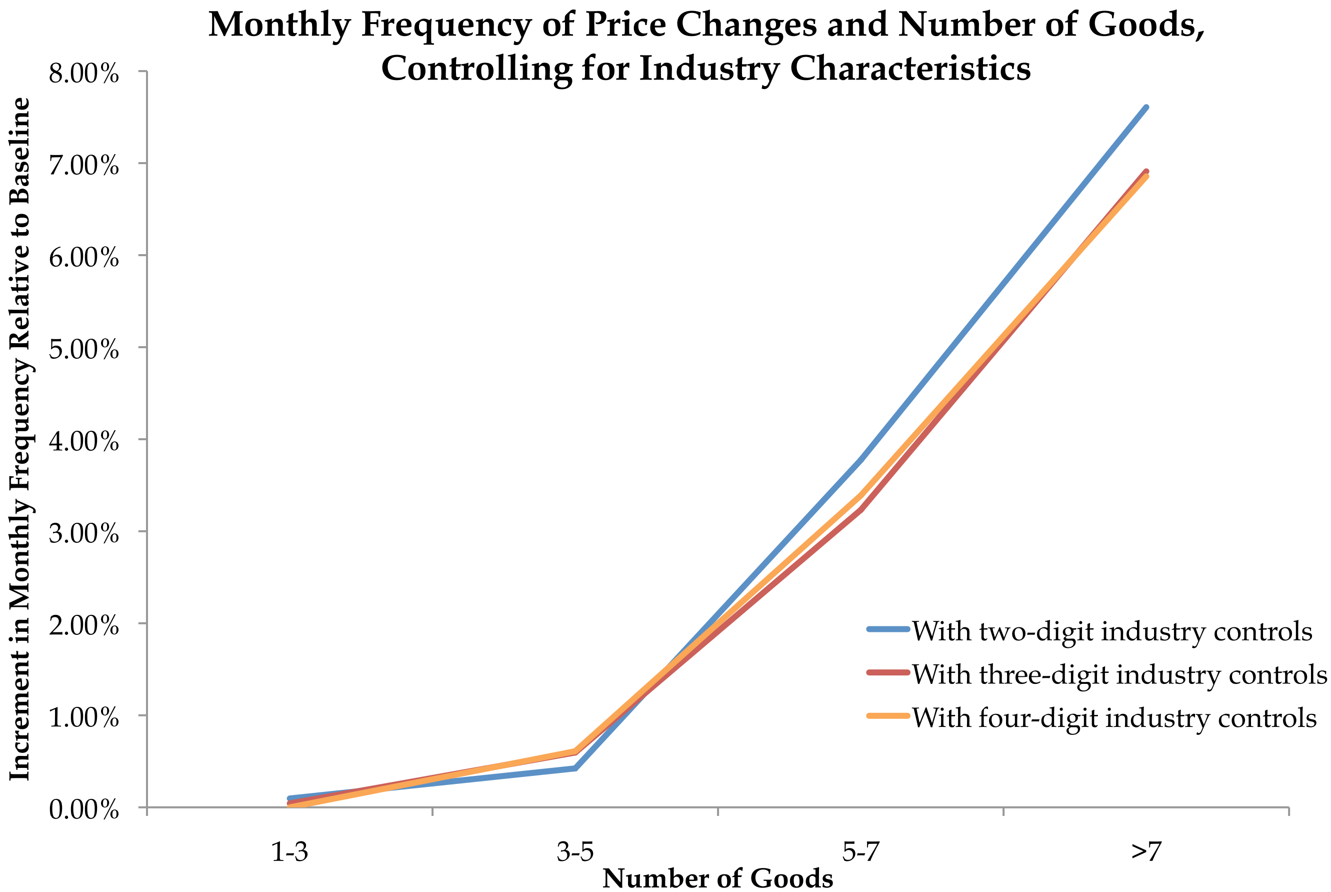


Figure 17: Increments in Mean Frequency of Price Changes Controlling for Sector Fixed Effects, Relative to Baseline

To obtain the frequency values shown, we estimate the following specification: $f_i = \sum_k \beta_k D_{k,i} + \sum_j beta_j IND_j + \epsilon_i$ where f_i is the median frequency of price changes for a firm i, IND a dummy variable for an industry defined at the 2-, 3-, or 4-digit level. We then graph $\beta_k - min(\{\beta_1\})$.

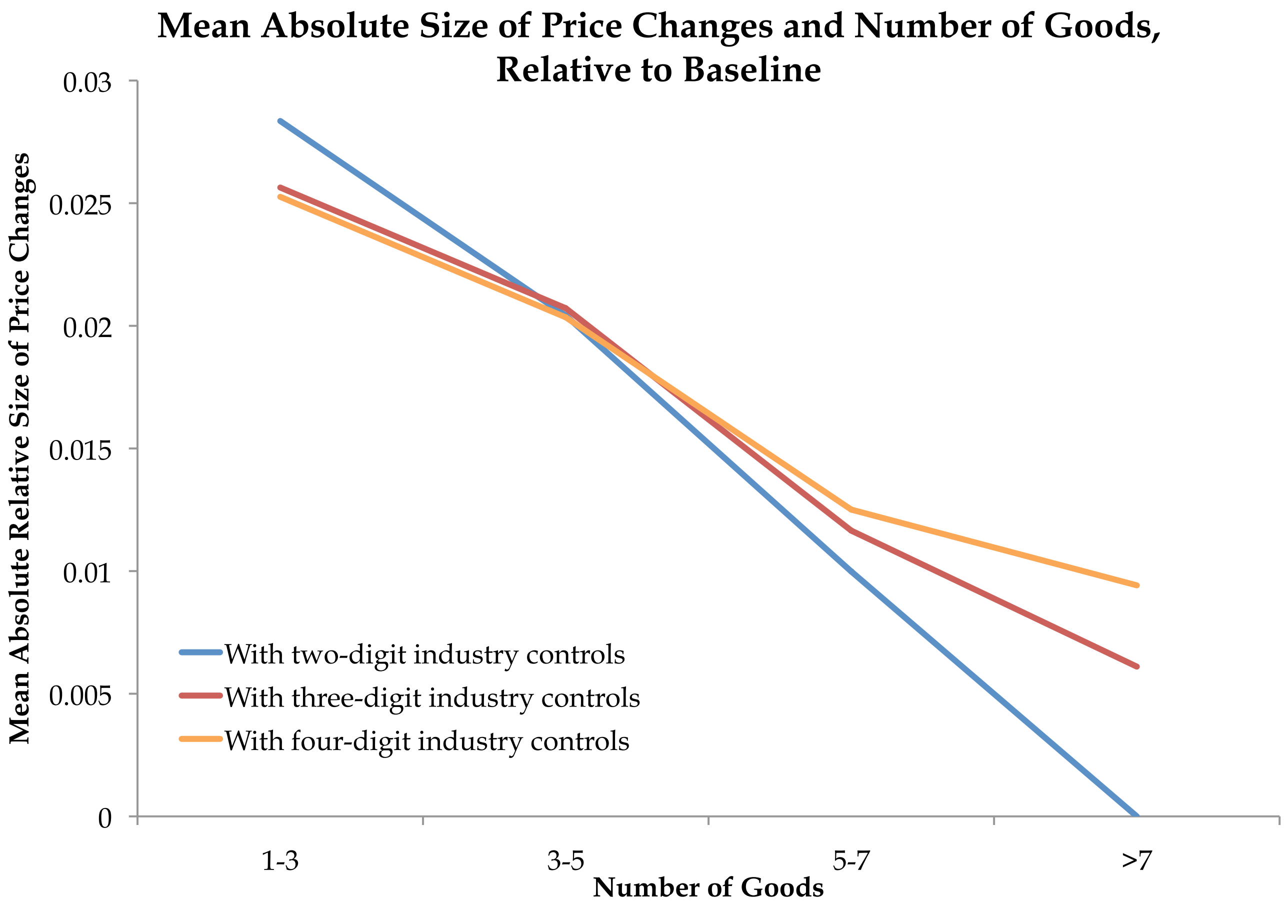


Figure 18: Increments in Mean Absolute Size of Price Changes Controlling for Sector Fixed Effects, Relative to Baseline

To obtain the frequency values shown, we estimate the following specification: $|\Delta p_i| = \sum_k \beta_k D_{k,i} + \sum_j beta_j IND_j + \epsilon_i$ where $|\Delta p_i|$ is the median absolute size of price changes for a firm i, IND a dummy variable for an industry defined at the 2-, 3-, or 4-digit level. We then graph $\beta_k - min(\{\beta_4\})$.

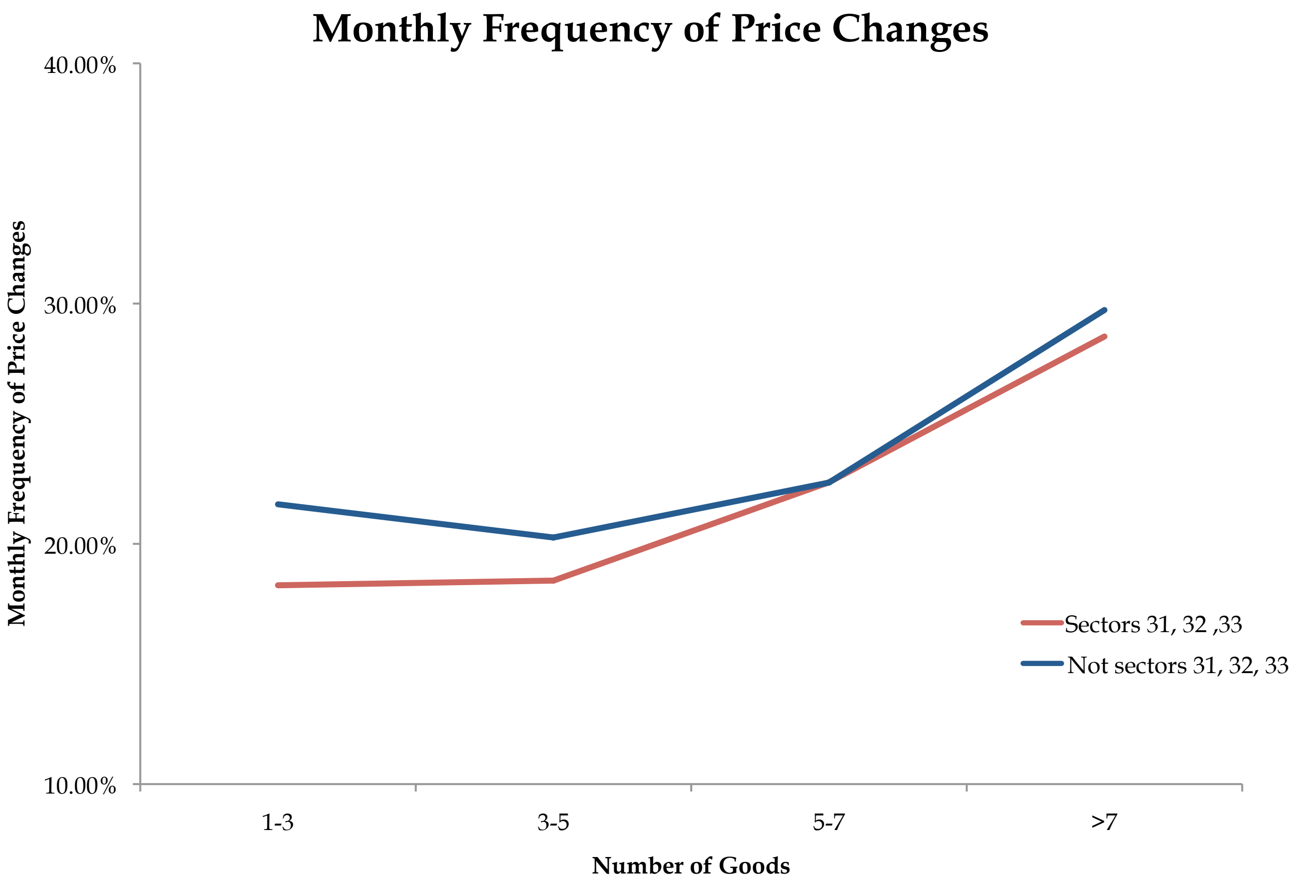


Figure 19: Mean Frequency of Price Changes and Sectoral Decomposition

We compute the frequency of price changes in exactly the same way as for Figure 1 but with one change: in the last step of aggregating firm frequencies, we take means for bin-sector group combinations as shown. The two relevant sector groupings are the two-digit NAICS manufacturing sectors, and all others.

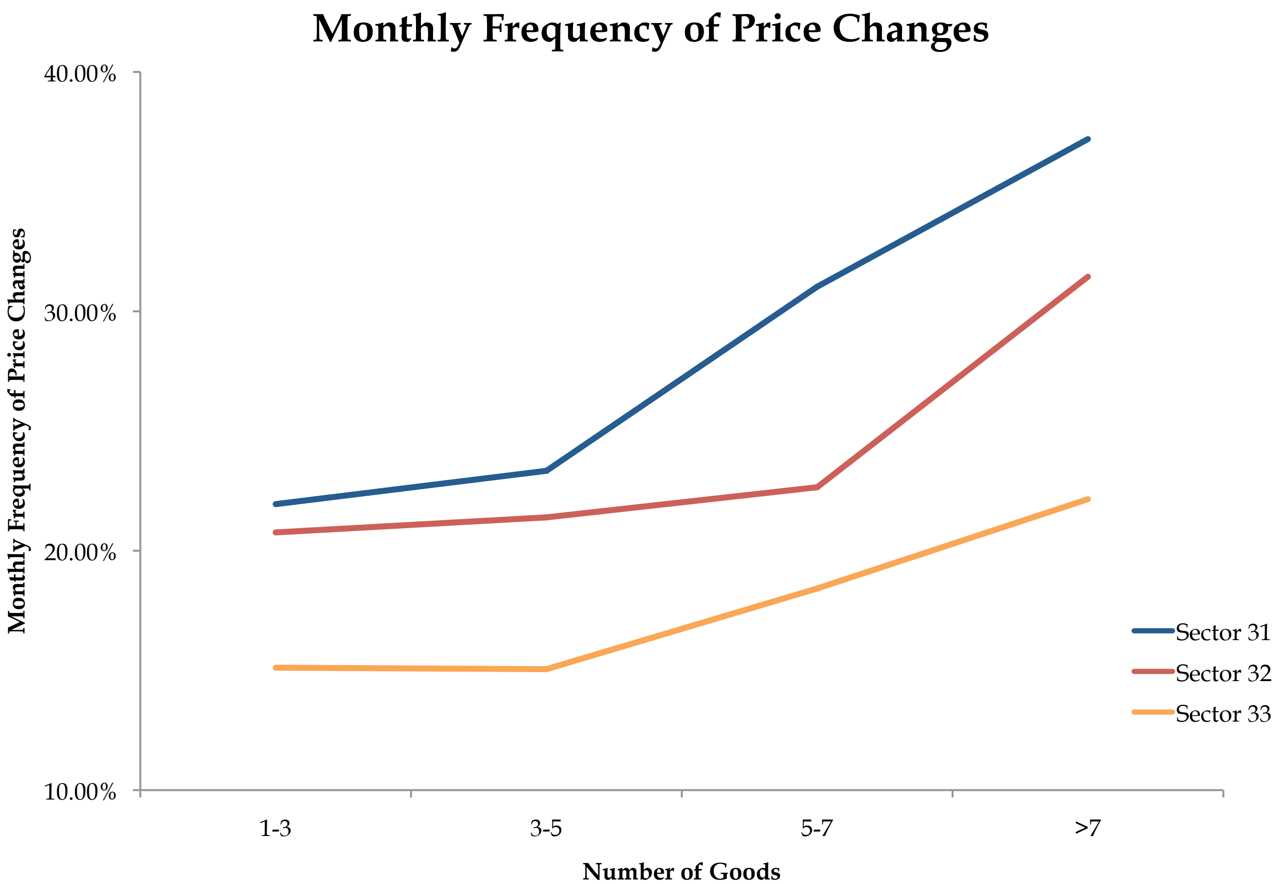


Figure 20: Mean Frequency of Price Changes and Manufacturing Sectors 31, 32, 33

We compute the frequency of price changes in exactly the same way as for Figure 1 but with one change: in the last step of aggregating firm frequencies, we take means for bin-sector combinations as shown. The relevant sectors are the two-digit NAICS manufacturing sectors 31, 32 and 33.

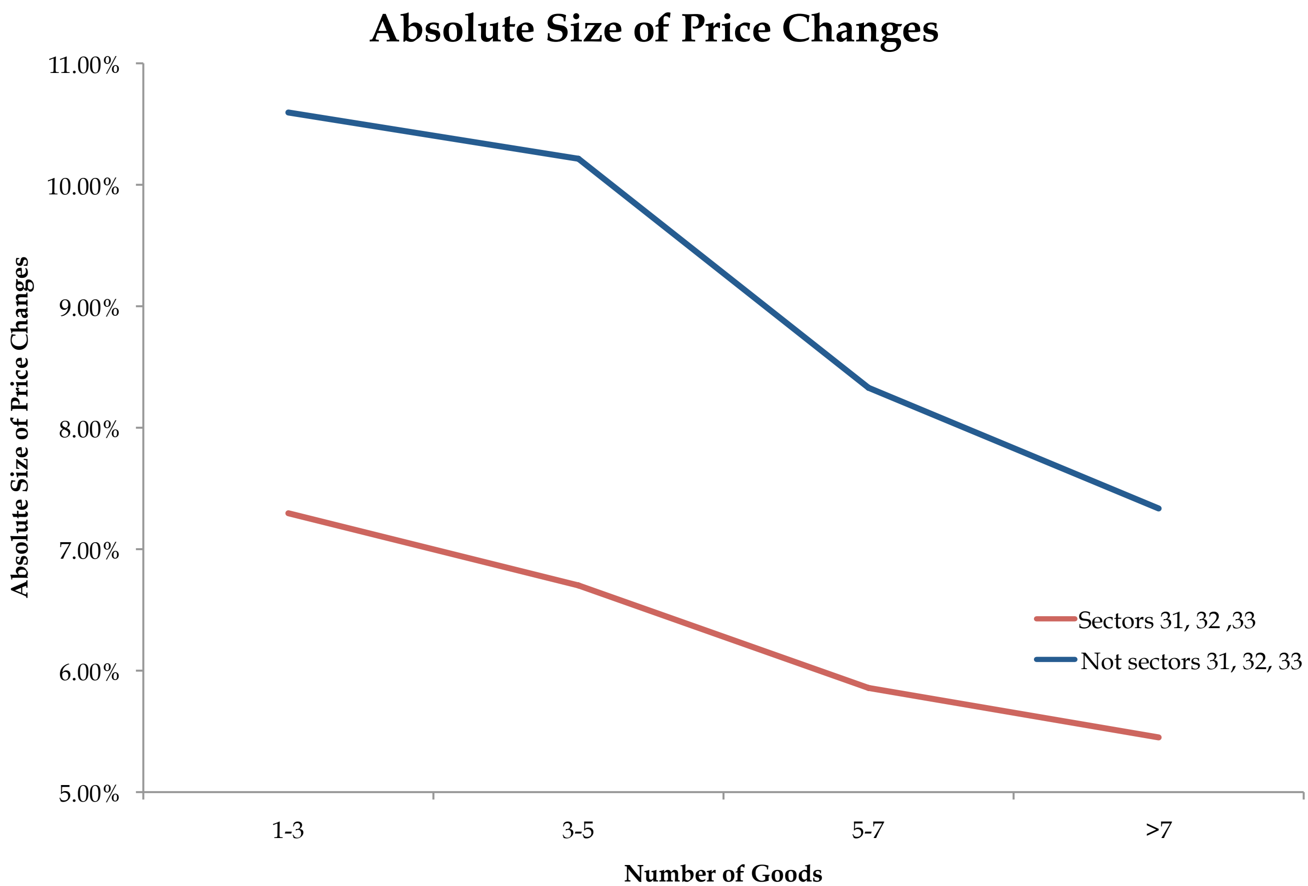


Figure 21: Mean Absolute Size of Price Changes and Manufacturing Sectors 31, 32, 33

We compute the absolute size of price changes in exactly the same way as for Figure 4 but with one change: in the last step of aggregating firm size of price change measures, we take means for bin-sector group combinations as shown. The two relevant sector groupings are the two-digit NAICS manufacturing sectors, and all others.

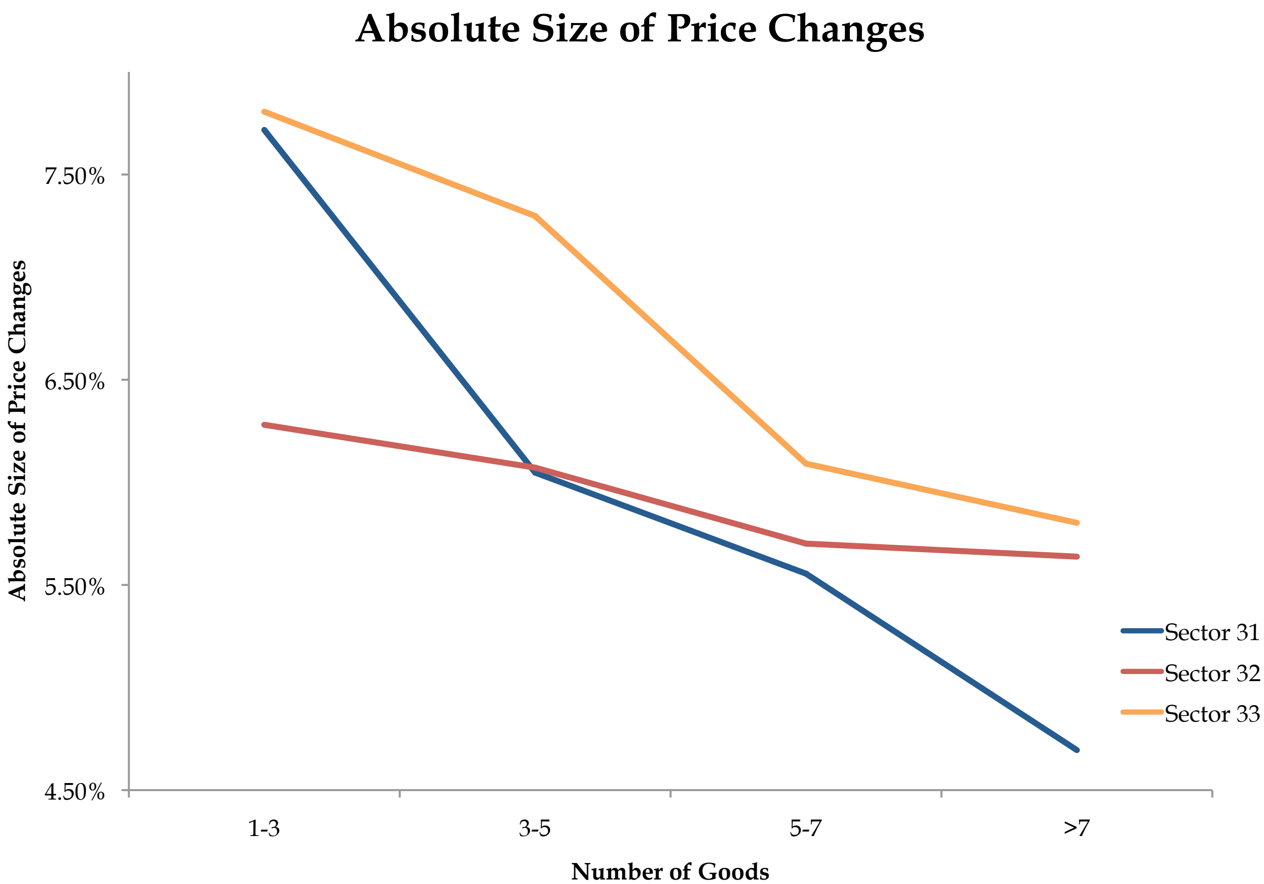


Figure 22: Mean Absolute Size of Price Changes and Manufacturing Sectors 31, 32, 33

We compute the absolute size of price changes in exactly the same way as for Figure 4 but with one change: in the last step of aggregating firm size of price change measures, we take means for bin-sector combinations as shown. The relevant sectors are the two-digit NAICS manufacturing sectors 31, 32 and 33.

APPENDIX 2

Here we describe in detail the computational algorithm used to solve the recursive problem of the firm. We also present robustness results discussed in the model section.

The state variables of the problem are last period's real prices, $\frac{p_{i,t-1}}{P_t}$, and the current productivity shocks, that is, $\mathbf{p}_{-1}=\left(\frac{p_{1,t-1}}{P_t}, \frac{p_{2,t-1}}{P_t}, ..., \frac{p_{n,t-1}}{P_t}\right)$ and $\mathbf{A}=(A_{1,t}, A_{2,t}, ..., A_{n,t})$. The value functions are given by:

$$V^a(\mathbf{A}) = \max_{\mathbf{p}} \left[\pi(\mathbf{p};\mathbf{A}) - K + \beta \int\int V\left(\mathbf{p}_{-1}^{'}, \mathbf{A}^{'}\right) dF\left(\epsilon_A^1, \epsilon_A^2, ..., \epsilon_A^n\right) dF(\epsilon_P)\right] \tag{A-1}$$

$$V^n(\mathbf{p}_{-1}, \mathbf{A}) = \pi(\mathbf{p}_{-1};\mathbf{A}) + \beta \int\int V\left(\mathbf{p}_{-1}^{'}, \mathbf{A}^{'}\right) dF\left(\epsilon_A^1, \epsilon_A^2, ..., \epsilon_A^n\right) dF(\epsilon_P) \tag{A-2}$$

where $V^a(\mathbf{A})$ is the firm's value of adjusting all prices, $V^n(\mathbf{p}_{-1}, \mathbf{A})$ is the firm's value of not adjusting prices, $'$ denotes the subsequent period, and

$$V = \max\ (V^a, V^n).$$

Our numerical strategy to solve for the value functions consists of two major steps. First, as described in Miranda and Fackler (2002), we approximate the value functions by projecting them onto a polynomial space. Second, we compute the coefficients of the polynomials that are a solution to the non-linear system of equations given by the value functions.

In particular, we approximate each value function, $V^a(\mathbf{A})$ and $V^n(\mathbf{p}_{-1}, \mathbf{A})$), by a set of higher order Chebychev polynomials and require (A-1) and (A-2) to hold exactly at a set of points given by the tensor product of a fixed set of collocation nodes of the state variables. This implies the following system of non-linear equations, the so-called collocation equations:

$$\Phi^a c^a = v^a(c^a) \tag{A-3}$$

$$\Phi^{na} c^{na} = v^{na}(c^{na}) \tag{A-4}$$

where c^a and c^{na} are basis function coefficients in the adjustment and non-adjustment cases and Φ^a and Φ^{na} are the collocation matrices. These matrices are given by the value of the basis functions evaluated at the set of nodes. The right-hand side contains the collocation functions evaluated at the set of the collocation nodes. Note that this is the same as the value of the right-hand side of the value functions evaluated at the collocation nodes, but where the value functions are replaced by their approximations.

We use the same number of collocation nodes as the order of the polynomial approximation. Therefore, we choose between 7-11 nodes for the productivity state variable and 15-20 nodes for the real prices. Moreover, we pick the approximation range to be $\pm$ 2.5 times the standard deviation from the mean of the underlying processes. We use Gaussian quadrature to calculate the expectations on the right-hand side, with 11-15 points for the real price transitions due to inflation while calculating the expectations due to productivity shocks exactly. For the adjustment case, we use a Nelder-Mead simplex method to find the maximum with an accuracy of the maximizer of 10^{-10}.

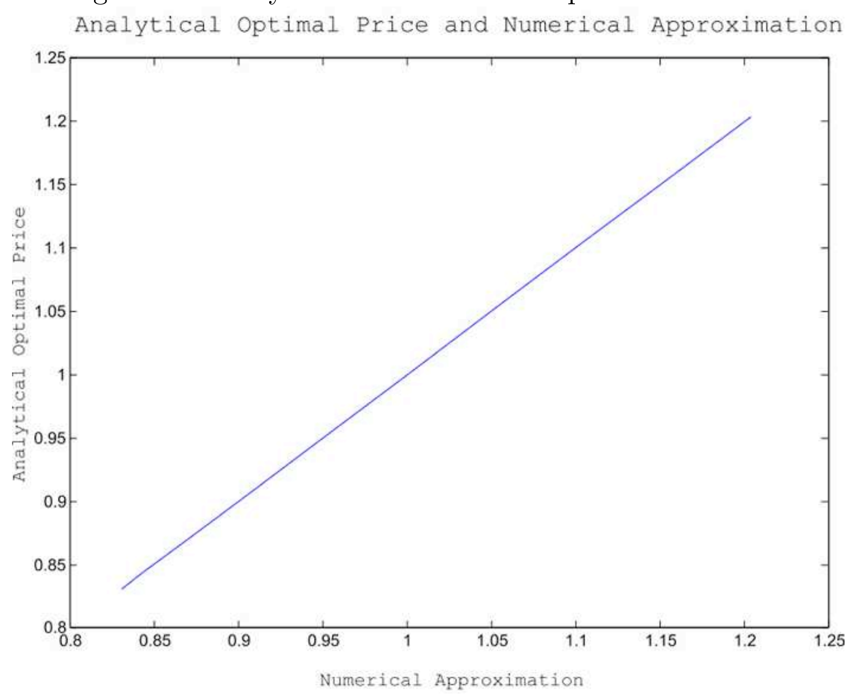
Next, we solve for the unknown basis function coefficients c^a and c^{na}. We express the collocation equations as two fixed-point problems:

$$c^a = \Phi^{a-1} v^a(c^a) \quad \text{(A-5)}$$
$$c^{na} = \Phi^{na-1} v^{na}(c^{na}) \quad \text{(A-6)}$$

and iteratively update the coefficients until the collocation equations are satisfied exactly.

Our solution method is standard in the relevant literature for example as in Midrigan (2010). We still conduct two sensitivity analyses. First, given that zero menu costs imply flex-pricing, we verify that the approximate solution is "good" given the known analytical solution. Figure 23 shows that optimal price policies and the price policies obtained by the approximation line up a 45-degree line in this case where we know the exact solution. The norm of the error is of order 10^{-9} and errors are equi-oscillatory, as is a usual property of approximations based on Chebychev polynomials. Second, we conduct standard stochastic simulations and find that the errors between the left- and right-hand sides of (A-1) and (A-2) at points other than the collocation nodes are on average of the order of 10^{-5} or less.

Figure 23: Analytical and Numerical Optimal Flex Price



We compute the numerical solution for optimal adjustment prices given productivity shocks and zero menu costs. We compare to the analytical solution known in the flex price case. Errors are of the order of 10^{-9}.

Table 21: Results of Simulation: Substitution

	1 Good	2 Goods	3 Goods
Frequency of price changes	15.22%	21.72%	30.75%
Absolute size of price changes	5.21%	4.31%	3.58%
Size of positive price changes	5.34%	4.45%	3.61%
Size of negative price changes	-5.02%	-4.11%	-3.53%
Fraction of positive price changes	61.68%	59.55%	59.20%
Fraction of small price changes	1.33%	2.86%	1.92%
Kurtosis	1.38	1.53	1.45
First Percentile	-6.84%	-6.19%	-5.58%
99th Percentile	7.09%	6.46%	5.64%
Synchronization measures:			
Fraction, Upwards Adjustments	-	0.48	10.39
Fraction, Downwards Adjustments	-	-0.62	10.06
Correlation coefficient	-	0	0
Menu Cost	0.35%	0.7%	1.05%
Elasticity of substitution	4	6	9

We perform stochastic simulation of our model in the 1-good, 2-good and 3-good cases and record price adjustment decisions in each case. Then, we calculate statistics for each case as described in the text. In the 2-good and the 3-good cases, we report the mean of the good-specific statistics. As we increase the number of goods, we increase the elasticity of substitution θ. We obtain the synchronization measure from a multinomial logit regression analogous to the empirical multinomial logit regression. We control for inflation. Menu costs are given as a percentage of steady state revenues.

Table 22: Results of Simulation: Correlation

	1 Good	2 Goods	3 Goods
Frequency of price changes	15.22%	17.09%	14.25%
Absolute size of price changes	5.21%	4.52%	4.75%
Size of positive price changes	5.34%	4.61%	4.91%
Size of negative price changes	-5.02%	-4.36%	-4.49%
Fraction of positive price changes	61.68%	62.35%	63.72%
Fraction of small price changes	1.33%	16.77%	18.69%
Kurtosis	1.38	1.77	2.05
First Percentile	-6.84%	-7.83%	-9.38%
99th Percentile	7.09%	8.28%	9.89%
Synchronization measures:			
Fraction, Upwards Adjustments	-	31.06	38.73
Fraction, Downwards Adjustments	-	30.41	37.88
Correlation coefficient	-	0.6	0.6
Menu Cost	0.35%	0.70%	1.05%

We perform stochastic simulation of our model in the 1-good, 2-good and 3-good cases and record price adjustment decisions in each case, allowing for correlation of the productivity shocks $A_{i,t}$ in the multi-good cases. Then, we calculate statistics for each case as described in the text. In the 2-good and the 3-good cases, we report the mean of the good-specific statistics. We obtain the synchronization measure from a multinomial logit regression analogous to the empirical multinomial logit regression. We control for inflation. Menu costs are given as a percentage of steady state revenues.

Table 23: Benchmark Case

	2 Goods MP Firm	2 Firms	3 Goods MP Firm	3 Firms
Frequency of price changes	18.05%	15.30%	19.72%	15.30%
Size of absolute price changes	4.29%	5.24%	3.96%	5.23%
Size of positive price changes	4.46%	5.35%	4.23%	5.35%
Size of negative price changes	-4.04%	-5.08%	-3.57%	-5.08%
Fraction of positive price changes	61.28%	62.14%	59.38%	62.14%
Fraction of small price changes	20.97%	3.01%	23.59%	3.01%
Kurtosis	1.76	1.55	1.97	1.52
1st Percentile	-7.60%	-7.47%	-8.06%	-7.47%
99th Percentile	8.07%	8.02%	8.63%	8.02%
Synchronization measures:				
Fraction, Upwards Adjustments	30.25	0.33	38.11	14.46
Fraction, Downwards Adjustments	29.39	-0.63	37.19	13.87
Correlation coefficient	0	0	0	0
Menu cost	0.65%	0.35%	0.75%	0.35%

We perform stochastic simulation of our model for the 2-good and 3-good multi-product firms as in Table 8. Results from these simulations are summarized under the columns "MP Firms." In addition, we simulate two, and respectively three 1-good firms subject to common inflationary shocks but completely independent productivity draws. We record price adjustment decisions and calculate statistics for each case as described in the text. In the 2-good and the 3-good cases, we report the mean of the good-specific statistics. We obtain the synchronization measure from a multinomial logit regression analogous to the empirical multinomial logit regression. We control for inflation. Menu costs are given as a percentage of steady state revenues.

Table 24: Results of Simulation: Menu of Menu Costs

	1 Good	2 Goods	
Frequency of price changes	15.22%	18.05%	26.98%
Size of absolute price changes	5.21%	4.29%	3.16%
Size of positive price changes	5.34%	4.46%	3.56%
Size of negative price changes	-5.02%	-4.04%	-2.67%
Fraction of positive price changes	61.68%	61.28%	55.34%
Fraction of small price changes	1.33%	20.97%	24.95%
Kurtosis	1.38	1.76	3.95
1st Percentile	-6.84%	-7.60%	-7.87%
99th Percentile	7.09%	8.07%	11.41%
Synchronization measures:			
Fraction, Upwards Adjustments	-	30.25	-0.20
Fraction, Downwards Adjustments	-	29.39	-0.48
Menu costs (K_1, K_2, K_{12})	(-,-,0.35)%	(-,-,0.65)%	(0.35,0.35,0.65)%
Correlation coefficient	-	0	0

We perform stochastic simulation of our model in the 1-good, and 2-good cases, allowing 2-good firms to adjust 0, 1, or 2 goods simultaneously. The cost of adjusting one good only is K_1 or K_2, and joint adjustment costs K_{12}. We record price adjustment decisions and calculate statistics for each case as described in the text. In the 2-good case, we report the mean of the good-specific statistics. We obtain the synchronization measure from a multinomial logit regression analogous to the empirical multinomial logit regression. We control for inflation. Menu costs are given as a percentage of steady state revenues.

Table 25: Results of Simulation: Demand Interactions

	1 Good	2 Goods	3 Goods	2 Goods	3 Goods
		$\gamma = -0.1$		$\gamma = 0.1$	
Frequency of price changes	15.22%	18.76%	19.36%	21.66%	20.76%
Size of absolute price changes	5.21%	4.143%	4.142%	3.90%	3.71%
Size of positive price changes	5.34%	4.34%	4.41%	4.20%	3.93%
Size of negative price changes	-5.02%	-3.85%	-3.77%	-3.50%	-3.39%
Fraction of positive price changes	61.68%	61.27%	59.14%	58.15%	59.92%
Fraction of small price changes	0.98%	22.05%	24.56%	21.81%	23.61%
Kurtosis	1.38	1.88	2.01	2.03	2.02
1st Percentile	-6.84%	-7.88%	-8.61%	-7.84%	-7.77%
99th Percentile	7.09%	8.35%	9.10%	8.53%	8.11%
Synchronization measures:					
Fraction, Upwards Adjustments	-	30.28	38.13	30.04	38.02
Fraction, Downwards Adjustments	-	29.45	37.13	29.38	36.98
Correlation coefficient	-	0	0	0	0
Menu Cost	0.35%	0.65%	0.75%	0.65%	0.75%

We perform stochastic simulation of our model in the 1-good, 2-good and 3-good cases, allowing for interactions in demand through a profit function $\pi_t = \sum_i^{n=n_k} \left(\frac{p_{i,t}}{P_t} - \frac{\bar{w}}{A_{i,t}}\right)\left(\frac{p_{i,t}}{P_t}\right)^{-\theta}\left(\frac{p_{-i,t}}{P_t}\right)^{-\gamma}$ and record price adjustment decisions in each case. Then, we calculate statistics for each case as described in the text. In the 2-good and the 3-good cases, we report the mean of the good-specific statistics. We obtain the synchronization measure from a multinomial logit regression analogous to the empirical multinomial logit regression. We control for inflation. Menu costs are given as a percentage of steady state revenues.

Table 26: Results of Simulation: Demand Shocks

	1 Good	2 Goods	3 Goods
Frequency of price changes	15.22%	5.14%	5.52%
Size of absolute price changes	5.21%	4.09%	3.94%
Size of positive price changes	5.34%	4.09%	3.94%
Size of negative price changes	-5.02%	0%	0%
Fraction of positive price changes	61.68%	100.00%	100.00%
Fraction of small price changes	1.33%	0.00%	0.00%
Kurtosis	1.38	3.71	3.90
1st Percentile	-6.84%	3.73%	3.49%
99th Percentile	7.09%	4.75%	4.71%
Correlation coefficient	-	0	0
Menu costs	0.35%	0.65%	0.75%

We perform stochastic simulation of our model in the 1-good, 2-good and 3-good cases, allowing for demand shocks $Z_{i,t}$ instead of productivity shocks. This implies a period profit function $\pi_t = \sum_i^{n=3} \left(\frac{p_{i,t}}{P_t} - \bar{w} \right) Z_{i,t} \left(\frac{p_{i,t}}{P_t} \right)^{-\theta}$. We record price adjustment decisions and calculate statistics for each case as described in the text. In the 2-good and the 3-good cases, we report the mean of the good-specific statistics. We obtain the synchronization measure from a multinomial logit regression analogous to the empirical multinomial logit regression. We control for inflation. Menu costs are given as a percentage of steady state revenues.

APPENDIX 3

In this appendix, we describe in further detail the sampling procedure of the BLS which implies a monotonic relationship between the actual and sampled number of goods produced by multi-product firms. First, we document that firms with more goods have larger total sales. More goods will therefore be sampled in total from large firms. Second, we show that sales shift to goods with lower sales rank in firms with more goods. Therefore, standard survey design implies that not only more, but different goods will be sampled from larger firms. Finally, we also summarize the fraction of joint price changes in firms.

Sales Values

First, we document that firms with more goods have larger total sales in the data. Because total sales value determines the sampling probabilities of firms in the sampling selection procedure,[31] this implies that on average more goods will therefore be sampled from large firms.

We compute our measure of total sales value for each n-good-type firm in the following way. First, we compute the total dollar-value sales in a given month, year, and firm by aggregating up the item dollar-value of sales from the last time the item was re-sampled. Second, we count the number of goods for each firm in a given month and year. Third, we compute the unweighted and weighted median total sales value across all firms for a given n-good type of firm and month and year. Fourth, we calculate the mean and median sales value for an n-good type of firm

We find that firms with more goods have larger total sales: there is a strong empirical, monotonic relationship between the number of goods and the natural logarithm of the total sales. Figure 24 summarizes this relationship. Because total sales value determines the sampling probabilities of firms in the BLS sampling selection procedure, on average a higher number of goods will be collected from large firms.

Within-Firm Sales Shares

Second, we show that sales shift to goods with lower sales rank in firms with more goods. Therefore, standard survey design such as sampling proportional to size implies that not only more, but different goods will likely be sampled from larger firms.

We compute within-firm sales shares and sales ranks in the following way. First, we compute the total dollar-value sales for a given month, year, and firm by aggregating up the dollar-value of sales of the good from the last time the item was re-sampled. Second, we calculate the good-specific sales shares for each firm in a given month and year. Third, we rank the goods in each firm according to these sales shares. Fourth, we count the number of goods for each firm in a given month and year. Fifth, we compute the mean sales shares for an r-ranked good in an n-good firm in a given month and year, across all firms. Sixth, we compute the sales-weighted mean for an r-ranked good in an n-good firm over time. These calculations give us the sales share representative of an r-ranked good in a firm with n goods.[32]

We find that sales shift to goods with lower sales rank in firms with more goods. For example, the representative sales share of the best-selling good in a two-good firm is 63% while it is 45% for the second good. For a three-good firm, the sales shares are 45%, 35%, and 30%. Table 27

[31] Employment is another measure of firm size. The exact same results hold for employment: firms with more goods have a larger number of employees.

[32] Note that these shares do not have to sum up to 100% in an n-good firm by way of computation.

summarizes sales shares by the number of goods and rank of the goods. The table covers firms with up to 11 goods which account for more than 98% of all prices in the data. Under standard survey designs such as sampling proportional to size and a fixed survey budget not only more, but different goods are more likely to be sampled when firms produce more goods.

Figure 24: Log Mean Firm Sales Value by Number of Goods

Table 27: Mean Sales Shares of r-Ranked Goods for n-Good Firms, Sales-Weighted

#Goods /#Rank	1	2	3	4	5	6	7	8	9	10	11
1	100.000%	62.861%	45.110%	35.916%	37.090%	28.301%	25.517%	19.084%	25.532%	14.393%	16.642%
	(0.000)%	(0.131)%	(0.075)%	(0.086)%	(0.413)%	(0.097)%	(0.337)%	(0.381)%	(0.480)%	(0.344)%	(0.427)
2		44.952%	34.453%	27.594%	22.966%	19.963%	18.396%	15.209%	15.749%	12.297%	10.748%
		(0.081%)	(0.051%)	(0.034%)	(0.035%)	(0.049%)	(0.170%)	(0.091%)	(0.260%)	(0.089%)	(0.106%)
3			29.499%	24.051%	19.703%	17.428%	15.896%	14.223%	13.160%	11.316%	10.514%
			(0.028%)	(0.030%)	(0.023%)	(0.031%)	(0.032%)	(0.069%)	(0.134%)	(0.073%)	(0.105%)
4				22.360%	18.251%	16.162%	14.357%	13.318%	11.375%	10.615%	9.835%
				(0.030%)	(0.039%)	(0.013%)	(0.034%)	(0.050%)	(0.049%)	(0.038%)	(0.057%)
5					17.579%	15.197%	13.577%	12.707%	10.600%	10.212%	9.393%
					(0.044%)	(0.007%)	(0.028%)	(0.052%)	(0.066%)	(0.028%)	(0.032%)
6						14.748%	12.629%	11.771%	10.185%	9.824%	9.051%
						(0.011%)	(0.038%)	(0.016%)	(0.070%)	(0.032%)	(0.017%)
7							12.356%	11.417%	10.072%	9.578%	8.924%
							(1.261%)	(1.165%)	(1.028%)	(0.978%)	(0.911)
8								11.302%	9.679%	9.357%	8.731%
								(1.153%)	(0.988%)	(0.955%)	(0.891%)
9									9.943%	9.257%	8.562
									(1.015%)	(0.945%)	(0.874%)
10										9.222%	8.456%
										(0.027%)	(0.064%)
11											8.528%
											(0.057%)

Based on the PPI data, we first compute the total dollar-value sales for a given month, year, and rm by aggregating up the dollar-value of sales of each good. Second, we calculate the good-specic sales shares for each rm in a given month and year. Third, we rank goods in each rm according to the sales shares. Fourth, we count the number of goods for each rm in a given month and year. Fifth, we compute mean sales shares for an r-ranked good in an n-good rm in a given month and year, across all rms. Sixth, we compute the sales-weighted mean for an r-ranked good in an n-good rm over time.