The Role of Industrial Composition in Driving the Frequency of Price Change [*]

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Abstract

By combining product-level microdata on the frequency of price change with data on US industry shares from 1947 through 2019, we document that shifts in industrial composition, particularly from primary and secondary towards service industries, led to a gradual reduction in the median monthly frequency of price change from 9.2% to 6.9% over this period. Other percentiles show similar reductions. In a calibrated multisector general equilibrium menu cost model, we find that this effect flattened the Phillips curve by 30.7% from 1947 to 2019.

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1 Introduction

One of the most crucial parameters in monetary economics is the frequency of price change. The frequency of price change determines the extent of nominal versus real adjustments in the economy in response to nominal demand shocks. If the frequency of price change is high, so that prices are perfectly flexible in the limit, nominal shocks impact only prices while leaving the real economy undisturbed, which implies that there is monetary neutrality. If the frequency of price change is low, then nominal shocks have real effects—because prices cannot adjust quickly enough, restoring equilibrium in the economy requires real changes. Thus, with a lower frequency of price change, the economy demonstrates greater monetary non-neutrality. This also implies that the stabilization trade-off of monetary policy depends crucially on the frequency of price change. When the frequency of price change is low, the sacrifice ratio is high; that is, achieving a given reduction in inflation requires a larger increase in unemployment.

The frequency of price change is a key determinant of the slope of the Phillips curve. The Phillips curve refers to the inverse relationship between inflation and the unemployment rate. Intuitively, as unemployment falls, labor markets become more competitive, so wages and prices tend to rise. In the United States, the slope of the Phillips curve has evolved through the years. The negative relationship was most clearly observed in the post–World War II period. However, it appeared to break down in the 1970s when the economy experienced stagflation. For the next two decades, inflation remained low and stable, about 2 percent to 4 percent . However, the relationship appeared weaker again during the Great Recession, when the unemployment rate rose to 10 percent but inflation fell only slightly (missing deflation). Then during the recovery from the Great Recession, the unemployment rate fell to historically low levels while inflation remained low—even below the Federal Reserve's 2 percent target for most of that period (missing inflation). The relationship seemed similarly weak during the COVID-19 pandemic, when the unemployment rate spiked to 14 percent while inflation fell only slightly.

One factor that could explain the flattening of the Phillips curve is the reduction in the frequency of price change. Since the flattening appears to have occurred over a long period of time, a natural candidate to explain it is similarly long-term structural changes in the US economy, namely the shifts in its industrial composition. Specifically, the flattening of the Phillips curve has coincided with a shift in the focus of the economy from primary and secondary industries (industries that extract raw materials and those that process them, respectively) toward tertiary industries (industries that provide services). The products associated with the primary and secondary industries typically have higher frequencies of price change relative to products in the tertiary industries. Therefore, it is reasonable to expect that as the share of the economy comprising tertiary industries has increased over time, there has been a concurrent downward shift in the distribution of the frequency of price change and that this shift has flattened the Phillips curve.

In this paper, we assess the degree to which changes in industrial composition in the United States have affected the distribution of the frequency of price change and therefore altered the slope of the Phillips curve and the associated inflation dynamics. We make three contributions to the literature. First, we demonstrate that the changes in industrial composition have led to large declines across the distribution of the frequency of price change over the 1947–2019 period, with the median monthly frequency falling from 9.2 percent in 1947 to 6.9 percent in 2019. Second, we demonstrate that these declines across the distribution of the frequency of price change were driven by the shift from primary and secondary industries to tertiary industries. Third, we demonstrate through a multisector menu cost model that these changes have led to a 30.7 percent flattening of the slope of the Phillips Curve. With a flatter Phillips curve, inflation is less responsive to real changes in the economy, which helps to explain why there was missing deflation during the recent recessions and missing inflation during the recoveries.

We compute the impact of shifts in the industrial composition of the US economy on the distribution of the frequency of price change for every year from 1947 through 2019. In any given year, the distribution of the frequency of price change is a function of the frequencies of the price change of the products and the relative shares of the products in the economy. We obtain static data on the frequency of price change of different Consumer Price Index (CPI) and Producer Price Index (PPI) products from Nakamura and Steinsson (2008). To compute the relative shares of the products in the economy, we follow a few steps. We first obtain annual data on industrial composition from the U.S. Bureau of Economic Analysis (BEA) and the World KLEMS Initiative. We then construct a mapping between products and industries. Finally, we compute the share of the economy assigned to a given product based on an algorithm that uses the share of the corresponding industry in the economy and the expenditure weight of the product in the relevant price index. In this way we obtain the economy's annual product composition based on its annual industrial composition data. Our data allow us to map economic shares for 51 industries to 613 products for the 1947–2019 period. To measure the impact of changes in industrial composition on the distribution of the frequency of price change, we then vary only the product shares (as implied by industrial composition changes) while holding fixed the frequency of price change at the product level.[1]

Our first contribution is to demonstrate that changes in industrial composition have led to a broad decline in the distribution of the frequency of price change. This decline has occurred gradually, which is in line with the gradual shifts in industrial composition over the period we consider. We find a decline in the monthly frequency of price change from 4.9, 9.2, 26.9, and 87.6 percent to 4.0, 6.9, 12.4, and 41.7 percent at the 25th, 50th, 75th, and 90th percentiles of the distribution, respectively. The exception is at the 10th percentile of the frequency of price change distribution, where we find no change. Our empirical results on changes in the distribution of the frequency of price change are robust to other specifications including to alternative mappings between industries and products in our algorithm, to dropping products that constitute a relatively large share of the distribution, to measuring the distribution with only CPI or only PPI products, to using alternative measures of industrial composition based on gross output, employment costs, and the degree to which industries are intermediate inputs, and to computing relative shares of products based on their consumption shares (that helps to account for the increasing role of international trade). Using our algorithm, we also find that changes in industrial composition have caused the distribution of the probability of positive price changes to shift up but have had no systematic impact on the distribution of the absolute size of price changes.[2]

Our second contribution is to examine which shifts in industrial composition have led to a decline in the distribution of the frequency of price change. The share of health, education, legal, technical, and financial services grew in the economy and many products in these industries have a low frequency of price change. Moreover, the five industries that grew the most are associated with services and have a low frequency of price change.[3] At the same time, three of the five industries that declined the most are primary or secondary industries and the other two relate to the sale or transport of these goods, and these industries have a high frequency of price change. This result fits with the findings of two existing literatures. One strand of literature has shown the growth of service industries (see (Kongsamut, Rebelo, and Xie, 2001), (Duarte and Restuccia, 2010), and (Herrendorf, Rogerson, and Valentinyi, 2014)) while another strand has documented that services have a relatively low frequency

[1] We implicitly assume that changes in industrial composition change only the relative shares of the products in the economy, while leaving the frequencies of price change of the products unchanged.

[2] In fact, we can use our algorithm to produce annual distributions for any statistic that is available at the level of the products that are included in our mapping. Our results imply that the changes in industrial composition cause products to exhibit price changes less frequently because the firms that comprise a larger share of the economy make fewer negative price changes rather than changing their prices by more when they do make a price change.

[3] The industries that grew the most include miscellaneous professional services and hospitals. The industries the declined the most include farms and the retail trade.

of price change ((Nakamura and Steinsson, 2008) and (Stock and Watson, 2020)). However, this is not the whole story. A countervailing force is that there has been a large decline in durable manufacturing which has a low frequency of price change (a median of 5.7 percent per monthyear). Furthermore, some services such as accommodation have a high frequency of price change and have demonstrated a large share increase.there have been declines in Therefore, our analysis remains necessary to verify the direction and quantify the impact of shifts in industrial composition on the distribution of the frequency of price change.

We then analyze the implications of shifts in the industrial composition and the consequent decline of the distribution of the frequency of price change for the slope of the Phillips curve by building a calibrated multisector menu cost model.[4] The model is a version of Nakamura and Steinsson (2010). It is a general-equilibrium model with a simple representative household, firms in multiple industries that set prices subject to industry-specific menu costs, and a simple monetary authority that targets nominal aggregate demand. The model includes idiosyncratic shocks to the firms' productivity that allow us to match the empirical price-setting decisions of firms in different industries as well as aggregate demand shocks that allow us to study the behavior of the Phillips curve over time. Given the presence of both aggregate and idiosyncratic shocks, we solve the model using a version of the method in Krusell and Smith (1998). We calibrate the model to match the empirical distributions of price-change statistics, namely the mean frequency of price change and the absolute size of price changes in each industry. We use the calibrated model to simulate a Phillips curve for every year from 1947 through 2019 by changing the industrial composition of the model economy in line with its changes in the data, all else being equal. We also use the model to assess how the inflation response to demand shocks of varying sizes has changed as a result of the shifts in the industrial composition and, finally, to analyze how persistent shocks affect the economy when the Phillips curve is relatively flat.

Our third contribution is to demonstrate that the changes in industrial composition in the United States can explain the flattening of the Phillips curve. Our model finds that shifts in the industrial composition have reduced the slope of the Phillips curve from –0.26 in 1947 to –0.18 in 2019, which amounts to a 30.7 percent flattening of the slope from the beginning to the end of that period.[5] A direct implication of a flatter Phillips curve is that inflation becomes less responsive to real changes in the economy. Therefore, a larger share of the service industry could account for some of the missing deflation during the Great Recession

[4]An alternative is to use the multisector Calvo model. However, Carvalho (2006) shows that in a multisector Calvo model, the aggregate rigidity is disproportionately driven by the sector with the lowest frequency of price adjustment.

[5]Rubbo (2020) finds a similar magnitude of decline in the slope in a multisector Calvo model calibrated to the changes in input-output production networks and consumption shares in the US economy over 1947–2017.

as well as the COVID-19 recession and missing inflation during the recovery from the Great Recession.

At the start of 2022, as the US economy recovered from the COVID-19 pandemic and the unemployment rate fell to its pre-pandemic levels, inflation spiked to heights unseen since the early 1980s. This outcome appears contradictory to the prediction of a flatter Phillips curve. Therefore, we additionally demonstrate that despite a flattening of the Phillips curve, large or persistent expansionary demand shocks still can cause a sharp rise in inflation. Additionally, Fornaro and Romei (2022) have shown that since the start of COVID-19, advanced economies have been characterized by a reallocation of consumption expenditures away from services towards goods. This reallocation could also help to explain the high inflation in light of our broader narrative.

Our paper is mostly closely related to but methodologically different from Nakamura et al. (2018). On the one hand, Nakamura et al. (2018) analyze the time-variation in the distribution of the frequency of price change arising from time-variation in the frequencies of price change of the products underlying the CPI and PPI, while holding fixed the relative shares of these products to their 2000 value. On the other hand, we analyze the time-variation in the distribution arising from time-variation in the relative shares of the products (arising due to industrial composition changes), while holding fixed the frequencies of price change for the products to their 1998–2005 average value. As discussed before, the distribution of the frequency of price change across products in the economy is a function of the frequencies of price change of the products and the relative shares of the products in the economy, and could therefore, shift over time due to changes in either of these two components. Our focus is on the latter.

Our paper also relates to several other strands of the literature. First, we contribute to the literature studying the impact of heterogeneity in the frequency of price change across products on monetary non-neutrality. Nakamura and Steinsson (2008) explore in detail the degree of heterogeneity across different products underlying the CPI and PPI in the United States. They incorporate this heterogeneity into a multisector menu cost model in Nakamura and Steinsson (2010) and demonstrate that including heterogeneity in price setting across sectors (aggregated products) boosts the degree of monetary non-neutrality by a factor of 3.[6] Carvalho (2006) considers the impact of heterogeneity in price stickiness in a multisector Calvo model and finds it implies that the frequency of price change in a homogeneous economy should be modeled as up to three times lower, although the effects

[6]Nakamura and Steinsson (2010) also find that incorporating intermediate goods in firms' production function further boosts the degree of monetary non-neutrality by a factor of 3.

in the multisector model with strategic complementarities are disproportionately driven by the sector with the lowest frequency of price adjustment. Our paper looks at how the distribution of the frequency of price change across products has evolved over time due to changes in industrial composition and what this evolution implies for the transmission of nominal demand shocks through the economy.

Second, our paper contributes to the literature analyzing the evolution over time of the slope of the Phillips curve and particularly, whether it has flattened. Blanchard, Cerutti, and Summers (2015) consider the evolution of the Phillips curve by studying aggregate data across a wide range of countries and find a decrease in its slope that predates the financial crisis. Blanchard (2016) emphasizes this point for the United States. Hazell et al. (2020) explore the Phillips curve across US states and find that once long-run inflation expectations are accounted for, the Phillips curve appears flat even in the 1980s and therefore, there has only been a small decrease in its slope since then.[7] The broad consensus of these papers is that there has been at least a small flattening of the Phillips curve and that this change started in the 1980s, so it is not attributable uniquely to the Great Recession. Our paper complements the results of these papers by providing an intuitive explanation for the long-term flattening of the Phillips curve over the 1947–2019 period.

Third, our paper contributes to the literature exploring reasons for the decrease in the slope of the Phillips curve for the United States. While some papers focus on explaining the disconnect between inflation and unemployment around the Great Recession, others explore structural reasons that can explain the decrease in the slope over a longer period involving more than just the Great Recession. The explanations in the former set of papers include mismeasurement of output gap (Crump et al., 2019), downward nominal wage rigidity (Daly and Hobijn, 2014), cyclical job ladders (Moscarini and Postel-Vinay, 2018; Daly and Hobijn, 2014), firms' inflation expectations driven by oil prices ((Coibion and Gorodnichenko, 2015)), and anchoring of inflation expectations (Bernanke et al., 2010; Jørgensen and Lansing, 2019). The explanations in the latter set include increased globalization and global competition, which may have made inflation less responsive to domestic demand (Borio and Filardo, 2007; Iakova, 2007); changes in production networks (Rubbo, 2020); changes in demographic trends (Mangiante, 2022); and changes in consumption patterns (Kaihatsu, Katagiri, and Shiraki, 2022). See Del Negro et al. (2020) for a comprehensive overview of this literature. Our contribution is to provide a simple explanation for why there has been a long-term decrease in the slope of the Phillips curve, namely the shifts in the industrial composition of the US economy. The main advantage of our approach is that it can help to explain the

[7] Consistent with Hazell et al. (2020), we too find that 16.6% (out of the total of 30.7%) slope decline had already occurred by 1983.

changes in the slope over a longer period that spans from the late 1940s to the present.

The remainder of this paper is organized as follows. We discuss our empirical strategy for mapping industry shares to product shares in section 2. We present the empirical results on how the distribution of the frequency of price change and other price-change statistics have evolved due to shifts in the industrial composition in section 3. We discuss the multisector menu cost model used to analyze the implications of changes in these distributions of price-change statistics for the slope of the Phillips curve and associated inflation dynamics in section 4. We present the model results in section 5. We conclude in Section 6.

2 Empirical Strategy

Our aim is to identify how the distribution of the frequency of price change varies over time as the industrial composition of firms within the economy changes. Products in different industries have different frequencies of price change. To identify the impact of changes in industrial composition on the distribution of the frequency of price change, we therefore measure how changes in industrial composition have changed the shares of different products in the economy while holding constant the frequency of price change of each product. Our approach allows us to sidestep the limited historical microdata available for product-level prices and obtain estimates of the distribution of the frequency of price change for the entire period for which we have industrial-composition data.[8] We use the same approach to compute the impact of industrial composition on the distributions of other price-setting-related statistics such as the absolute size of price changes and the probability of positive price changes.

We have annual industrial composition data from 1947 through 2019 for a wide array of industries. These data come from two sources—the BEA and World KLEMS—both of which cover the annual share of industries in the economy over time.[9] The BEA data cover the entire period of interest, but before 1962 the shares are available for only less disaggregated

[8]There are two main limitations of historical microdata on prices at the product level. One, the U.S. Bureau of Labor Statistics (BLS) has limited data on product pricing; the data don't begin until the late 1970s. Two, there were frequent reclassifications of products underlying the CPI including in both 1987 and 1998, which makes it difficult to compare products over time (Nakamura et al., 2018). We are unaware of other data sets that would offer better coverage.

[9]The BEA data are available on the BEA website. Note that the 1947–1997 data are in separate historical tables that can easily be merged with the newer, post-1997 data. The World KLEMS data are available at `http://www.worldklems.net/data.htm`. We used the March 2017 release of World KLEMS. We obtained value-added GDP numbers, which is the standard way of measuring industry size, for each industry by subtracting the intermediate goods used from the gross output in each industry.

industries. The World KLEMS data are available for a more disaggregated set of industries before 1962 but cover only through 2014. Fortunately, the industries in the BEA and World KLEMS data line up, so merging these data sets adds data points without imposing costs. With this approach, we are able to obtain shares for 65 industries for each year from 1947 through 2019.

We obtain the data on the average frequency of price change, the absolute size of price changes, and the probability of positive price change of products from Nakamura and Steinsson (2008). The data give the price-change statistics for both CPI and PPI products throughout the 1998–2005 period.[10] There are 272 CPI products covering goods sold to consumers. We first consider only the price-change statistics excluding sales, which is in line with Nakamura and Steinsson (2008), though our results still hold if we include sales in the price-change statistics. The data include CPI weights attributing the weight given to a product within the CPI in the years 1998 through 2005. There are also 348 PPI products covering goods sold to producers. These do not include weights and contain only one measure of the frequency of price change without sales because sales are less common with the PPI products.

To compute the distribution of these price-change statistics over time, we need to translate the industry shares of the economy in any given year into the CPI/PPI product shares. We are not aware of a standardized method for doing this, so we devised our own. First, we created a mapping from CPI/PPI products to 2017 six-digit NAICS industries. For each product, we chose the NAICS industry that corresponds closest to it. We chose multiple NAICS industries for a single product if we felt that these industries would reasonably sell the product, though selecting only one industry for each product does not materially change the results. Fortunately, many products, particularly in the PPI, correspond closely to six-digit NAICS industries. We were able to map 613 CPI/PPI products to 51 industries.[11] Second, we aggregated the six-digit industries up to the level of the industries for which we have historical industry-share data.[12] Third, we applied a simple algorithm to determine

[10] The data are taken from Tables 19 and 23 of the supplementary materials.

[11] The products that do not correspond to any industry are "general purpose and auto," "club membership dues," "fees for lessons or instructions," "state vehicle registration," "local automobile registration," "other finishing of textiles," and "personal aid equipment."

[12] The industries that do not correspond to a CPI/PPI product are "forestry, fishing, and related activities," "support activities for mining," "pipeline transportation," "warehousing and storage," "securities, commodity contracts, and investments," "funds, trusts, and other financial vehicles," "real estate," "computer systems design and related services," "management of companies and enterprises," "amusements, gambling, and recreation industries," "federal general government," "federal government enterprises," "state general government," "state government enterprises." The common feature among these industries is that measuring prices for them is difficult.

the share of the economy assigned to a given CPI/PPI product in each year.[13] To aid with exposition of the algorithm, please allow us to introduce some notation. i denotes CPI/PPI products; there are I products in total. j denotes an industry; there are J industries in total. ω_i is the weight of CPI/PPI product i. We set the weight of each CPI product equal to the weight given in Nakamura and Steinsson (2008). We set the weight of each PPI product equal to 1 divided by the number of PPI products, since we do not have PPI weights that correspond directly to the categories in Nakamura and Steinsson (2008).[14, 15] $\nu_{j,t}$ is industry j's share of the economy at time t. Given that we have industry shares for the whole economy, $\sum_{j=1}^{J} \nu_{j,t} = 1$. λ_i is the frequency of price change of product i. The algorithm then proceeds as follows:

1. Construct $a_{i,j}$ such that $a_{i,j}$ is 1 if product i is sold in industry j and 0 otherwise. Drop any product i that we cannot assign to an industry; that is, a product i s.t. $a_{i,j} = 0 \forall j$. This is necessary, otherwise we would divide by 0 in step 2. We also need to drop the corresponding i in ω_i, λ_i. Drop any industry j that has no products assigned to it; that is, an industry j s.t. $a_{i,j} = 0 \forall i$. This is necessary, otherwise we would divide by 0 in step 3. We also need to drop the corresponding j in ν_j.

2. The raw weight of product i sold in industry j is: $b_{i,j} = \frac{a_{i,j}}{\sum_{j=1}^{J} a_{i,j}}$. Note that $\sum_{j=1}^{J} b_{i,j} = 1$; that is, the sum of the raw weights of product i sold in all industries equals 1. The idea here is that if product $i1$ is sold in two industries $j1, j2$, while product $i2$ is sold in one industry $j2$, then we will give a lower raw weight to product $i1$ in industry $j2$.

3. The proportion of industry j sold by product i is: $c_{i,j} = \frac{\omega_i b_{i,j}}{\sum_{i=1}^{I} \omega_i b_{i,j}}$. Note that $\sum_{i=1}^{I} c_{i,j} = 1$; that is, the sum of the proportions of industry j sold across all products sums to 1. The idea here is that if an industry sells multiple products, the relative weight of product i in industry j is determined by the combination of the raw weights we computed in step 2, which were based on how many industries product i is sold in, and the weight of product i in the CPI/PPI.

[13] The reason that this is not a straightforward exercise is because one industry can be associated with multiple products and one product can also be associated with multiple industries.

[14] It is not ideal to compare weights in the CPI with those in the PPI. However, there are only two industries (utilities and publishing) that are associated with both CPI and PPI products, so we do not consider this to be a major concern. We also consider two robustness tests—dropping all weights from the analysis or using CPI and PPI products one at a time—and our results remain effectively unchanged.

[15] We conduct a robustness check where we consider only those PPI products for which we have weights over time and which are available in Nakamura and Steinsson (2008). These weights data are available starting in 1998. We find that the median frequency of price change is broadly similar under the fixed (unit) and time-varying weights (see Table 21). This makes sense because in our algorithm, the product weights only matter for multi-industry products or multi-product industries, which occurs rarely for PPI products, since they map quite well with NAICS industries.

4. The share of the economy attributed to industry j selling product i at time t is: $d_{i,j,t} = c_{i,j}\nu_{j,t}$. Note that $\sum_{j=1}^{J}\sum_{i=1}^{I} d_{i,j,t} = 1$. The idea here is that if we know that the proportion of industry j sold by product i is $c_{i,j}$ and the proportion of the economy at time t attributed to industry j is $\nu_{j,t}$, then the proportion of the economy attributed to industry j selling product i is found simply by multiplying these together.

5. The share of the economy assigned to product i with price rigidity λ_i at time t is given by $e_{i,t} = \sum_{j=1}^{J} d_{i,j,t}$. The idea here is that to determine the proportion of the economy selling product i and therefore having frequency of price change λ_i, we can simply sum up the shares of product i in each industry at time t to determine the share of product i for the whole economy.

The algorithm outputs $e_{i,t}$, which is the share of the economy assigned to CPI/PPI product i at time t. We can combine this share measure with any statistic available at the level of the products to determine the economy-wide distribution of that statistic at time t.

For all of the empirical results in section 3 we consider how the percentiles of the distribution of different statistics associated with firms' price-setting behavior have changed over time. To do this, we sort the CPI/PPI products by the statistic of interest. We then compute the cumulative distribution across this statistic of interest. To compute how the 25th percentile of the distribution of the statistic of interest evolves, we can then simply follow how the 25th percentile of this cumulative distribution changes throughout the years for which we have computed the distribution.

The most important statistic of interest is the frequency of price change. To enable easier analysis, we sometimes aggregate the distribution of the frequency of price change across products to the industry level. We do this because our algorithm yields a distribution across 613 products over time, which can be difficult to analyze and assess trends. Therefore, we aggregate the distribution up to the level of the industry, of which there are 51. We set the frequency of price change for an industry to be the median of the frequency of price change of products in that industry weighted by the relative share of the products in the industry. The full list of industries; their corresponding price-change frequencies; their shares of the economy in 1947, 1983, and 2019; and the products that make up these industries are given in Table 7. The table is ordered by the frequency of price change of the industries.[16] This approximate distribution of the frequency of price change across the 51

[16] We choose to present the results for these three years because they correspond to the start of our sample, middle of our sample, and end of our sample, respectively. The corresponding analysis in section 5 will focus on these three years as well.

industries is a reasonable approximation of the distribution across the 613 products.[17]

We consider a further aggregation to 12 aggregate industries to enable easier identification of potential trends. The mapping between the 12 aggregate industries and the 51 industries is given in Table 8. The aggregation is performed by aggregating similar NAICS industries, and it results in aggregated groups that are nearly the same as those considered by the BEA. We set the frequency of price change for an aggregate industry to be the median of the frequency of price change of products in that aggregate industry weighted by the relative share of the products in the aggregate industry in 1983.[18] The annual economic shares of these 12 aggregate industries are computed by summing the shares of their respective industries in each year. This approximate distribution is a fairly imprecise approximation of the distribution across the 613 products but does enable easier interpretation of trends.[19]

3 Empirical Results on Industrial Share and Price Rigidity

We start by presenting the results for the distribution of our statistic of primary interest: the frequency of price change. Table 1 and Figure 1 show how changes in industrial composition from 1947 through 2019 affected the distribution of the frequency of price change. The frequency of price change is measured as the probability each month that a price is changed. We find that the median monthly frequency with which a firm changes its price fell from 9.2 percent in 1947 to 6.9 percent in 2019. Other percentiles show similar falls. The 25th percentile drops from 4.9 percent to 4.0 percent . The 75th percentile drops from 26.9 percent to 12.4 percent . The 90th percentile drops from 87.6 percent to 41.7 percent . The exception is the 10th percentile, for which the frequency of price change remains the same. The decreases occur throughout the 1947–2019 period.These results show that there has been a broad decline in the aggregate frequency of price change due to changes in industry composition from 1947 through 2019.[20]

[17]The relative shares of product i in industry j are determined in step 3 of the algorithm and do not vary over time. Therefore, the only approximation we use is a common frequency of price change for all the products in a single industry, which is not likely to induce large changes in the distribution.

[18]The reason we need to compute the median using weights from a particular year is that the share of a product i in an aggregate industry varies over time with the shares of the industries that comprise that aggregate industry.

[19]There are two approximations here. First, we use one frequency of price change to capture the frequency of price change of all products in the aggregate industry. Second, we do not allow the distribution of products in different industries to vary over time, even though the economic shares of those industries within the aggregate industry may differ from their shares in 1983.

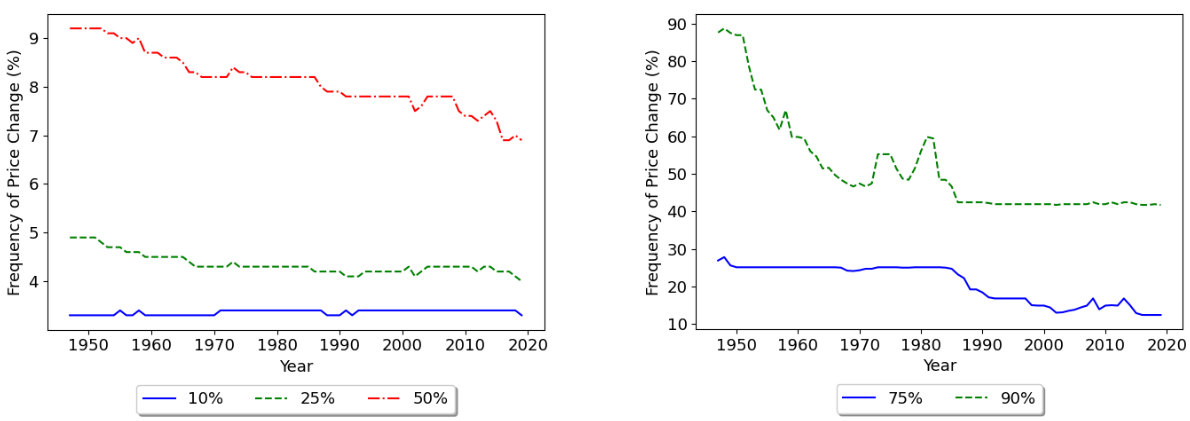
[20]In Table 9, we show the evolution of additional moments of the distribution of the frequency of price change. The mean frequency of price change shows a similar persistent decline. There has also been a fall in the standard deviation of the distribution as the relative shares of industries with very high frequencies of price

Table 1: Evolution of the Distribution of the Frequency of Price Change: 1947–2019

Year	10	25	50	75	90
1947	3.3	4.9	9.2	26.9	87.6
1957	3.3	4.6	8.9	25.1	61.7
1967	3.3	4.3	8.3	25.0	48.4
1977	3.4	4.3	8.2	25.0	48.7
1987	3.4	4.2	8.0	22.2	42.4
1997	3.4	4.2	7.8	16.8	41.9
2007	3.4	4.3	7.8	14.9	41.9
2017	3.4	4.2	6.9	12.4	41.7
2019	3.3	4.0	6.9	12.4	41.7

The table shows percentiles of the distribution of the frequency of price change from 1947 through 2019 computed using our standard method. The frequency of price change is the probability (in percentage terms) with which firms change their prices each month. So the 50th percentile here shows the probability with which the median firm in the distribution of the frequency of price change changes its price each month in different years. Sources: BEA, BLS, World KLEMS.

Figure 1: Evolution of the Distribution of the Frequency of Price Change: 1947–2019



(a) For Low Percentiles

(b) For High Percentiles

The figure shows percentiles of the distribution of the frequency of price change from 1947 through 2019 computed using our standard method. The frequency of price change is the probability (in percentage terms) with which firms change their prices each month. So the 50th percentile here shows the probability with which the median firm in the distribution of the frequency of price change changes its price every month in each year of our sample. Sources: BEA, BLS, World KLEMS.

Next, we consider which industries are driving the changes in the distribution of the frequency of price change. Figure 2 shows the share of 12 aggregate industries in the economy

change have declined. However, even as the mean and standard deviation fell, there remain some industries with very high frequencies of price changes so the skewness and kurtosis of the distribution have risen over time.

from 1947 through 2019 ordered from the lowest to the highest frequency of price change; that is, the aggregate industry with the lowest frequency of price change (finance/insurance) is at the bottom of the graph. The 1983-weighted median frequencies of price change of the aggregate industries are displayed in the legend in brackets; for example the frequency of price change of the aggregate industry finance/insurance is 3.5 percent . This is an aggregation from our distribution over 613 products to 12 aggregate industries, so it is quite approximate, but it does offer valuable insights. The finance/insurance, legal/scientific/technical, and education/health industries have grown significantly over time, and all of these industries have relatively low frequencies of price change. On the flip side, durable manufacturing, nondurable manufacturing, and agriculture/mining/utilities all have diminished in size significantly. Durable manufacturing has a relatively low frequency of price change, but the other two aggregate industries have higher frequencies of price change. This suggests that the shift from primary and secondary industries toward tertiary industries has led to an overall reduction in the frequency of price change.[21,22]

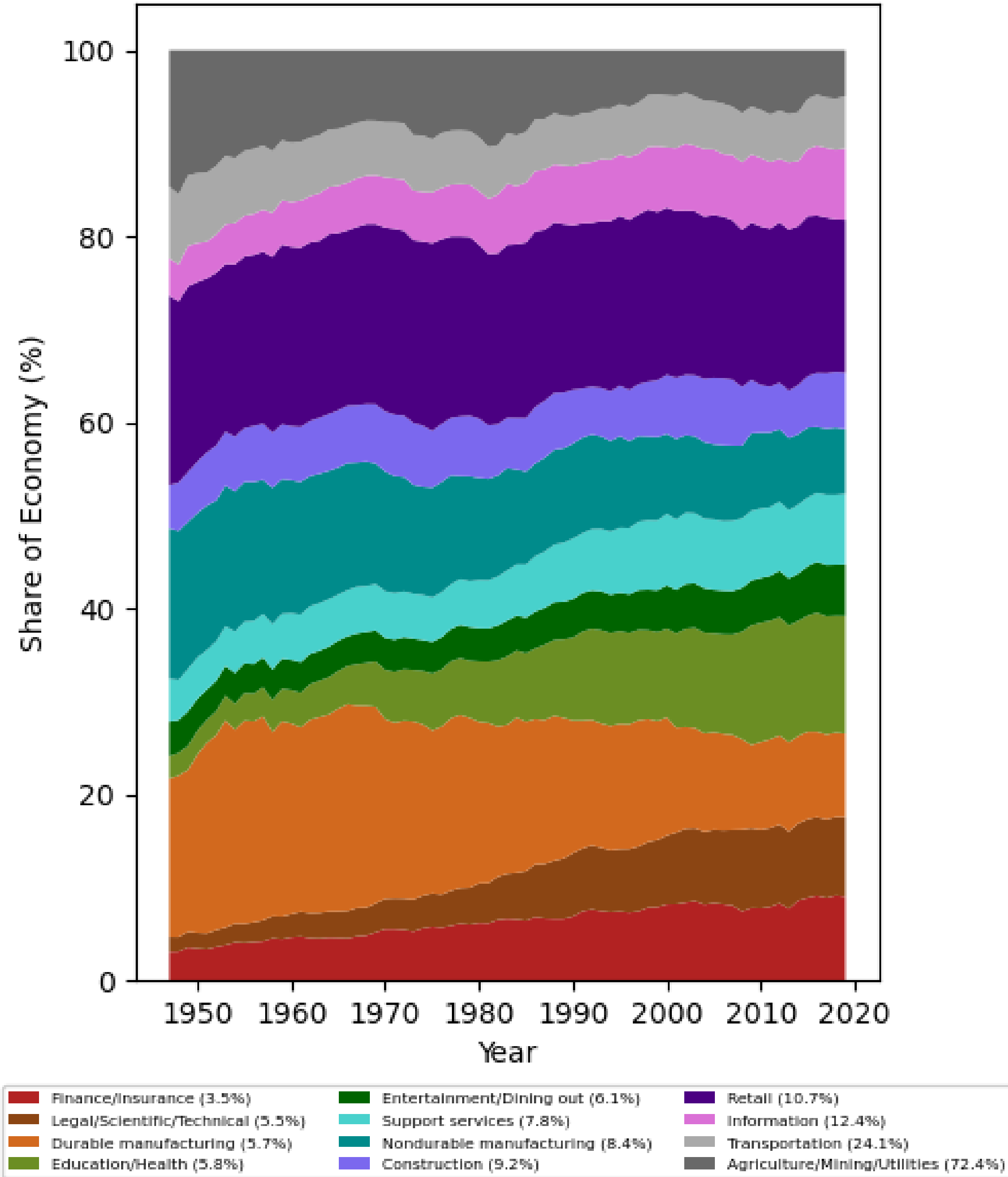
We also consider a more disaggregated distribution across the 51 industries. The purpose here is to examine more closely what the distribution across industries looks like, since Figure 2 requires a large degree of approximation of the product-level distribution to draw clean conclusions. Figure 3 shows the shares of each of the 51 industries in the economy from 1947 through 2019 ordered from the lowest to the highest frequency of price change; that is, the industry with the lowest frequency of price change is at the bottom of the graph. We label the large industries and color-code the industries by their aggregate industry (in the 12-industry classification). The industries associated with products that have a low frequency of price change grew in relative importance in the economy throughout the 1947–2019 period. These include legal services, ambulatory health care (walk-in visits for health care), and banking. Industries with high frequencies of price change whose shares of the economy fell substantially over the 1947–2019 period include farms and food and beverage.

To further verify these conclusions, Table 2 and Table 3 report the five industries with the largest increase and the five with the largest decrease in their shares of the economy from

[21]While we take the frequencies of price change of products as given, a separate literature analyzes the reasons for a lower frequency of price change of products in the service sector. The studies provide two main explanations. One, wages make up a greater proportion of input costs in the service sector compared with the manufacturing sector, which combined with wage rigidity, means prices are more stable (Bobeica, Ciccarelli, and Vansteenkiste, 2019). Two, there is less competition in the service sector (markups are higher, on average) than in the manufacturing sector, which allows service sector firms to make less frequent price adjustments (McAdam et al., 2019).

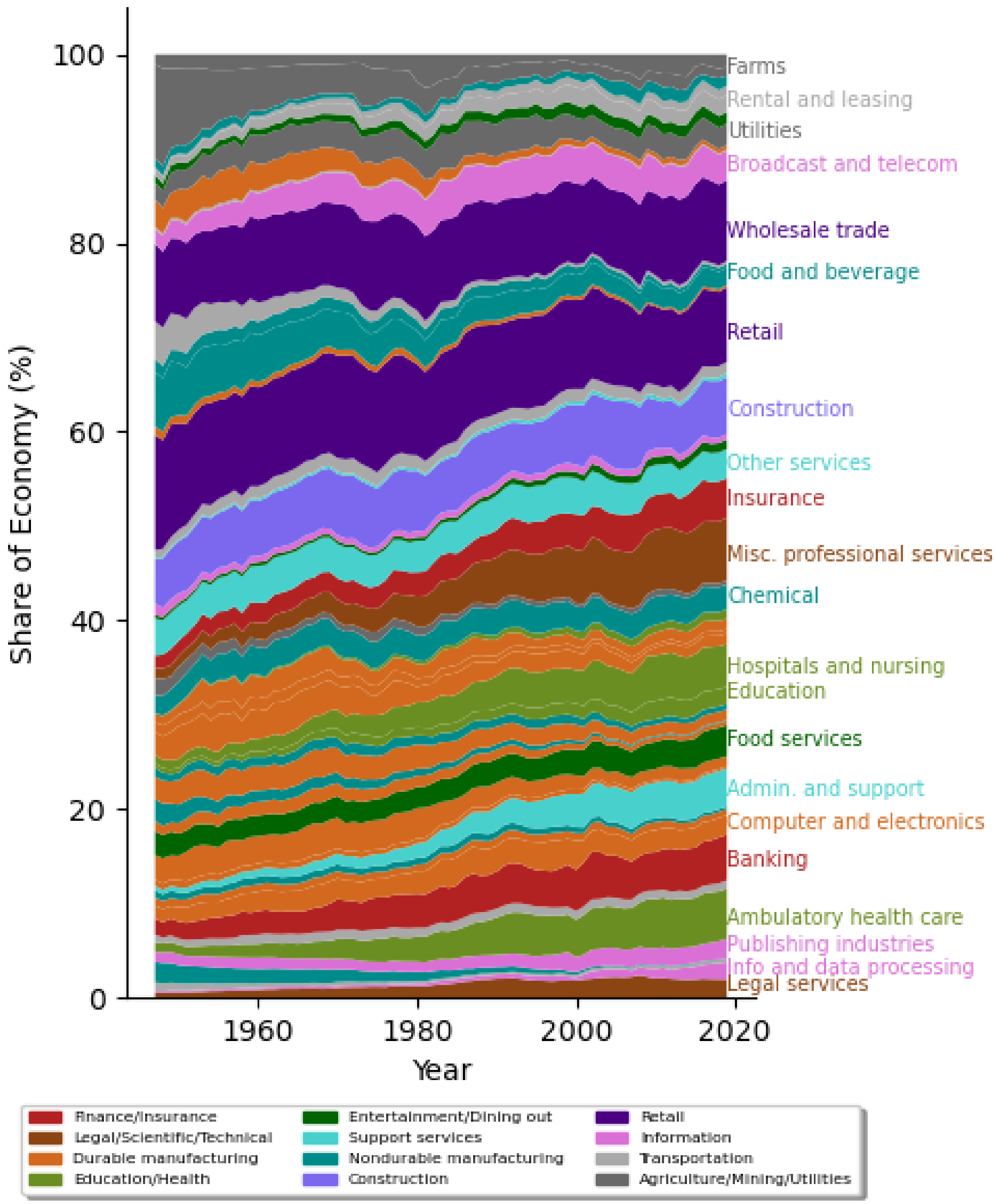
[22]The rise of services in the US economy along with the reasons for this structural transformation have been well-documented by other papers in the literature, for example, Kongsamut, Rebelo, and Xie (2001), Duarte and Restuccia (2010), Herrendorf, Rogerson, and Valentinyi (2014). Our contribution is to study how this transformation interacts with the distribution of the frequency of price change.

Figure 2: Aggregate Industries' Shares of the Economy Ordered by Frequency of Price Change



The figure shows aggregate industries' shares of the economy over time. The x-axis represents the year, and the y-axis represents the aggregate industries' shares of the economy. The industries are sorted from the lowest (1983-weighted) median frequency of price change to the highest. The aggregate industry at the bottom of the graph is finance/insurance, with a median frequency of price change of 3.5 percent . The finance/insurance industry's share of the economy is displayed in red (at the bottom of the graph) and grows over time. The aggregate industry at the top of the graph is agriculture/mining/utilities, with a median frequency of price change of 72.4 percent . Its share of the economy is displayed in gray and shrinks over time. Other aggregate industries may be interpreted in a similar manner. Sources: BEA, BLS, World KLEMS.

Figure 3: Industries' Shares of the Economy Ordered by Frequency of Price Change



The figure shows industries' shares of the economy over time. The x-axis represents the year and the y-axis represents the aggregate industries' shares of the economy. The industries are sorted from the lowest median frequency of price change to the highest. So the first (starting from the bottom) industry in the graph is legal/scientific/technical, which is actually legal services and has a (1983-weighted) median frequency of price change of 1.6 percent . The color of an industry represents its aggregate industry in the 12-industry classification. Sources: BEA, BLS, World KLEMS.

1947 to 2019, respectively. All five of the industries that increased in size the most are tertiary industries. "Miscellaneous professional scientific and technical services" includes personal accounting and veterinary services. "Ambulatory health services" means health services for walk-in patients (not just emergency room services). "Other support services" includes household cleaning/gardening and automobile services. The banking category includes standard personal banking. Three of the five industries whose shares of the economy decreased the most are primary or secondary industries[23] and the other two categories relate to the sale and transportation of these goods. In particular, there was a very large fall in agriculture. All of the five industries whose shares of the economy increased the most show substantially lower frequencies of price change compared with the five industries that decreased in size the most.

Table 2: Industries with the Top 5 Largest Increases in Shares of the Economy: 1947 to 2019

Industry Name	Freq.	1947	1983	2019
Miscellaneous professional scientific and technical services	8.2	1.1	3.5	6.7
Ambulatory health care services	3.4	1.0	3.0	5.3
Hospitals Nursing and residential care facilities	6.3	0.9	3.1	4.6
Administrative and support services	4.3	0.5	1.8	4.1
Federal Reserve banks credit intermediation and related activities	3.5	1.7	3.9	4.8

The table reports the five industries whose shares in the economy increased the most from 1947 to 2019 (measured in absolute terms). The columns represent the industry name, the median frequency of price change of the industry, the share in 1947, the share in 1983, and the share in 2019. Sources: BEA, BLS, World KLEMS.

Table 3: Industries with the Top 5 Largest Decreases in Shares of the Economy: 1947 to 2019

Industry Name	Freq.	1947	1983	2019
Farms	94.8	10.0	1.7	0.9
Retail Trade	10.7	12.2	9.9	7.9
Food and beverage and tobacco products	22.2	5.8	3.1	1.8
Rail transportation	24.1	4.0	0.8	0.3
Primary metals	34.8	2.8	1.2	0.4

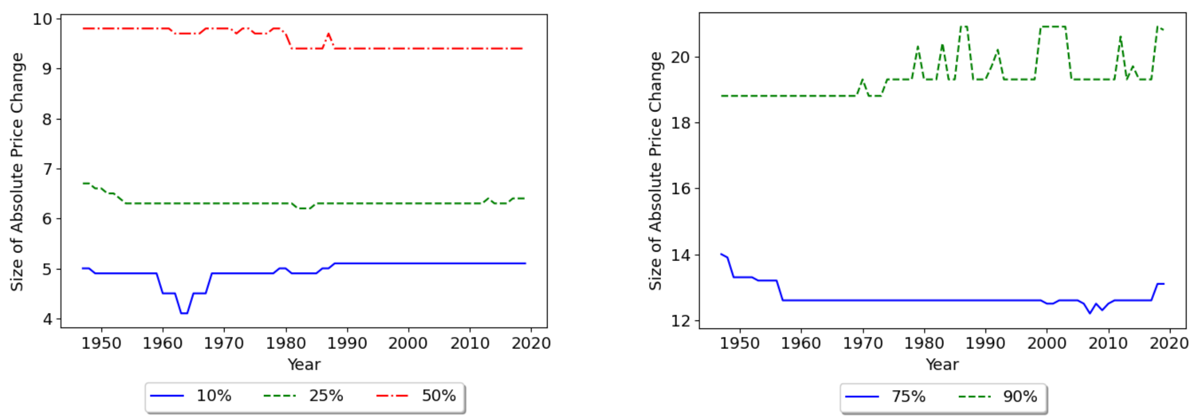
The table reports the five industries whose shares in the economy fell the most from 1947 to 2019 (measured in absolute terms). The columns represent the industry name, the median frequency of price change of the industry, the share in 1947, the share in 1983, and the share in 2019. Sources: BEA, BLS, World KLEMS.

We also look at how industrial composition over the 1947–2019 period affected the distribution of other price-setting statistics. For the frequency of price change to fall conditional on

[23] The category "Food and beverage and tobacco products" relates to the manufacture of these goods.

inflation remaining the same, the probability of a positive price change must rise or firms must raise their prices by more.[24] In Figure 4 and Figure 5, we consider how changes in industrial composition affected the distribution of the absolute size of price changes and the probability of a price change being positive, respectively.[25] We find no obvious pattern to the manner in which the size of absolute price changes moved during the period.[26] The median and the 75th percentile sizes fall slightly, while the 90th percentile rises. On the other hand, there appears to be a clear increase in the distribution of the probability with which a price change is positive. There is an increase in this statistic in every percentile of its distribution. These results suggest that changes in industrial composition have shifted the distribution of the economy toward firms that make less frequent price changes because they make fewer price cuts rather than because they make larger price changes when they change their prices.

Figure 4: Evolution of the Distribution of Size of Absolute Price Change: 1947–2019



(a) For Low Percentiles (b) For High Percentiles

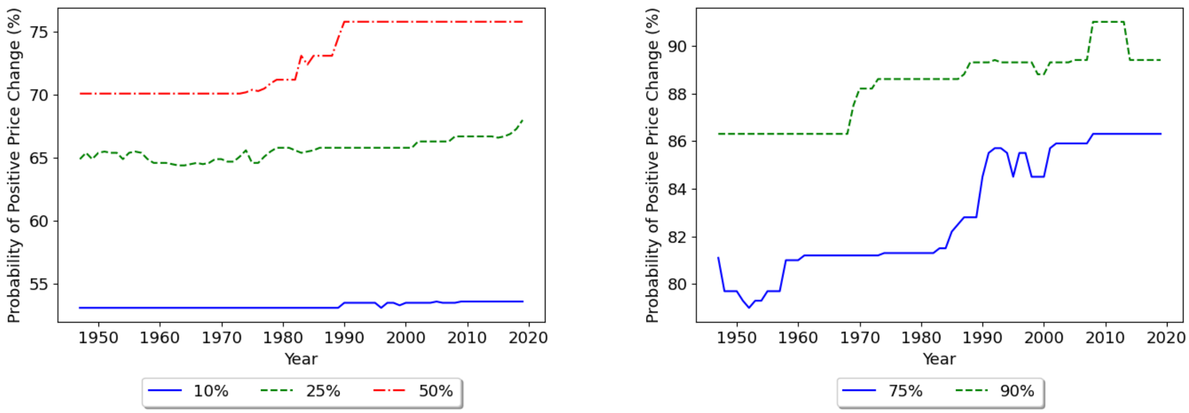
The figure shows percentiles of the size of the absolute price change distribution from 1947 through 2019 computed using our standard method. The size of the absolute price changes is the absolute size of log changes in consumer prices conditional on a change occurring. Sources: BEA, BLS, World KLEMS.

[24]Note that inflation is held constant in our algorithm since the only element that we are changing is industrial composition. The frequency of price change is still measured under the same degree of aggregate inflation.

[25]See Table 10 and Table 11, which display these results in tabular form.

[26]This finding is consistent with that of Nakamura et al. (2018), who find no systematic decline across various quintiles of the absolute size of price changes even when analyzing the issue using the time series of microdata underlying CPI products over the 1975–2015 period. The difference between our measure and Nakamura et al. (2018) is that we look at the change in the distribution of the frequency of price change due to shifts in industrial composition holding constant the frequency of price change of products while Nakamura et al. (2018) look at the change in the distribution due to shifts in the frequency of price change of products holding constant product weights and industrial composition shares.

Figure 5: Evolution of the Distribution of Probability of Positive Price Change: 1947–2019



(a) For Low Percentiles

(b) For High Percentiles

The figure shows percentiles of the distribution of the probability of a positive price change for 1947 through 2019 computed using our standard method. The probability of a positive price change is the fraction of price changes that are positive. Sources: BEA, BLS, World KLEMS.

3.1 Robustness

Table 4: Robustness Checks with Alternative Specifications

Method	1947	1983	2019
A. Main	9.2	8.2	6.9
B. Any price change	11.5	8.7	7.8
C. One Klems	9.2	8.2	6.9
D. Same weight	9.1	8.0	7.2
E. No large products	9.4	7.8	6.9
F. Aggregate by industry	10.7	8.4	8.2
G. CPI Only	9.2	8.2	6.9
H. PPI Only	9.7	7.4	7.2
I. Gross Output	9.0	8.2	7.8
J. Intermediate Inputs	9.5	8.7	8.2
K. Labor Compensation	8.9	7.2	6.3
L. Consumption Share	10.9	10.9	9.2
M. Consumption Share with Shelter	10.9	8.0	8.0

This table presents the median frequency of price change in 1947, 1983, and 2019. The specifications used to compute the median frequency of price change are A, the standard method; B, measuring the frequency of price change including sales (which implies the frequencies will generally be higher); C, mapping each product to only one industry in our algorithm; D, applying the same weight to all products in each industry; E, excluding products with a weight of more than 1 percent in 1983; F, aggregating the products up to the level of the 51 industries; G, considering only CPI products; H, considering only PPI products; I, weighting the industrial composition share by the gross output of the industries rather than the value-added; J, weighting the industrial composition share by the degree to which an industry's products are used as intermediate inputs are used in other industries; K, weighting the industrial composition share by the labor compensation provided by an industry; L, weighting by the consumption share of products; and M, weighting by the consumption share of products including housing. The frequency of price change is measured as the probability that a firm changes its price in a given month. Sources: BEA, BLS, World KLEMS.

In Table 4, we show that our results are robust to other specifications. Row A of the table presents the median frequency of price change in 1947, 1983, and 2019 computed using our standard method. In the standard method, we follow Nakamura and Steinsson (2008) by considering the frequency of price change for CPI products excluding sales. Our first alternative method considers the frequency of price change including sales. These results are presented in row B. We see that in each year considered the frequencies in row B are higher than the frequencies in row A. This is unsurprising since including sales mechanically implies that firms are changing their prices more often. However, even when including sales, we continue to observe a clear decline in the median frequency of price change from 1947 to 2019. In our algorithm, we allow for the use of the same product in multiple industries. In row C, we consider the case where each product can be used only in the industry we marked as the most relevant. Only 13 of the 613 products straddle multiple industries, so this change has very little effect on our results; it does not change the median for 1947, 1983, or 2019 relative to the results from our standard method. The CPI data provide the expenditure weights for each product. We use these weights when determining how much a product is weighted within an industry because we believe that it gives a more accurate sense of the importance of the product in the economy and the consequent distribution of the frequency of price change. In row D, we consider the case where we weight all products equally. The results remain essentially unchanged. In our algorithm, there were some industries that we could map to only a limited number of products, thereby giving these products a relatively large role in driving our results. Therefore, we also construct our distribution by dropping products that made up more than 1 percent of the share of the economy in 1983. Through this process, we drop 20 products that collectively accounted for 41 percent of the economy in 1983. Despite dropping these products from our analysis, we still see in row E a clear (slightly stronger than under the standard method) decline in the median frequency of price change from 1947 to 2019. As we discussed earlier, an alternative method to obtain the distribution of the frequency of price change is to first estimate the frequency of price change for an industry by taking the median frequency of price change of products in that industry, and then to compute the distribution of the frequency of price change across industries rather than products. We consider this alternative in row F and again find a decline in the median frequency of price change. In rows G and H, we consider restricting products to only products in the CPI and only products in the PPI, respectively. We still find a similar decline in the median frequency of price change over time. We also show in Appendix C that allowing the share of products sold in an industry to vary over time makes effectively no difference to the results.[27] Appendix B demonstrates that there are similar declines in the frequency of price change for other percentiles of the distribution as well under all of these alternative specifications.

We also verify that our results hold under alternative measures of industrial composition. In the baseline analysis, we determine an industry's share of the economy based its value-added contribution to GDP. However, there are other ways to characterize the importance of an industry. In Row I, we show that measuring an industry's GDP with gross output rather than value-added yields similar results. Galesi and Rachedi (2019) argue that the transmission of monetary policy in an economy relies more heavily on the economy's intensity of services in intermediate production rather than the size of value added GDP. Therefore, in row J, we verify whether computing the industrial composition based on the degree to which an industry's output is used as an intermediate input alters our results. We still find a

[27] We find that allowing the weights of products to vary across the timespan for which we have weight data yields similar results to the case where we hold the weights fixed (as in our baseline). We conduct this exercise for the PPI products that we can map to the frequency of price changes in Nakamura and Steinsson (2008).

similar decline in the distribution. We also find similar results when we measure industrial composition based on an industry's share in labor compensation in row K.

An alternative approach to measure the relative shares of products in the economy is to directly consider their weights in the consumption basket underlying the CPI. CPI weights are available from the BLS going back to 1947, but there are significant compositional shifts in the products included in the basket as the methodology behind the CPI has changed. Therefore, to be able to draw reliable estimates, we aggregate the products to 12 sectors. We can directly map the frequency of price change for 11 of these sectors from Nakamura and Steinsson (2008). Considering these 11 sectors, we find that the median frequency of price change declines in row L of Table 4.[28] For the remaining sector, which is shelter (the cost of housing), we can also set the frequency of price change such that a price lasts on average for one year.[29] In this case, we also find that the median frequency of price change declines in row M of Table 4. This decline is driven by a shift over time in the consumption patterns towards services, recreation goods, and shelter (see Figure 18). This approach additionally assuages fears that accounting for the role of international trade might affect our results.[30]

One additional concern that has been raised about our work is that we may imperfectly measure changes in the distribution of the frequency of price change because we fix the frequency of price change of individual products. We accept this critique. Our focus is on measuring how shifts in industrial composition have affected the distribution rather than how the overall distribution has moved generally. Measuring how the overall distribution of the frequency of price change has moved would be an interesting question to answer but would require access to BLS microdata which is not currently forthcoming.[31] Moreover, the BLS microdata only goes back to the late-1970s and we find that much of the shift in

[28]The reason that the median frequency does not change between 1947 and 1983 in row L is because we consider 11 sectors that have much larger weights than in our main approach. So the median sector remains the same from 1947 to 1983 even though there were shifts in the distribution of the frequency of price change from 1947 to 1983. This is also why the median frequency does not change between 1983 and 2019 in row M. We show that the frequency of price change declines for other percentiles in Figure 17 and Figure 18.

[29]While the BLS does not provide the frequency of price change for shelter with its other micro-price data, an annual duration is sensible for two reasons. One, most renters have annual contracts that are renegotiated once a year. Two, using micro-price data provided by Davies (2021) for the United Kingdom, we find that the median duration of rent for unfurnished rental homes is 13 months. Under constant hazard, this constitutes a monthly frequency of price change of roughly 8 percent .

[30]The importance of international trade in the US economy has increased over our sample. For example, the share of imports in US GDP has increased from 3.5% in 1947 to 14.6% in 2019. The increase may have affected some industries more than others. For example, Autor, Dorn, and Hanson (2013) show that imports replaced US manufacturing, which would reduce the value added share of manufacturing industries, while the expenditure shares on manufacturing may not have changed. However, we find similar results under the value-added and expenditure/consumption-shares approach, which is reassuring.

[31]There are currently delays in accessing BLS microdata. We applied to access this data for another project in December 2020 but our application remains under review.

the distribution of the frequency of price change (due to industrial composition) predates this period.[32] Therefore, limiting our sample to start in the late 1970s would cause us to lose much of the apparent shift in the distribution. Additionally, there have been significant reclassifications to which products are assessed for the CPI, which could introduce misleading shifts in the distribution of the frequency of price change. That being said, we can estimate how the overall distribution may move by turning to Figure A.4 of Nakamura et al. (2018), which we reproduce in Figure 19. The figure shows that the (weighted) median frequency of price change for products in the service industries (holding fixed their weights) has declined between 1978 to 2015. At the same time, our results show that the dominant factor driving shifts in industrial composition to lower the frequency of price change is that service industries have grown. Taken together, this implies that as the service sector has grown, its frequency of price change has fallen. Therefore, by relaxing the assumption of constant price flexibility over time for each product, we will likely find a larger decline in the distribution of price flexibility and therefore, a further flattening of the Phillips curve. As such, we think that our estimates constitute a lower bound for the overall shift in the distribution of price change frequency over 1947 to 2019.

4 Multisector Menu Cost Model

Our next aim is to understand how changes in the distributions of the price-change statistics arising due to shifts in the industrial composition of the US economy over the 1947–2019 period have altered the transmission of nominal demand shocks through the economy. We are particularly interested in evaluating the impact on the slope of the Phillips curve. We also explore the impact on inflation dynamics more generally and analyze whether high inflation is possible in the face of large or persistent demand shocks despite a flatter Phillips curve.

Our empirical results showed that the aggregate price stickiness in the United States has increased due to shifts in industrial composition. However, there is no model-free way to assess the impact of this increase on the transmission of nominal shocks through the economy and, consequently, on the slope of the Phillips curve. Therefore, we now turn to a general equilibrium multisector menu cost model. We use a menu cost model rather than a Calvo (1983) model of nominal rigidity mainly because, as shown by Carvalho (2006), in a multisector Calvo model the aggregate price stickiness is disproportionately driven by the

[32] Our model estimates that over half (16.6% out of the total of 30.7%) of the Phillips Curve slope decline had already occurred by 1983.

sector with the lowest frequency of price change. This is because, even under high inflation, many firms in the sector with the lowest frequency of price change will not change their price for a long time while they wait to be hit by the Calvo fairy. Menu cost models do not have this problem, because firms optimally choose to pay a menu cost to change their price when they move too far from their desired price.

We construct a version of a multisector menu cost model in Nakamura and Steinsson (2010). The model includes three types of agents: a representative household, monopolistic firms operating across multiple sectors of production, and a central monetary authority. The model features both firm-specific idiosyncratic productivity shocks that are drawn from a sector-specific distribution and aggregate nominal demand shocks. The idiosyncratic productivity shocks are necessary to realistically model firm pricing decisions that differ within each sector, while the aggregate shocks are necessary to investigate the dynamics of the macroeconomic aggregates such as aggregate consumption and aggregate inflation and, particularly, the slope of the Phillips curve.

Household A representative household maximizes expected discounted utility over an infinite horizon:

$$E_t \sum_{\tau=0}^{\infty} \beta^{\tau} \left[\frac{1}{1-\gamma} C_{t+\tau}^{1-\gamma} - \frac{\omega}{\psi+1} L_{t+\tau}^{\psi+1} \right], \tag{1}$$

where E_t denotes the mathematical expectation conditional on information available in period t, $\beta \in (0,1)$ is the discount factor, L_t denotes the hours worked in period t, γ is the coefficient of relative risk aversion, ω and ψ are the level and convexity parameters for labor disutility. C_t is a Dixit-Stiglitz aggregate of consumption in period t given by:

$$C_t = \left[\int_0^1 c_t(z)^{\frac{\theta-1}{\theta}} dz \right]^{\frac{\theta}{\theta-1}}, \tag{2}$$

where $c_t(z)$ denotes the household consumption of good z at time t, and $\theta > 1$ is the elasticity of substitution between the differentiated goods.

Expenditure minimization by the household implies that the demand for differentiated good z in period t is given by:

$$c_t(z) = C_t \left(\frac{p_t(z)}{P_t} \right)^{-\theta}, \tag{3}$$

where $p_t(z)$ is the price of differentiated good z in period t,and P_t is the aggregate price level in period t, given by:

$$P_t = \left[\int_0^1 p_t(z)^{1-\theta} dz\right]^{\frac{1}{1-\theta}}. \tag{4}$$

The budget constraint of the household is given by:

$$P_t C_t + E_t[D_{t,t+1} B_{t+1}] \leq B_t + W_t L_t + \int_0^1 \Pi_t(z) dz, \tag{5}$$

where B_{t+1} is a random variable that denotes the state-contingent payoffs of the portfolio of financial assets purchased by the households in period t and sold in period $t+1$, $D_{t,t+1}$ denotes the stochastic discount factor that prices these payoffs in period t, W_t is the wage rate at time t, and $\Pi_t(z)$ denotes the profits of firm z in period t.

The first-order conditions of the household's utility maximization subject to their budget constraint are:

$$D_{t,T} = \beta^{T-t} \left(\frac{C_T}{C_t}\right)^{-\gamma} \frac{P_t}{P_T}, \tag{6}$$

$$\frac{W_t}{P_t} = \omega L_t^{\psi} C_t^{\gamma}, \tag{7}$$

where equation 6 is the standard intertemporal Euler equation linking asset prices to the path of consumption, and equation 7 is the optimal labor supply condition.

Firms The economy is divided into J sectors. In each sector, there is a continuum of firms indexed by z. Each firm produces a differentiated good using intermediate products as well as labor. We follow Nakamura and Steinsson (2010) in incorporating intermediate products, but excluding them by setting $s_m = 0$ does not alter our results. The firm's production function is of the form:

$$y_t(z) = A_t(z) L_t(z)^{1-s_m} M_t(z)^{s_m}, \tag{8}$$

where $L_t(z)$ denotes the labor hours employed by firm z in period t, $M_t(z)$ is a composite of intermediate inputs used by firm z in period t, and $A_t(z)$ denotes firm z's productivity in period t. The composite of intermediate inputs is given by:

$$M_t(z) = \left[\int_0^1 m_t(z, z')^{\frac{\theta-1}{\theta}} dz'\right]^{\frac{\theta}{\theta-1}}, \tag{9}$$

where $m(z, z')$ denotes the quantity of firm z''s output used as an input by firm z.

Cost minimization by the firm implies that the demand for intermediate good z' by firm z in period t is given by:

$$m_t(z, z') = M_t(z) \left(\frac{p_t(z')}{P_t} \right)^{-\theta}. \tag{10}$$

Adding consumer demand in equation 3 to intermediate demand in equation 10 yields the total demand for firm z's output as a function of its relative price, given by:

$$y_t(z) = Y_t \left(\frac{p_t(z)}{P_t} \right)^{-\theta}, \tag{11}$$

where $Y_t = C_t + \int_0^1 M_t(z)dz$.

Finally, we assume that the firm's idiosyncratic productivity follows an AR(1) process in logs:

$$\log A_t(z) = \rho \log A_{t-1}(z) + \epsilon_t(z), \tag{12}$$

where $\epsilon_t \sim N(0, \sigma_{\epsilon,j}^2)$ are independent, and the variance of the firm's idiosyncratic shocks is sector-specific.

Each firm z maximizes the expected discounted value of its lifetime profit stream, given by:

$$E_t \sum_{\tau=0}^{\infty} D_{t,t+\tau} \Pi_{t+\tau}(z), \tag{13}$$

subject to its production function in equation 8 and demand for its product in equation 11.

Firm z's profits in period t are given by:

$$\Pi_t(z) = p_t(z)y_t(z) - W_t L_t(z) - P_t M_t(z) - \chi_j W_t I_t(z) - P_t U, \tag{14}$$

where $I_t(z)$ is an indicator variable equal to 1 if the firm changes its price in period t and 0 otherwise. We introduce nominal rigidity into the model in the form of a menu cost χ_j by assuming that a firm in sector j needs to hire an additional χ_j units of labor if it wants to change its price. U is a fixed cost of production in terms of the real output—it does not affect the firm's optimal decision but is needed to reconcile the large estimated markups with the small profits observed in the national accounts data.

The presence of nominal rigidity makes the firm's optimization problem dynamic. We can write it in a recursive form as[33]:

$$V\left(A_t(z), \frac{p_{t-1}(z)}{P_t}, \frac{S_t}{P_t}\right) = \max_{p_t(z)} \left\{\Pi_t^R(z) + E_t\left[D_{t,t+1}^R V\left(A_{t+1}(z), \frac{p_t(z)}{P_{t+1}}, \frac{S_{t+1}}{P_{t+1}}\right)\right]\right\}. \tag{15}$$

Monetary Authority We assume that the monetary authority targets a path for the nominal aggregate demand, $S_t = P_t C_t$. Specifically, the log of the nominal aggregate demand follows a random walk with drift:

$$\log S_t = \mu + \log S_{t-1} + \eta_t, \tag{16}$$

where μ represents trend inflation, and $\eta_t \sim N(0, \sigma_\eta^2)$ are independent.

Equilibrium The general equilibrium of the model consists of a sequence of stochastic price and quantity variables that satisfy the household's utility maximization problem, firms' profit maximization problems, and market clearing conditions, and are consistent with the given evolution of exogenous variables.

Solving for the equilibrium is an intractable problem as the state space of the firm's problem includes the aggregate price level P_t, which is an infinite dimensional endogenous state as per equation 4. To make the model tractable, we follow Nakamura and Steinsson (2010) and assume that the firm's perceived evolution of the aggregate price level depends only on the nominal aggregate demand deflated by the preceding period's aggregate price level:

$$\frac{P_t}{P_{t-1}} = \Gamma\left(\frac{S_t}{P_{t-1}}\right). \tag{17}$$

This assumption makes the model tractable, as P_{t-1}, though endogenous, is in the firm's information set at time t, and S_t follows an exogenous process. The general equilibrium solution is then obtained using value function iteration on a discretized state space. We refer the reader interested in the details of the solution to the online appendix of Nakamura and Steinsson (2010).

4.1 Calibration

Our goal is to calibrate the model to match the empirical distribution of price-change statistics across products. Our empirical distribution of price-change statistics is over 613 CPI/PPI products. To reduce the computational time needed for our analysis, we aggregate our

[33] See appendix D for details.

distribution over 613 products to 14 sectors. We do this by separating the products into 14 different sectors ranked by their frequencies of price change; that is, each group contains products that have similar frequencies of price change.[34] We then compute the sector-level frequency of price change and absolute size of price changes by taking the weighted mean of the corresponding statistics for products within each of the 14 sector using the weights for the products from their distribution in 1983, which is the mid-point of our sample period.[35] We then translate the distribution of products in the economy to the distribution of sectors. We compute the weight for each sector by simply summing up the share of the economy assigned to each product that is included in that sector. We do this for every year from 1947 through 2019 to obtain a distribution of sectors across the years. See appendix E for more details about how the distribution of sectors changed over our sample period.

When calibrating the model to match the distribution of price-change statistics across the sectors in 1983, we estimate only the parameters pertaining to nominal rigidity (menu costs) and firms' idiosyncratic productivity, that is, χ_j and $\sigma_{\epsilon,j}$. We calibrate the remaining parameters prior to the estimation, based on Nakamura and Steinsson (2010). On the household side, we assume log utility of consumption ($\gamma = 1$), linear disutility of labor ($\psi = 0$), and a monthly discount factor $\beta = 0.96^{1/12}$. We set ω so that the labor supply in the flexible-price steady state is $1/3$ and set $\theta = 4$. In the nominal aggregate demand process, we set $\mu = 0.0028$ and $\sigma_\eta = 0.0065$. In the firm's productivity process, we set $\rho = 0.7$.

We estimate the sector-specific menu costs (χ_j) and standard deviation of firms' idiosyncratic productivity shocks ($\sigma_{\epsilon,j}$) to match the mean frequency of price change and absolute size of price changes for all 14 sectors. Our estimation uses a simulated method of moments (SMM) based on minimizing the sum of squared deviations between the sectoral data moments and their model counterparts. The SMM estimates depend on the distribution of sectors or the sector weights that we input into the model, which we set to its 1983 value.

Since we need to estimate a large number of parameters (14×2) in general equilibrium, and numerical computation of the Γ function (that pins down the perceived inflation) is

[34] These groups are not identical in size because sometimes many products have the same median frequency of price change and we ensure that all products with the same frequency of price change are in the same sector.

[35] An alternative aggregation would have involved grouping products into similar industries or aggregate industries. The reason we do not aggregate to a 51-industry menu cost model as in figure 3 is that the industries associated only with PPI products do not have a corresponding statistic for the absolute size of price changes, which is one of the two moments that we target for each sector in our calibration. The reason we do not consider a menu cost model with our 12 aggregated industries as in figure 2 is because such an aggregation fixed the frequency of price change for the aggregate industry, even though we know that the relative share of different products within an aggregate industry may change over time, which could alter the frequency of price change. We largely avoid this problem by instead aggregating products by their frequency of price change, so that changes in the weights of different industries have little impact on the mean frequency of price change at the sectoral level.

time-consuming, we speed up the estimation by proceeding in two steps. First, we guess a function Γ and estimate the menu cost and standard deviation parameters holding Γ fixed. At the end of the first step, we have "naive" estimates of menu costs and standard deviations of the firms' idiosyncratic productivity shocks for all 14 sectors. Second, we solve the general equilibrium of the full multisector menu cost model using the naive parameter estimates obtained in the first step. At the end of the second step, we have the model-consistent Γ as well as correct model moments based on the naive parameter estimates. We check to see if the model moments are close enough to the data moments. If they are, we have successfully estimated our parameters of interest. If they are not, we update our guessed Γ to be equal to the model-consistent Γ and redo steps 1 and 2. We repeat this process until convergence.[36]

Table 5 provides a summary of our estimation exercise. For each sector it shows the two target moments, the sector's weight in the economy in 1983, and the SMM-estimated menu cost and standard deviation of the idiosyncratic productivity shocks for its firms. While there is no one-to-one mapping between the frequency of price change and the menu cost parameter (χ_j) across the sectors, there is an overall negative correlation between the two, as, all else being equal, a higher menu cost implies that firms change their prices less frequently.

Our calibrated model reasonably matches moments that we did not target in 1983 as well as across other years, which supports its validity. Table 6 summarizes the performance of the model with respect to two moments—mean and median—for three different price-change statistics in 1947, 1983, and 2019. Our estimation attempts to match the sectoral means for the frequency of price change and the absolute size of price changes in 1983 to their data values. One test of the validity of our model is to compare the mean frequency of price change and mean absolute size of price changes in our model in years other than 1983 with their corresponding values obtained in our empirical analysis. This is because the only element of the model that we change when considering alternative years are the weights of the sectors. As shown in Panel A of table 6, the mean frequency of price change is 24.24 percent , 18.67 percent , and 15.11 percent in 1947, 1983, and 2019, respectively, in the data, and 24.03 percent , 18.57 percent , and 14.97 percent in 1947, 1983, and 2019, respectively, in the model. We obtain a similarly good match for the absolute size of price changes: 10.7 percent , 10.01 percent , and 10.29 percent in 1947, 1983, and 2019, respectively, in the data, and 9.39 percent , 10.09 percent , and 10.33 percent in 1947, 1983, and 2019,

[36] To obtain good initial values for the *fminsearch* in MATLAB, we start by estimating the model on a sector-by-sector basis, that is, by estimating 14 different one-sector models, thereby estimating only two parameters at a time to match the two data moments of the sector in question. We use the results of this estimation as initial values in the next part, where we add one additional sector to the model in each run. That is, we first estimate a one-sector model, then a two-sector model, then a three-sector model, and so on, until we get to a 14-sector model. The sector weights are set equal to their respective weights in the data in 1983 in each of these runs, with the total weight of all the sectors normalized to 1.

Table 5: Calibration

Sector #	Target Moments: Price change		Estimated Parameters		Weight (%)
	Frequency (%)	Absolute Size (%)	χ_j	$\sigma_{\epsilon,j}$	(1983)
1	2.34	13.59	0.0057	0.0685	7.93
2	3.34	14.16	0.0074	0.0824	3.72
3	3.64	17.54	0.0043	0.0877	11.24
4	4.39	9.94	0.0013	0.0471	6.03
5	5.34	8.54	0.0008	0.0403	6.74
6	6.15	10.92	0.0011	0.0531	7.27
7	7.59	6.44	0.0004	0.0306	8.97
8	8.99	9.31	0.0005	0.0377	9.64
9	10.11	8.38	0.0005	0.0396	3.02
10	13.25	6.75	0.0001	0.0242	7.15
11	22.34	13.93	0.0000	0.0195	3.18
12	30.23	8.71	0.0004	0.0712	11.60
13	49.61	7.78	0.0002	0.0857	6.16
14	92.95	5.31	0.0000	0.0513	7.30

The table summarizes, for each sector (numbered in column 1), target moments from the 1983-weighted price-change distribution of the 14-sector aggregation in columns 2 and 3. Columns 4 and 5 contain the estimated parameters—menu costs and standard deviation of the firms' idiosyncratic productivity shocks—for all 14 sectors. The last column provides the sector weights used in the estimation. Source: Authors' calculations.

respectively, in the model. Another test is to compare the mean of an untargeted statistic, such as the probability of positive price change, from our model with the mean from the data. We again find reasonably close numbers: 70.21 percent , 71.92 percent , and 74.85 percent in 1947, 1983, and 2019, respectively, in the data, and 71.25 percent , 73.04 percent , and 75.08 percent in 1947, 1983, and 2019, respectively, in the model. Panel B of table 6 shows the corresponding analysis for the medians of the distributions of the three price-change statistics, which is an altogether untargeted moment in our estimation exercise. The trend in the model matches the data reasonably well across all three years even when we consider the median.[37] Therefore, overall our calibrated model appears to be fairly consistent with our data.

Table 6: Moments of the Distributions of Price-Change Statistics: Data versus Model

Year	Frequency (%)		Absolute Size (%)		Prob. Positive (%)	
	Data	Model	Data	Model	Data	Model
Panel A. *Mean*						
1947	24.2	24.0	10.8	9.4	70.2	71.2
1983	18.7	18.6	10.0	10.1	71.9	73.0
2019	15.1	15.0	10.3	10.3	74.9	75.0
Panel B. *Median*						
1947	9.2	9.2	9.8	8.6	70.1	70.5
1983	8.2	7.4	9.4	9.9	73.1	73.4
2019	6.9	7.3	9.4	9.9	75.8	73.6

The table compares the moments of the distributions of three different price-change statistics from the model with the data for three different years. Panel A compares the means, while Panel B compares the medians. The three different years (in rows) are 1947, 1983, and 2019. The three price-change statistics (in columns) are frequency of price change, absolute size of price changes, and probability of a positive price change. Source: Authors' calculations.

5 Model Results

Our primary goal is to the use the model to analyze the impact of shifts in the industrial composition of the US economy and the consequent shifts in the distribution of products (and hence, sectors) on the slope of the Phillips curve. To do this, we first solve the calibrated model given the baseline distribution of sector weights (set to its 1983 value) and obtain

[37]The reason that we do not obtain a more precise match between the median numbers from the model and those from the data is that the model has only 14 aggregate sectors compared to 613 products in the data, which means there is a much smaller set of possible median values in the model.

a Phillips curve for 1983. To derive the Phillips curve from the model, we simulate the response of inflation and consumption to aggregate nominal demand shocks η_t (in equation 16). We then plot a version of the Phillips curve—the simulated (log) inflation against the negative of the simulated (log) consumption.[38]

To investigate the impact of a shift in the industrial composition on the slope of the Phillips curve, we change the distribution of sectors (that represent aggregated products) in the model to that implied by the shift in industrial composition in the data, all else being equal. Among the things that we hold constant, we include the parameters of the model (including the estimated menu costs and standard deviations of idiosyncratic productivity shocks) as well as the series of aggregate nominal demand shocks. In this way, we are able to isolate the change in the slope of the Phillips curve due to shifts in the distribution of products that arise solely due to a shift in the industrial composition. Since our data allow us to compute a distribution of sectors for every year from 1947 through 2019 (see figure 20 in appendix E), we can re-solve the model and simulate a Phillips curve for every year over this period.

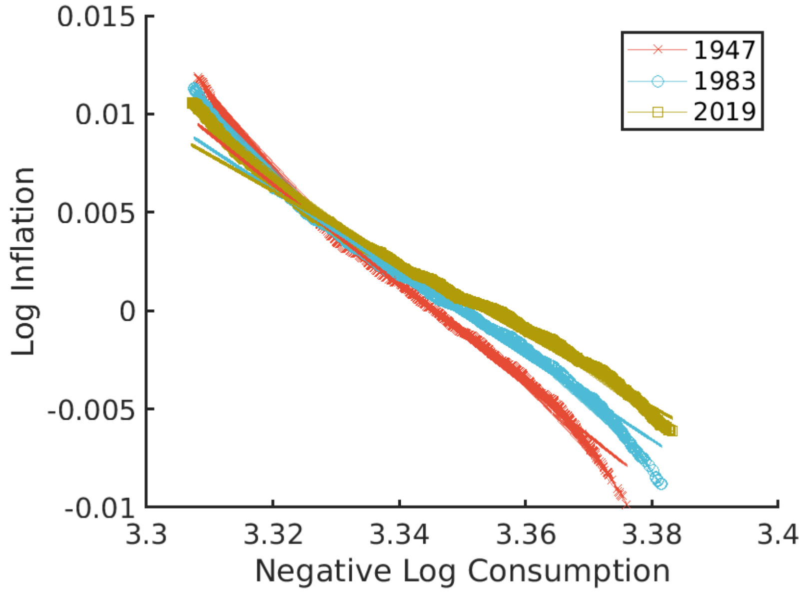
The Phillips curves for three years—1947, 1983, and 2019—are shown in Figure 6.[39] The graph's color-symbols (olive, blue, and red) plot the nonlinear relationship between inflation and negative consumption, with each color-symbol corresponding to a different year. In order to assess the slope of the nonlinear Phillips curve, we then overlay a line of best linear fit onto the graph for every year, color coded to match the nonlinear Phillips curve for that year. We measure the slope of the Phillips curve as the slope of this line of best linear fit. Using this measure, we find that there was a gradual decline in the slope from 1947 to 2019. In particular, the slope of the Phillips curve flattened from –0.26 in 1947 to –0.21 in 1983 to –0.18 in 2019. This finding implies that shifts in the industrial composition of the US economy over the 1947–2019 period caused a 30.7 percent decrease in the slope of the Phillips curve.[40]

[38]While the empirical Phillips curve is based on the relationship between inflation and unemployment, we show the relationship between inflation and negative consumption, since there is no unemployment in our model, as wages are flexible and therefore the labor market always clears.

[39]While we simulate a Phillips curve for every year from 1947 through 2019, we choose to show the curves for only three years for the sake of legibility in the graph.

[40]The Phillips curves using the full sample of 5 million simulation points is shown in Figure 21 in Appendix F. We see that the curves across the years have some flat sections (initial few points) that arise due to our numerical computation method, which relies on discretizing the grid for firms' real prices. Importantly, however, our finding on the flattening of the Phillips curve is not driven by these flat sections. In fact, these flat sections constitute a very small proportion of the total number of simulation points in each year—0.03 percent , 0.03 percent , and 0.04 percent in 1947, 1983, and 2019, respectively. Therefore, even if we include these flat sections in our slope computations, the slopes remain precisely unchanged. We present the Phillips curve ignoring these flat sections in the main text, but the full graph is included in the appendix for interested reader.

Figure 6: Evolution of the Phillips Curve: 1947–2019



The figure shows the relationship between (log) inflation and negative (log) consumption for three years: 1947, 1983, and 2019. The graph's color-symbols plot the nonlinear relationship for different years: olive for 2019, blue for 1983, and red for 1947. The graph's lines of the same colors show the approximate linear relationship (estimated using a regression line through the nonlinear curve) for the corresponding year. Source: Authors' calculations.

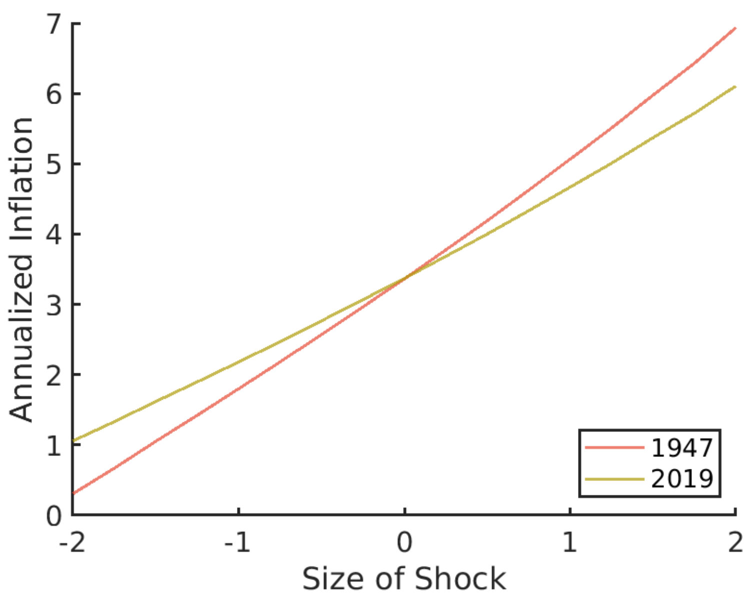
In appendix G, we show that a single-sector New Keynesian model with Calvo price stickiness, calibrated to the median frequency of price change that we estimate in the data, implies a similarly large decline in the slope of the Phillips curve.[41]

A direct implication of a flatter Phillips curve is that inflation becomes relatively less responsive to nominal demand shocks. To show this more formally using our simulations across the years, we categorize the simulation points into bins based on the size of the shock. Specifically, we define the size of the shock depending on how many standard deviations it is away from zero (which is the mean of the nominal aggregate demand shock, η_t, in the model). We define bins of 0.25 standard deviations each and assign the size of the bin as

[41] There are alternative methods to model multisector general equilibrium menu cost models (for example see Mongey (2021). However, we feel confident that shifts in industrial composition have led to a decline in the slope of the Phillips Curve, because we find this results under both a standard multisector menu cost model and a Calvo price model. Our finding on the magnitude of the decline in the slope also matches the the decline estimated in Rubbo (2020) who focuses on the role of rising intermediate flows in production. Rubbo (2020), however, calibrates a much smaller slope ($\sim$ 0.12 to 0.08 vs $\sim$ 0.25 to 0.18), which is probably due to Calvo assumption in her framework relative to the menu cost assumption in ours. Importantly also, we recognize that there are certainly forces other than industrial composition that matter for the slope of the Phillips curve and that our framework does not capture. For example, Hazell et al. (2020) show the importance of inflation expectations in affecting the slope. Therefore, we do not intend to target the slope (level) with our model but rather analyze the implications of shifts in industrial composition for its change.

the median of the shock sizes that fall within that bin. By this definition, the size $= 0$ bin includes shocks from –0.125 to +0.125 standard deviations (SD), the size $= 0.25$ bin includes shocks from +0.125 to +.375 SD, and so on, until the size $= 2$ bin includes shocks from +1.875 to +2.125 SD. We define the negative size bins similarly. We then compute the inflation response for the different shock sizes as the mean of the simulated inflation rates across the simulation points that are included in the given bin. Since our model is calibrated at a monthly frequency, we then annualize the mean inflation response.[42] We repeat this exercise for each year to enable a comparison of the inflation response to demand shocks across the years as the industrial composition of the United States changed. The results of this exercise are shown in figure 7, which plots the inflation response to positive and negative shocks of varying sizes.

Figure 7: Missing Deflation and Missing Inflation



The figure shows the response of annualized inflation (y-axis) to nominal aggregate demand shocks of varying sizes (x-axis) for three different years.The sizes of the shocks vary from –2 SD to +2 SD, with 25 bins within these extremes spaced out by 0.25 SD each. The sizes of the bins on the x-axis refer to the midpoints of the respective bins. The bins (sizes) are as follows: –2.125 to –1.875 SD (–2 SD), –1.875 to –1.625 SD (–1.75 SD), . . ., –0.375 to –0.125 SD (0.25 SD), –0.125 to +0.125 SD (0 SD), +0.125 to +0.375 SD (0.25 SD), . . ., +1.875 to +2.125 SD (2 SD). The inflation on the y-axis is the annualized mean of the simulated inflation response across all the shocks that fall within the corresponding bin on the x-axis. Source: Authors' calculations.

We find that the graph for 2019 is overall flatter relative to 1947. This implies that in 2019, the response of inflation to nominal demand shocks was relatively muted compared with 1947.

[42]The model solves for log inflation. If the monthly log gross inflation is π, then the annualized percentage change in inflation is $[exp(12\pi) - 1] \times 100\%$.

Thus, changes in industrial composition can indeed help to explain the missing deflation during the recent recessions.[43] [44]

As the economy reopened following the COVID-19 pandemic, there was a large increase in inflation—it was 6.8 percent in November 2021 and reached 8.5 percent in March 2022. These elevated inflation levels may seem incompatible with our finding that the Phillips Curve has flattened due to shifts in industrial composition. However, we demonstrate in appendix H that this is not the case. We show that, even in 2019 under a flatter Phillips Curve, large, positive demand shocks as well as persistent positive demand shocks, both small and large, cause significant inflation. We find the effect is not much smaller than under the 1947 Phillips Curve. For example, small positive demand shocks hitting the economy for six consecutive months would have resulted in 8.7 percent inflation in 2019 compared with 9.5 percent in 1947. Therefore, our model and the finding that the Phillips Curve has flattened due to shifts in industrial composition remains valid despite high inflation in 2022.

6 Conclusion

In this paper, we isolated the impact of changes in industrial composition on the distribution of products and consequently the distribution of the frequency of price change across the products for the US economy. We then analyzed the degree to which these distributional changes affected the slope of the Phillips curve over the 1947–2019 period. By combining annual data on the industrial composition of the US economy with static data on the frequency of price change of products underlying the CPI and PPI, we estimated yearly distributions of the frequency of price change across the CPI/PPI products for the US economy. We found that firms have been changing their prices less frequently across the entire distribution, with the median frequency of price change per month falling from 9.2 percent in 1947 to 6.9 percent in 2019. The corresponding means also fell from 24.2 percent to 15.1 percent . This finding implies that the US economy exhibited greater aggregate price stickiness in 2019 than in 1947. Using a similar methodology, we also analyzed the impact of shifts in the

[43] Our model can explain only the part of the missing deflation puzzle that was due to shifts in the industrial composition and the consequent flattening of the Phillips curve. Other papers highlight the role of firm's inflation expectations driven by oil price changes ((Coibion and Gorodnichenko, 2015)) as well as anchored inflation expectations in explaining the puzzle, so those could certainly be additional explanations that are unrelated to the slope of the Phillips curve.

[44] This result is of a similar flavor to (Galesi and Rachedi, 2019), which finds monetary policy transmission to inflation is weaker in countries that have greater services deepening (higher share of services in intermediate inputs). However, we consider a richer industry composition (51 sectors) in our empirics as well as model (14-sector with menu costs).

industrial composition on the distribution of the absolute size of price changes as well as the probability that a given price change is positive.

Higher aggregate price stickiness has crucial implications for the transmission of nominal shocks to the real economy. In order to investigate these implications, we used a calibrated general equilibrium multisector menu cost model. The model, in particular, allowed us to analyze the implications for the slope of the Phillips curve of shifts in the distributions of price-change statistics arising due to to shifts in the industrial composition of the economy. We found that shifts in the industrial composition of the US economy over the 1947–2019 period flattened the slope of the Phillips by 30.7 percent . We then showed that despite a flatter Phillips curve, large or persistent positive shocks to nominal aggregate demand still result in significant inflation. This helps to reconcile the inflation spikes observed in the first quarter of 2022 for the United States, which may at first appear to contradict the predictions of a flatter Phillips curve.

A flatter Phillips curve implies that monetary policymakers face a greater trade-off in stabilizing inflation versus output (or employment). Our paper reveals that the slope of the Phillips curve is more than one-quarter flatter than it was seven decades ago due to long-term structural forces that are unlikely to revert in the short run. Thus, monetary policymakers must account for the flattening in their policy decisions. We hope more broadly that our paper inspires further work to study the aggregate implications of the evolution of heterogeneity across the economy over time.

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Online Appendix

A Empirics Summary Tables

Table 7: Summary of Industry Price Frequencies, Shares, and Corresponding Products

Industry	Freq. (%)	1947 (%)	1983 (%)	2019 (%)	CPI, PPI	Products (Weight, Frequency (%))
Legal services	1.6	0.5	1.4	1.9	CPI	Legal services (1, 1.6).
Data processing, internet publishing, and other information services	2.1	0.2	0.4	1.8	CPI	Other information services (1, 2.1).
Transit and ground passenger transportation	2.3	0.9	0.2	0.4	CPI	Intracity mass transit (0.68, 2.3). Taxi fare (0.21, 4.4). Intercity bus fare (0.11, 27.8).
Apparel and leather and allied products	3.1	2.1	0.9	0.1	PPI	All other footwear (0.11, 0.4). Leather/leather-like goods, n.e.c. (0.11, 0.5). Apparel (0.11, 2.3). Women's footwear (0.11, 2.9). Gloves (0.11, 3.1). Men's footwear (0.11, 4.3). Athletic footwear (0.11, 5.9). Finished and unfinished leather (0.11, 17.1). Hides and skins, incl. cattle (0.11, 59.9).
Publishing industries, except internet (includes software)	3.3	1.1	1.2	2.1	CPI, PPI	Book publishing (0.51, 3.3). Books purchased through book clubs (0.2, 8.3). College textbooks (0.12, 12.6). Elementary and high school books and supplies (0.07, 5.5). Encyclopedias and other sets of reference books (0.05, 2.4). Computer software (0.04, 7.9).
Ambulatory health care services	3.4	1.0	3.0	5.3	CPI	General medical practice (0.5, 3.4). Prosthodontics and implants (0.29, 4.5). Optometrists/opticians (0.09, 5.5). Physical medicine (0.09, 2.4). Dental preparations (0.03, 6.1).
Other transportation and support activities	3.5	0.8	0.9	0.9	CPI	First class mail (0.98, 3.5). Delivery services (0.02, 29.3).
Federal Reserve banks, credit intermediation, and related activities	3.5	1.7	3.9	4.8	CPI	Periodic chk act fees, trans fees, pers chks (1, 3.5).
Computer and electronic products	3.8	1.4	2.8	2.1	PPI	Integrating and measuring instruments (0.06, 2.4). Communication and related equipment (0.06, 2.7). Computer terminals and parts (0.06, 2.9). Fluid meters and counting devices (0.06, 3.3). Process control instruments (0.06, 3.5). Measuring & controlling devices, n.e.c. (0.06, 3.5). Speakers and commercial sound equipment (0.06, 3.5). Computer peripheral equipment and parts (0.06, 3.8). Precorded cd/tape/record producing (0.06, 3.9). Environmental controls (0.06, 5.0). Transformers and power regulators (0.06, 6.3). Television receivers (0.06, 6.6). Computer storage devices (0.06, 10.6). Other home electronic equipment (0.06, 13.2). Electronic computers (0.06, 29.9). Electronic components and accessories (0.03, 3.1). Engineering and scientific instruments (0.03, 5.1). Miscellaneous electrical mach and equip (0.03, 5.5).
Miscellaneous manufacturing	3.8	0.8	0.7	0.7	PPI	Pens, pencils, and marking devices (0.06, 1.7). Jewelry and jewelry products (0.06, 2.0). Gaskets, packing, and sealing devices (0.06, 2.4). Brooms and brushes (0.06, 2.4). Needles, pins, and fasteners (0.06, 2.5). Toys, games, and children's vehicles (0.06, 2.7). Miscellaneous products, n.e.c. (0.06, 3.2). Ophthalmic goods (0.06, 3.6). Buttons, button blanks, and parts (0.06, 3.8). Sporting and athletic goods (0.06, 4.7). Surgical appliances and supplies (0.06, 5.1). Industrial safety equipment (0.06, 5.1). Musical instruments (0.06, 6.1). Caskets (0.06, 7.5). Dental equipment and supplies (0.06, 8.4). Medical instruments and equipment (0.06, 8.5). Engineering and scientific instruments (0.03, 5.1).

Printing and related support activities	3.9	0.7	0.7	0.3	PPI	Services for the printing trade (0.14, 0.3). Blankbooks, binders, and bookbinding work (0.14, 2.7). Commercial printing (0.14, 3.6). Newspapers (0.14, 3.9). Periodicals (0.14, 4.4). Manifold business forms (0.14, 9.7). Book printing (0.14, 11.0).
Administrative and support services	4.3	0.5	1.8	4.1	CPI	Domestic services (0.52, 4.3). Gardening or lawn care services (0.43, 7.8). Automobile service clubs (0.05, 4.3).
Furniture and related products	4.6	0.6	0.5	0.2	PPI	Furniture and fixtures n.e.c. (0.09, 2.7). Metal household furniture (0.09, 3.3). Household furniture, n.e.c. (0.09, 3.4). Metal office furniture and store fixtures (0.09, 3.8). Wood office furniture and store fixtures (0.09, 3.9). Upholstered household furniture (0.09, 4.6). Household durables, n.e.c. (0.09, 4.8). Wood household furniture (0.09, 5.1). Bedding (0.09, 5.9). Public building furniture (0.09, 6.4). Porch and lawn furniture (0.09, 8.0).
Machinery	4.7	2.6	2.4	1.1	PPI	Printing trades machinery and equipment (0.02, 2.2). Metal forming machine tools (0.02, 2.3). Scales and balances (0.02, 2.3). Textile machinery and equipment (0.02, 2.5). Oil field and gas field machinery (0.02, 2.6). Office and store machines and equipment (0.02, 2.6). Cutting tools and accessories (0.02, 2.8). Elevators, escalators, and other lifts (0.02, 3.2). Tools, dies, jigs, fixtures & ind. molds (0.02, 3.3). Other special industry machinery (0.02, 3.3). Parts for construction machinery (0.02, 3.3). Industrial process furnaces and ovens (0.02, 3.4). Metal cutting machine tools (0.02, 3.5). Optical instruments and lenses (0.02, 3.7). Photographic equipment (0.02, 3.8). Packing and packaging machinery (0.02, 4.0). Fans and blowers, except portable (0.02, 4.1). Industrial material handling equipment (0.02, 4.2). Service industry machinery and parts (0.02, 4.2). Metalworking machinery n. e. c. (0.02, 4.2). Fluid power equipment (0.02, 4.3). Woodworking machinery and equipment (0.02, 4.4). Conversion burners (0.02, 4.7). Food products machinery (0.02, 4.7). Steam, gas, & hydraulic turbines & parts (0.02, 4.7). Welding machines and equipment (0.02, 4.8). Commercial laundry & dry cleaning equip. (0.02, 4.9). Mining machinery and equipment (0.02, 4.9). Pumps, compressors, and equipment (0.02, 5.0). Lawn and garden equip., ex. garden tractors (0.02, 5.2). Mechanical power transmission equipment (0.02, 5.5). Internal combustion engines (0.02, 5.7). Steam and hot water equipment (0.02, 5.8). Domestic heating stoves (0.02, 6.0). Paper industries machinery (0.02, 6.1). Agricultural machinery and equipment (0.02, 6.8). Power driven hand tools (0.02, 7.4). Power cranes, excavators and equipment (0.02, 7.5). Mixers, pavers, spreaders etc. (0.02, 7.5). Tractors and attachments, excluding parts (0.02, 8.3). Off-highway equipment, excluding parts (0.02, 8.3). Air conditioning and refrigeration equip (0.02, 8.4). Warm air furnaces (0.02, 9.3). Construction machinery and equipment sold (0.02, 15.2). Turbine generator sets and parts (0.02, 23.6). Miscellaneous general purpose equipment (0.01, 3.8).
Food services and drinking places	5.0	2.6	2.4	3.3	CPI	Full service meals and snacks (0.51, 5.0). Limited service meals and snacks (0.28, 6.1). Food at employee sites and schools (0.11, 2.9). Beer, ale, and other malt beverages away from home (0.06, 5.0). Board (0.03, 5.4). Prepared salads (0.01, 7.0).
Electrical equipment, appliances, and components	5.0	1.0	1.1	0.4	PPI	Electric lamps (0.09, 1.0). Lighting fixtures (0.09, 3.2). Electric housewares and fans (0.09, 3.7). Switchgear, switchboard, etc. equipment (0.09, 3.8). Household vacuum cleaners, parts, & attach. (0.09, 4.7). Wiring devices (0.09, 5.0). Major appliances (0.09, 5.4). Motors, generators, motor generator sets (0.09, 5.6). Water heaters, domestic (0.09, 13.3). Electric lamps/bulbs and parts (0.09, 24.2). Electronic components and accessories (0.05, 3.1). Miscellaneous electrical mach and equip (0.05, 5.5).

Textile mills and textile product mills	5.1	2.3	0.7	0.1	PPI	Embroideries and lace goods (0.07, 1.5). Narrow fabrics (0.07, 2.1). Textile housefurnishings (0.07, 2.1). Fabricated products, n.e.c. (0.07, 2.8). Nonwovens and felt goods (0.07, 3.1). Coated fabrics, not rubberized (0.07, 3.3). Threads (0.07, 4.7). Knit fabrics,finished in knitting mills (0.07, 5.1). Knits (0.07, 5.2). Yarns (0.07, 8.3). Textile fibers, yarns and fabrics, n.e.c. (0.07, 8.4). Other fabrics (0.07, 10.8). Soft surface floor coverings (0.07, 10.8). Broadwovens (0.07, 22.4). Broadwovens (0.07, 28.8).
Fabricated metal products	5.2	2.4	2.1	1.1	PPI	Nuclear steam supply systems (0.05, 1.7). Bolts, nuts, screws, rivets, and washers (0.05, 2.0). Cutlery, razors and razor blades (0.05, 2.7). Steel power boilers (0.05, 3.1). Metal tanks (0.05, 3.4). Household flatware (0.05, 3.4). Other miscellaneous metal products (0.05, 3.8). Sheet metal products (0.05, 4.5). Hand and edge tools (0.05, 4.7). Machine shop products (0.05, 5.1). Brass fittings (0.05, 5.2). Small arms and ammunition (0.05, 6.4). Barrels, drums, and pails (0.05, 6.5). Hardware, n.e.c. (0.05, 6.7). Heat exchanges and condensers (0.05, 7.0). Metal doors, sash, and trim (0.05, 7.6). Prefabricated metal buildings (0.05, 8.0). Nonferrous forage shop products (0.05, 9.1). Metal sanitary ware (0.05, 9.5). Metal cans and can components (0.05, 9.8). Struct., arch., pre-eng. metal products (0.05, 10.5). Miscellaneous general purpose equipment (0.02, 3.8). Foundry and forge shop products (0.02, 5.7).
Plastics and rubber products	5.3	0.9	1.0	0.6	PPI	Miscellaneous rubber products (0.11, 3.2). Consumer, institut., & comm. prod., nec. (0.11, 3.2). Hard surface floor coverings (0.11, 4.6). Plastic parts and components for mfg. (0.11, 5.1). Laminated plastic sheets, rods, and tubes (0.11, 5.3). Tires, tubes, tread, & repair materials (0.11, 6.9). Plastic construction products (0.11, 16.1). Unsupp. plastic film/sheet/other shapes (0.11, 17.6). Plastic packaging (0.11, 19.2).
Educational services	5.8	0.4	0.9	1.8	CPI	Full college tuition and fixed fees (0.64, 5.8). Elementary and high school tuition and fixed fees (0.2, 6.2). Housing at school, excluding board (0.13, 4.7). Technical and business school tuition and fixed fees (0.03, 9.2).
Hospitals and nursing and residential care facilities	6.3	0.9	3.1	4.6	CPI	Hospital services (0.96, 6.3). Nursing and convalescent home care (0.04, 5.7).
Motor vehicles, bodies and trailers, and parts	6.5	2.4	2.0	1.1	PPI	Truck and bus bodies (0.18, 5.6). Motor vehicle parts (0.18, 5.7). Truck trailers (0.18, 6.5). Travel trailers and campers (0.18, 8.6). Motor vehicles (0.18, 27.3). Transportation equipment, n.e.c. (0.09, 6.0).
Nonmetallic mineral products	6.9	1.0	0.8	0.4	PPI	Hollowware (0.05, 1.8). Abrasive products (0.05, 3.1). Tableware, kitchenware and other pottery (0.05, 3.1). Cut stone and stone products (0.05, 3.2). Other finished glassware (0.05, 4.1). Clay refractories (0.05, 4.1). Concrete pipe (0.05, 4.2). Precast concrete products (0.05, 4.3). Household glassware (0.05, 4.4). Refractories, non clay (0.05, 4.8). Nonmetallic minerals and products, n.e.c. (0.05, 5.7). Structural clay products, n.e.c. (0.05, 6.9). Brick and structural clay tile (0.05, 8.0). Concrete block and brick (0.05, 8.7). Prestressed concrete products (0.05, 10.2). Mirrors (0.05, 10.3). Flat glass (0.05, 10.4). Ready-mixed concrete (0.05, 11.3). Vitreous china fixtures (0.05, 12.1). Cement (0.05, 18.4). Insulation materials (0.05, 34.1). Gypsum products (0.05, 64.9).
Other transportation equipment	6.9	0.9	1.9	1.1	PPI	Railroad cars and car parts (0.13, 3.4). Aircraft parts and auxiliary equipment, nec (0.13, 4.6). Aircraft engines and engine parts (0.13, 6.6). Aircraft (0.13, 6.9). Ships (0.13, 7.5). Boats (0.13, 11.0). Locomotives and parts (0.13, 11.5). Transportation equipment, n.e.c. (0.07, 6.0).
Social assistance	6.9	0.1	0.4	1.0	CPI	Day care and nursery school (0.89, 6.9). Care of invalids, elderly and convalescents in the home (0.11, 2.8).

Chemical products	7.2	1.9	2.8	2.7	PPI	Cosmetics and other toilet preparations (0.05, 2.8). Medicinal and botanical chemicals (0.05, 3.7). Allied and miscellaneous paint products (0.05, 4.2). Other agricultural chemicals (0.05, 4.2). Photographic supplies (0.05, 4.2). Preparations, veterinary (0.05, 4.9). Prepared paint (0.05, 5.5). Soap and synthetic detergents (0.05, 5.9). Pharmaceutical preparations (0.05, 6.1). Biological products (0.05, 7.2). Other plastic products (0.05, 7.2). Specialty cleaning, polish. & san. prods. (0.05, 7.3). Unprocessed filament yarns (0.05, 8.4). Mixed fertilizers (0.05, 12.9). Basic inorganic chemicals (0.05, 13.9). Misc. chemical prod. and preparations (0.05, 14.9). Thermosetting resins (0.05, 16.8). Paint materials (0.05, 19.7). Basic organic chemicals (0.05, 30.7). Thermoplastic resins (0.05, 46.5). Fertilizer materials (0.05, 56.0).
Mining, except oil and gas	8.0	1.7	0.8	0.4	PPI	Construction sand, gravel, and crushed stone (0.33, 4.9). Anthracite (0.33, 8.0). Bituminous coal and Lignite (0.33, 24.7).
Miscellaneous professional, scientific, and technical services	8.2	1.1	3.5	6.7	CPI	Tax return preparation and other accounting fees (0.48, 5.5). Veterinarian services (0.36, 8.7). Photographer's fees (0.17, 8.2).
Insurance carriers and related activities	8.2	1.4	2.7	4.2	CPI	Motor vehicle insurance (0.87, 8.2). Tenants' insurance (0.13, 7.9).
Other services, except government	8.4	3.9	3.4	3.1	CPI	Beauty parlor services for females (0.31, 3.1). Clutch repair (0.31, 16.8). Funeral expenses (0.11, 8.9). Coin-operated apparel laundry and dry cleaning (0.07, 3.0). Parking fees (0.05, 2.9). Painting entire motor vehicle (0.04, 14.4). Pet services (0.04, 5.8). Film processing (0.03, 9.7). Reupholstery of furniture (0.01, 8.4). Women's and girls' clothing alterations and repairs (0.01, 3.8). Appliance repair (0.01, 11.1). Shoe repair and other shoe services (0.01, 3.8). Replacement of setting for women's rings (0.0, 5.4).
Performing arts, spectator sports, museums, and related activities	9.0	0.4	0.4	1.0	CPI	Admis. to movies, theaters, concerts and other recurring events (0.56, 9.0). Admission to sporting events (0.44, 5.8).
Motion picture and sound recording industries	9.0	1.2	0.7	0.6	CPI	Admis. to movies, theaters, concerts and other recurring events (1, 9.0).
Construction	9.2	4.7	5.4	6.1	CPI	Inside home maintenance and repair services (1, 9.2).
Waste management and remediation services	9.4	0.2	0.3	0.4	CPI	Garbage/trash collection (1, 9.4).
Truck transportation	10.5	0.9	1.3	1.2	CPI	Moving, storage, freight express (1, 10.5).

Retail trade	10.7	12.2	9.9	7.9	CPI	Women's sweaters, and sweater vests (0.01, 3.6). Women's skirts (0.01, 3.8). Women's dress and casual shoes and boots (0.01, 3.5). Jewelry (0.01, 4.1). Cereal (0.01, 11.8). White bread (0.01, 9.8). Men's dress and casual shoes and boots (0.01, 3.2). Men's pants and shorts (0.01, 3.3). Men's shirts (0.01, 4.0). Women's dresses (0.01, 2.4). Diapers and diaper liners (0.0, 7.6). Women's bras, bra sets, girdles and corselets (0.0, 2.7). Cookies (0.0, 9.6). Rice (0.0, 9.9). Fresh rolls, biscuits, and muffins (0.0, 7.2). Women's pantyhose and stockings (0.0, 2.5). Women's swimsuits (0.0, 2.4). Men's suits and formal wear (0.0, 4.5). Cakes and cupcakes excluding frozen (0.0, 6.3). Infants' and toddlers' outerwear (0.0, 3.5). Women's outerwear (0.0, 2.8). Boys' suits and vests (0.0, 3.8). Boys' dress and casual shoes and boots (0.0, 4.6). Girls' dress and casual shoes and boots (0.0, 3.1). Men's plastic raincoats and rain sets (0.0, 1.7). Men's underwear (0.0, 5.1). Men's sweaters and vests (0.0, 1.8). Men's swimsuits (0.0, 2.5). Men's outerwear (0.0, 4.0). Women's suits and suit components (0.0, 5.4). Girls' pants and shorts (0.0, 4.4). Flour (0.0, 11.5). Boys' shirts (0.0, 3.9). Watches (0.0, 3.1). Girls' sweaters (0.0, 5.0). College textbooks (0.0, 12.6). Girls' dresses (0.0, 3.0). Personal computers and peripheral equipment (0.0, 25.8). Men's sport coats and tailored jackets (0.0, 3.7). Girls' underwear (0.0, 1.8). Boys' underwear (0.0, 5.0). Boys' outerwear (0.0, 4.3). Elementary and high school books and supplies (0.0, 5.5). Girls' swimsuits (0.0, 2.9). Boys' swimsuits (0.0, 6.0). Girls' outerwear (0.0, 0.0). Encyclopedias and other sets of reference books (0.0, 2.4). Telephones (0.0, 10.3). Computer software (0.0, 7.9). Calculators and adding machines (0.0, 5.9).
Wood products	18.2	0.9	0.5	0.3	PPI	Miscellaneous millwork products (0.05, 1.3). Boxes (0.05, 3.4). General millwork (0.05, 4.9). Hardwood plywood and related products (0.05, 4.9). Hardwood plywood veneer (0.05, 6.3). Other sawmill & planing mill products (0.05, 6.7). Wood pallets and skids (0.05, 6.8). Prefabricated wood buildings & components (0.05, 8.9). Hardboard, particleboard & fiberboard prods. (0.05, 11.3). Building board, const. paper & felt stock (0.05, 13.7). Mobile homes, nonresidential (0.05, 18.2). Treated wood and contract wood preserving (0.05, 18.4). Mobile homes, residential, double wide (0.05, 18.7). Mobile homes, residential, single wide (0.05, 19.2). Prefabricated structural members (0.05, 20.6). Hardwood lumber (0.05, 21.9). Logs, bolts, timber and pulpwood (0.05, 27.6). Softwood plywood veneer (0.05, 55.2). Softwood lumber (0.05, 61.9). Softwood plywood (0.05, 68.2).
Food and beverage and tobacco products	22.2	5.8	3.1	1.8	PPI	Canned specialties (0.02, 1.5). Confectionery end products (0.02, 2.7). Jams, jellies, and preserves (0.02, 3.6). Meat sauces (0.02, 3.9). Bakery products (0.02, 4.1). Other miscellaneous processed foods (0.02, 4.5). Frozen specialties (0.02, 5.4). Other beverage materials (0.02, 5.7). Cigars (0.02, 5.9). Alcoholic beverages (0.02, 6.6). Pickles and pickle products (0.02, 7.3). Canned vegetables and juices (0.02, 7.4). Other tobacco products (0.02, 8.1). Packaged beverage materials (0.02, 8.7). Stemmed and redried tobacco (0.02, 9.6). Confectionery materials (0.02, 11.9). Canned fruits and juices (0.02, 12.0). Corn oil (0.02, 12.9). Ice cream and frozen desserts (0.02, 14.9). Cigarettes (0.02, 16.5). Frozen fruits, juices and ades (0.02, 22.2). Milled rice (0.02, 25.0). Soft drinks (0.02, 26.3). Frozen vegetables (0.02, 30.5). Raw cane sugar (0.02, 30.9). Flour and flour base mixes and doughs (0.02, 37.7). Unprocessed and packaged fish (0.02, 38.6). Other cereals (0.02, 39.2). Condensed and evaporated milk (0.02, 41.7). Refined sugar (0.02, 42.2). Natural and processed cheese (0.02, 47.4). Processed poultry (0.02, 49.7). Shortening and cooking oil (0.02, 51.4). Meats (0.02, 51.6). Miscellaneous feedstuffs (0.02, 52.4). Processed eggs (0.02, 60.7). Fluid milk products (0.02, 61.7). Formula feeds (0.02, 69.9). Animal fats and oils (0.02, 71.9). Fats and oils, inedible (0.02, 77.2). Vegetable cake and meal feeds (0.02, 78.7). Butter (0.02, 95.3).

Paper products	23.8	1.4	1.1	0.4	PPI	Pressure sensitive products (0.17, 5.9). Converted paper and paperboard products (0.17, 7.3). Paper (0.17, 13.3). Paperboard (0.17, 23.8). Wastepaper (0.17, 43.1). Woodpulp (0.17, 48.4).
Rail transportation	24.1	4.0	0.8	0.3	CPI	Intercity train fare (1, 24.1).
Wholesale trade	25.1	8.2	8.7	8.6	PPI	Luggage and small leather goods (0.5, 3.8). Crude rubber (0.5, 25.1).
Broadcasting and telecommunications	28.4	1.6	4.2	3.2	CPI	Interstate telephone services (0.34, 41.9). Main station charges (0.34, 28.4). Community antenna or cable tv (0.28, 12.4). Cellular telephones (0.02, 13.0). Personal computers and peripheral equipment (0.02, 25.8). Telephones (0.01, 10.3).
Water transportation	30.2	0.2	0.1	0.1	CPI	Ship fares (1, 30.2).
Primary metals	34.8	2.8	1.2	0.4	PPI	Fabricated steel plate (0.07, 2.2). Iron ore (0.07, 5.8). Fabricated ferrous wire products (0.07, 7.5). Nonferrous foundry shop products (0.07, 9.2). Blast and electric furnace products (0.07, 25.6). Nonferrous wire and cable (0.07, 26.9). Steel mill products (0.07, 34.8). Nonferrous mill shapes (0.07, 42.7). Nonferrous metal ores (0.07, 43.0). Secondary nonferrous metals (0.07, 59.4). Nonferrous scrap (0.07, 65.0). Iron and steel scrap (0.07, 66.9). Primary nonferrous metals (0.07, 94.2). Foundry and forge shop products (0.04, 5.7).
Utilities	38.1	1.8	3.7	2.3	CPI, PPI	Electricity (0.44, 38.1). Utility natural gas service (0.19, 72.4). Water and sewerage service (0.12, 10.7). Commercial power, 40 kw demand (0.04, 24.0). Residential electric power (0.04, 25.6). Industrial power, 500 kw demand (0.04, 28.6). Commercial natural gas (0.04, 46.6). Residential natural gas (0.04, 48.7). Industrial natural gas (0.04, 61.7). Natural gas to electric utilities (0.04, 75.6).
Accommodation	41.7	0.8	1.0	1.3	CPI	Rental of lodging away from home (1, 41.7).
Rental and leasing services and lessors of intangible assets	42.4	0.7	1.5	1.8	CPI	Vehicle leasing (0.74, 42.4). Automobile rental (0.16, 56.1). Rental of video tapes and discs (0.1, 10.0).
Air transportation	59.8	0.1	0.6	1.0	CPI	Airline fare (1, 59.8).
Petroleum and coal products	93.7	0.9	0.8	1.1	PPI	Other asphalt roofing (0.1, 5.4). Finished lubricants (0.1, 7.7). Paving mixtures and blocks (0.1, 12.3). Prep. asphalt & tar roofing & siding prod. (0.1, 21.4). Lubricating oil materials (0.1, 80.2). Residual fuels (0.1, 93.7). Petroleum and coal products, n.e.c. (0.1, 97.0). Gasoline (0.1, 99.5). Light fuel oils (0.1, 99.5). Kerosene and jet fuels (0.1, 100.0).
Farms	94.8	10.0	1.7	0.9	PPI	Slaughter ducks (0.05, 7.8). Tree nuts (0.05, 46.0). Domestic apparel wool (0.05, 54.6). Louisiana rough rice (0.05, 76.2). Other grains (0.05, 84.1). Fresh and dried vegetables (0.05, 87.5). Fresh fruits (0.05, 88.7). Hay (0.05, 92.7). Oilseeds (0.05, 94.6). Milk eligible for fluid use (0.05, 94.8). Milk, manufacturing grade (0.05, 94.8). Turkeys (0.05, 96.0). Eggs (0.05, 96.0). Lambs (0.05, 96.1). Leaf tobacco (0.05, 96.9). Cattle (0.05, 98.3). Wheat (0.05, 98.7). Hogs (0.05, 99.3). Chickens (0.05, 100.0). Raw cotton (0.05, 100.0).
Oil and gas extraction	99.6	1.0	2.8	1.3	PPI	Crude petroleum domestic production (0.33, 98.9). Natural gas (0.33, 99.6). Liquefied petroleum gas (0.33, 99.7).

Each row represents one of the industries that we consider in our data. The columns represent the name of the industry, the median monthly frequency of price change (excluding sales) for this industry, whether the products that correspond to this industry are from the CPI or the PPI or both, the industry's share of the economy in 1947, the industry's share of the economy in 1983, the industry's share of the economy in 2019, and the names of the products that correspond to this industry (with the share of the product in its industry and the monthly frequency of price change for the product in brackets), respectively. The industry "Retail Trade" is restricted to the top 50 largest products to save space. Sources: BEA, BLS, World KLEMS.

Aggregate Industry	Industries
Agriculture/Mining/Utilities	Farms; Oil and gas extraction; Mining except oil and gas; Utilities
Construction	Construction
Durable manufacturing	Wood products; Nonmetallic mineral products; Primary metals; Fabricated metal products; Machinery; Computer and electronic products; Electrical equipment appliances and components; Motor vehicles bodies and trailers and parts; Other transportation equipment; Furniture and related products; Miscellaneous manufacturing
Education/Health	Educational services; Ambulatory health care services; Hospitals Nursing and residential care facilities; Social assistance
Entertainment/Dining out	Performing arts spectator sports museums and related activities; Accommodation; Food services and drinking places
Finance/Insurance	Federal Reserve banks credit intermediation and related activities; Insurance carriers and related activities
Information	Publishing industries (includes software); Motion picture and sound recording industries; Broadcasting and telecommunications; Information and data processing services
Legal/Scientific/Technical	Legal services; Miscellaneous professional scientific and technical services
Nondurable manufacturing	Food and beverage and tobacco products; Textile mills and textile product mills; Apparel and leather and allied products; Paper products; Printing and related support activities; Petroleum and coal products; Chemical products; Plastics and rubber products
Retail	Wholesale Trade; Retail Trade
Support services	Administrative and support services; Waste management and remediation services; Other services except government
Transportation	Air transportation; Rail transportation; Water transportation; Truck transportation; Transit and ground passenger transportation; Other transportation and support activities; Rental and leasing services and lessors of intangible assets

Table 8: Aggregated Industry Mapping to Industries

Each row in the table shows an aggregated industry in the left column and the industries that are assigned to that aggregated industry. The mapping is based on BEA standard aggregations of industries. There are 12 aggregated industries and 51 industries. Sources: BEA, BLS, World KLEMS.

B Additional Empirical Results

Table 9: Other Moments of the Distribution of the Frequency of Price Change

Year	Mean	St. Dev.	Skew	Kurtosis
1947	24.24	29.79	1.57	4.10
1957	20.67	26.37	1.92	5.64
1967	18.59	24.09	2.13	6.79
1977	18.65	24.40	2.14	6.77
1987	17.13	22.71	2.31	7.83
1997	16.04	21.41	2.46	8.76
2007	16.53	22.88	2.47	8.49
2017	15.24	21.11	2.62	9.62
2019	15.11	21.00	2.65	9.76

This table provides additional moments of the distribution of the frequency of price change for various years. It is a companion to Table 1. Sources: BEA, BLS, World KLEMS.

Table 10: Size of Absolute Price Change

Year	10	25	50	75	90
1947	5.0	6.7	9.8	14.0	18.8
1957	4.9	6.3	9.8	12.6	18.8
1967	4.5	6.3	9.8	12.6	18.8
1977	4.9	6.3	9.7	12.6	19.3
1987	5.0	6.3	9.7	12.6	20.9
1997	5.1	6.3	9.4	12.6	19.3
2007	5.1	6.3	9.4	12.2	19.3
2017	5.1	6.4	9.4	12.6	19.3
2019	5.1	6.4	9.4	13.1	20.8

The table shows percentiles of the size of the absolute price change distribution from 1947 through 2019 computed using our standard method. This corresponds to Figure 4. The size of the absolute price change is the absolute size of the log change in the price conditional on a change occurring. Sources: BEA, BLS, World KLEMS.

Table 11: Probability of Positive Price Change

Year	10	25	50	75	90
1947	53.1	64.9	70.1	81.1	86.3
1957	53.1	65.4	70.1	79.7	86.3
1967	53.1	64.5	70.1	81.2	86.3
1977	53.1	65.1	70.5	81.3	88.6
1987	53.1	65.8	73.1	82.8	88.8
1997	53.5	65.8	75.8	85.5	89.3
2007	53.5	66.3	75.8	85.9	89.4
2017	53.6	66.9	75.8	86.3	89.4
2019	53.6	68.0	75.8	86.3	89.4

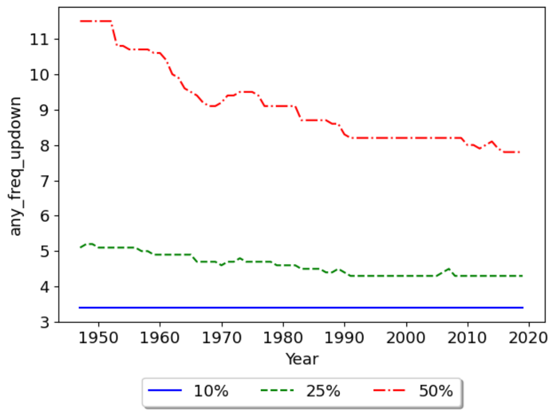
The table shows percentiles of the distribution of the probability with which firms will change their price from 1947 through 2019 computed using our standard method. This corresponds to Figure 5. The probability of a positive price change is the probability with which a price change will be positive. At the risk of belaboring the point, if it is 60 percent , then the probability of a negative price change is 40 percent . Sources: BEA, BLS, World KLEMS.

Table 12: Frequency of Price Change - Including Sales

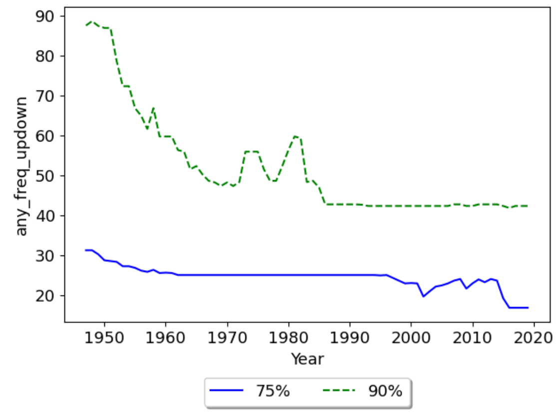
Year	10	25	50	75	90
1947	3.4	5.1	11.5	31.3	87.6
1957	3.4	5.0	10.7	25.9	61.7
1967	3.4	4.7	9.2	25.1	48.7
1977	3.4	4.7	9.1	25.1	48.7
1987	3.4	4.4	8.7	25.1	42.8
1997	3.4	4.3	8.2	24.4	42.4
2007	3.4	4.5	8.2	23.7	42.8
2017	3.4	4.3	7.8	16.9	42.4
2019	3.4	4.3	7.8	16.9	42.4

The table shows percentiles of the frequency of price change distribution from 1947 through 2019. The distribution is computed using an alternative method in which we measure the frequency of price change including sales (so the frequency is higher than in the case without sales). This corresponds to Figure 8. The frequency of price change is the probability (in percentage terms) with which firms change their price each month. Sources: BEA, BLS, World KLEMS.

Figure 8: Frequency of Price Change - Including Sales



(a) For Low Percentiles



(b) For High Percentiles

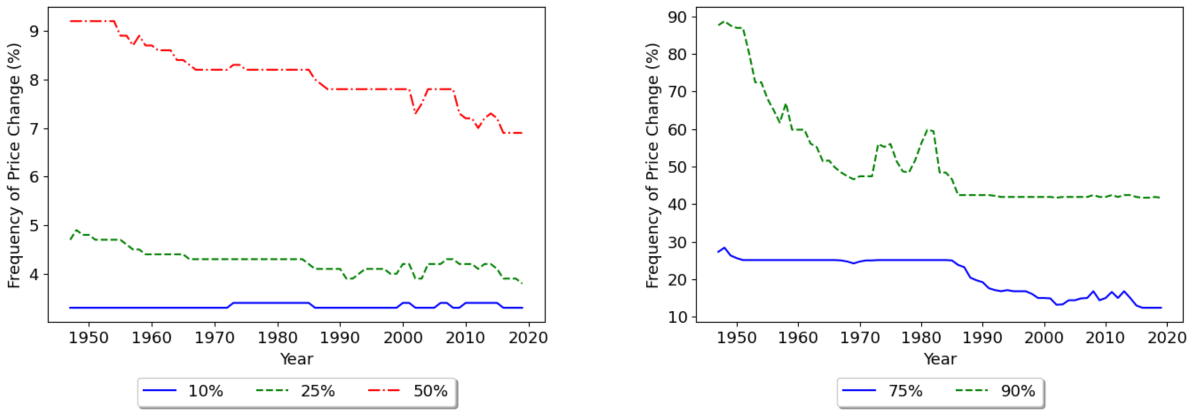
The figure shows percentiles of the frequency of price change distribution from 1947 through 2019. It is computed using an alternative method in which we measure the frequency of price change including sales (so the frequency is higher than in the case without sales). The frequency of price change is the probability (in percentage terms) with which firms change their price each month. Sources: BEA, BLS, World KLEMS.

Table 13: Frequency of Price Change - Mapping Products to One Industry

Year	10	25	50	75	90
1947	3.3	4.7	9.2	27.3	87.6
1957	3.3	4.5	8.7	25.1	61.7
1967	3.3	4.3	8.2	25.0	48.4
1977	3.4	4.3	8.2	25.1	48.7
1987	3.3	4.1	7.9	23.2	42.4
1997	3.3	4.1	7.8	16.8	41.9
2007	3.4	4.3	7.8	15.0	41.9
2017	3.3	3.9	6.9	12.4	41.7
2019	3.3	3.8	6.9	12.4	41.7

The table shows percentiles of the frequency of price change distribution from 1947 through 2019. It is computed using an alternative method in which we map each CPI/PPI product to only one industry. This corresponds to Figure 9. The frequency of price change is the probability (in percentage terms) with which firms change their price each month. Sources: BEA, BLS, World KLEMS.

Figure 9: Frequency of Price Change - Mapping Products to One Industry



(a) For Low Percentiles

(b) For High Percentiles

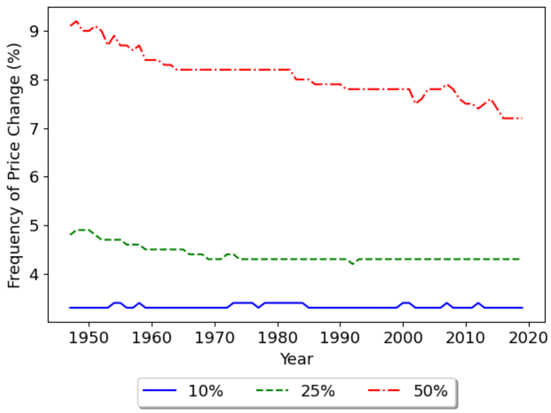
The figure shows percentiles of the frequency of price change distribution from 1947 through 2019. It is computed using an alternative method in which we map each CPI/PPI product to only one industry. The frequency of price change is the probability (in percentage terms) with which firms change their price each month. Sources: BEA, BLS, World KLEMS.

Table 14: Frequency of Price Change - Same Weight for Products

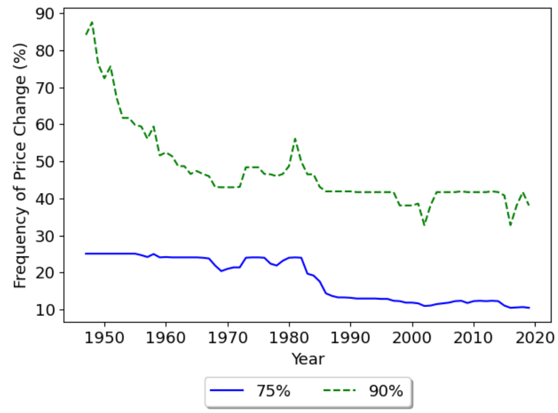
Year	10	25	50	75	90
1947	3.3	4.8	9.1	25.1	84.1
1957	3.3	4.6	8.6	24.2	56.1
1967	3.3	4.4	8.2	23.8	46.0
1977	3.3	4.3	8.2	22.4	46.5
1987	3.3	4.3	7.9	13.7	41.9
1997	3.3	4.3	7.8	12.4	41.7
2007	3.4	4.3	7.9	12.3	41.7
2017	3.3	4.3	7.2	10.6	38.1
2019	3.3	4.3	7.2	10.5	38.1

The table shows percentiles of the frequency of price change distribution from 1947 through 2019. It is computed using an alternative method in which we use the same weights for all products. This corresponds to Figure 10. The frequency of price change is the probability (in percentage terms) with which firms change their price each month. Sources: BEA, BLS, World KLEMS.

Figure 10: Frequency of Price Change - Same Weight for Products



(a) For Low Percentiles



(b) For High Percentiles

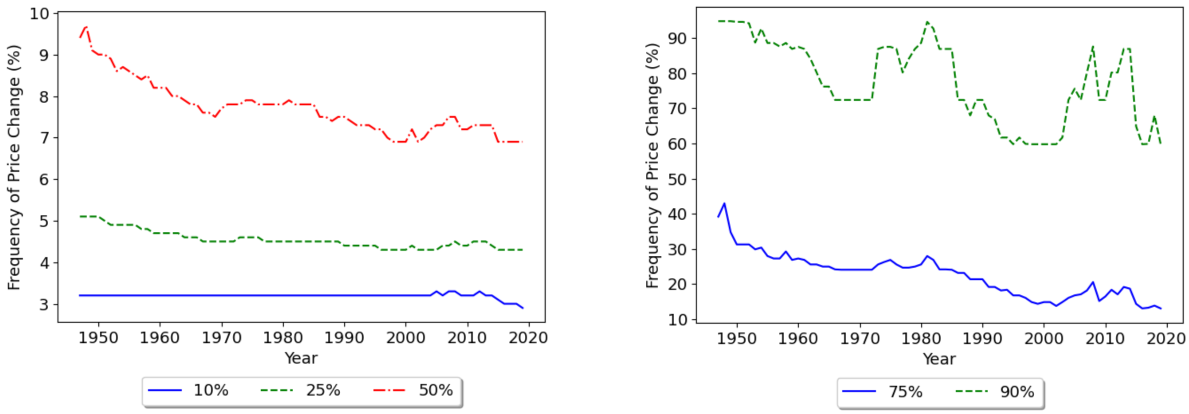
The figure shows percentiles of the frequency of price change distribution from 1947 through 2019. It is computed using an alternative method in which we use the same weights for all products. The frequency of price change is the probability (in percentage terms) with which firms change their price each month. Sources: BEA, BLS, World KLEMS.

Table 15: Frequency of Price Change - Dropping Large Products

Year	10	25	50	75	90
1947	3.2	5.1	9.4	39.2	94.8
1957	3.2	4.8	8.4	27.3	87.6
1967	3.2	4.5	7.6	24.1	72.4
1977	3.2	4.5	7.8	24.7	80.2
1987	3.2	4.5	7.5	23.2	72.4
1997	3.2	4.3	7.0	16.1	59.9
2007	3.3	4.4	7.5	18.2	80.2
2017	3.0	4.3	6.9	13.3	59.9
2019	2.9	4.3	6.9	13.1	59.8

The table shows percentiles of the frequency of price change distribution from 1947 through 2019. It is computed using an alternative method in which we measure the frequency of price change excluding products that have a weight of more than 1 percent of the distribution in 1983. This corresponds to Figure 11. The frequency of price change is the probability (in percentage terms) with which firms change their price each month. Sources: BEA, BLS, World KLEMS.

Figure 11: Frequency of Price Change - Dropping Large Products



(a) For Low Percentiles

(b) For High Percentiles

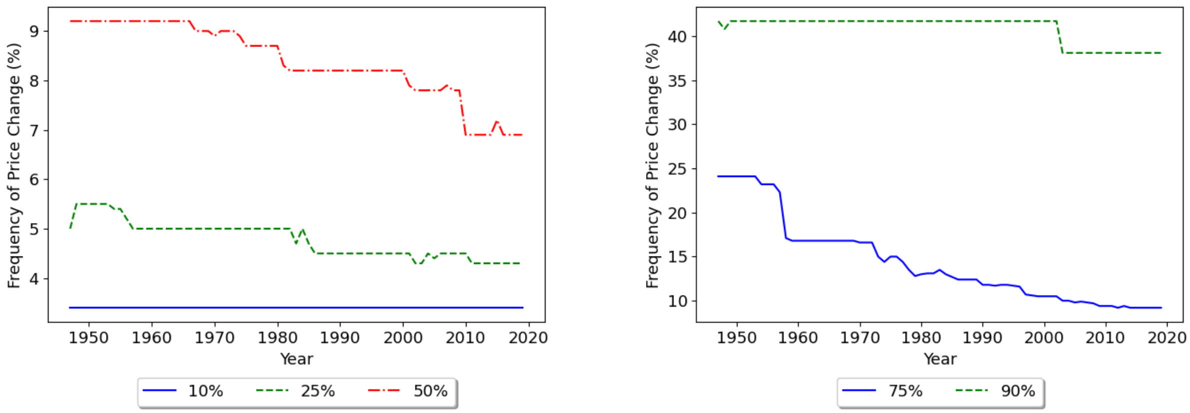
The figure shows percentiles of the frequency of price change distribution from 1947 through 2019. It is computed using an alternative method in which we measure the frequency of price change excluding products that have a weight of more than 1 percent of the distribution in 1983. The frequency of price change is the probability (in percentage terms) with which firms change their price each month. Sources: BEA, BLS, World KLEMS.

Table 16: Frequency of Price Change - CPI Only

Year	10	25	50	75	90
1947	3.4	5.0	9.2	24.1	41.7
1957	3.4	5.0	9.2	22.3	41.7
1967	3.4	5.0	9.0	16.8	41.7
1977	3.4	5.0	8.7	14.4	41.7
1987	3.4	4.5	8.2	12.4	41.7
1997	3.4	4.5	8.2	10.7	41.7
2007	3.4	4.5	7.9	9.8	38.1
2017	3.4	4.3	6.9	9.2	38.1
2019	3.4	4.3	6.9	9.2	38.1

The table shows percentiles of the frequency of price change distribution from 1947 through 2019 for only CPI products. This corresponds to Figure 12. The frequency of price change is the probability (in percentage terms) with which firms change their price each month. Sources: BEA, BLS, World KLEMS.

Figure 12: Frequency of Price Change - CPI Only



(a) For Low Percentiles

(b) For High Percentiles

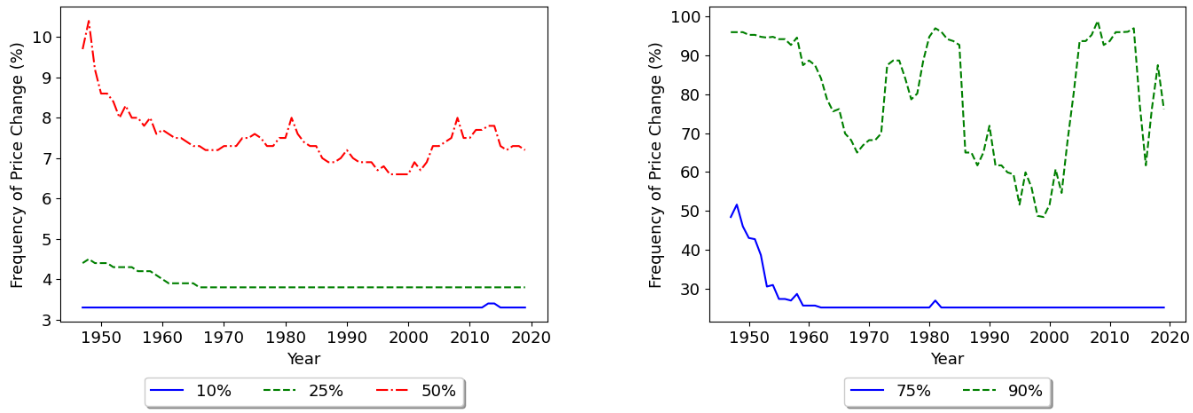
The figure shows percentiles of the frequency of price change distribution from 1947 through 2019 for only CPI products. The frequency of price change is the probability (in percentage terms) with which firms change their price each month. Sources: BEA, BLS, World KLEMS.

Table 17: Frequency of Price Change - PPI Only

Year	10	25	50	75	90
1947	3.3	4.4	9.7	48.4	96.0
1957	3.3	4.2	7.8	26.9	92.7
1967	3.3	3.8	7.2	25.1	68.2
1977	3.3	3.8	7.3	25.1	78.7
1987	3.3	3.8	6.9	25.1	65.0
1997	3.3	3.8	6.6	25.1	56.0
2007	3.3	3.8	7.5	25.1	95.3
2017	3.3	3.8	7.3	25.1	76.2
2019	3.3	3.8	7.2	25.1	76.2

The table shows percentiles of the frequency of price change distribution from 1947 through 2019 for only PPI products. This corresponds to Figure 12. The frequency of price change is the probability (in percentage terms) with which firms change their price each month. Sources: BEA, BLS, World KLEMS.

Figure 13: Frequency of Price Change - PPI Only



(a) For Low Percentiles

(b) For High Percentiles

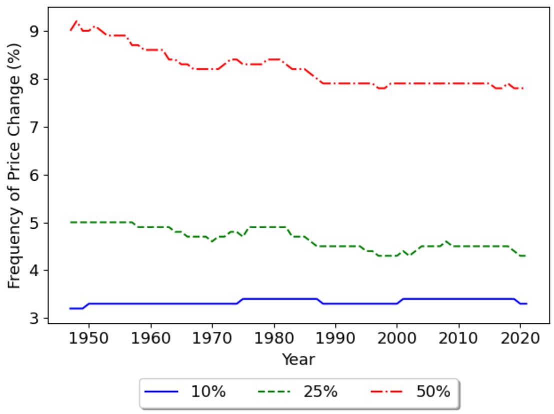
The figure shows percentiles of the frequency of price change distribution from 1947 through 2019 for only PPI products. The frequency of price change is the probability (in percentage terms) with which firms change their price each month. Sources: BEA, BLS, World KLEMS.

Table 18: Frequency of Price Change - Gross Output

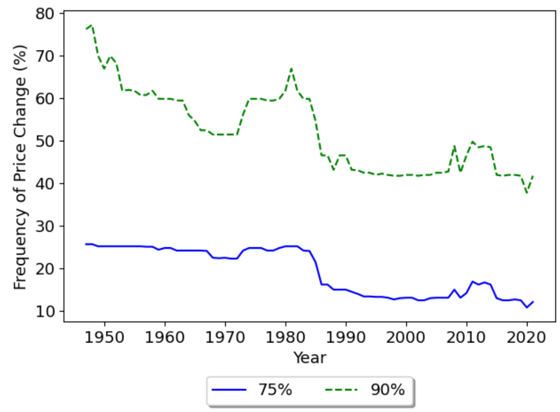
Year	10	25	50	75	90
1947	3.2	5.0	9.0	25.6	76.2
1957	3.3	5.0	8.7	25.0	60.7
1967	3.3	4.7	8.2	24.0	52.4
1977	3.4	4.9	8.3	24.1	59.4
1987	3.4	4.5	8.0	16.1	46.5
1997	3.3	4.3	7.8	13.0	41.9
2007	3.4	4.5	7.9	13.0	42.7
2017	3.4	4.5	7.8	12.4	41.9
2019	3.4	4.4	7.8	12.4	41.7

The table shows percentiles of the frequency of price change distribution from 1947 through 2019 where industrial shares are measured using gross output rather than value-added GDP. This corresponds to Figure 14. The frequency of price change is the probability (in percentage terms) with which firms change their price each month. Sources: BEA, BLS, World KLEMS.

Figure 14: Frequency of Price Change - Gross Output



(a) For Low Percentiles



(b) For High Percentiles

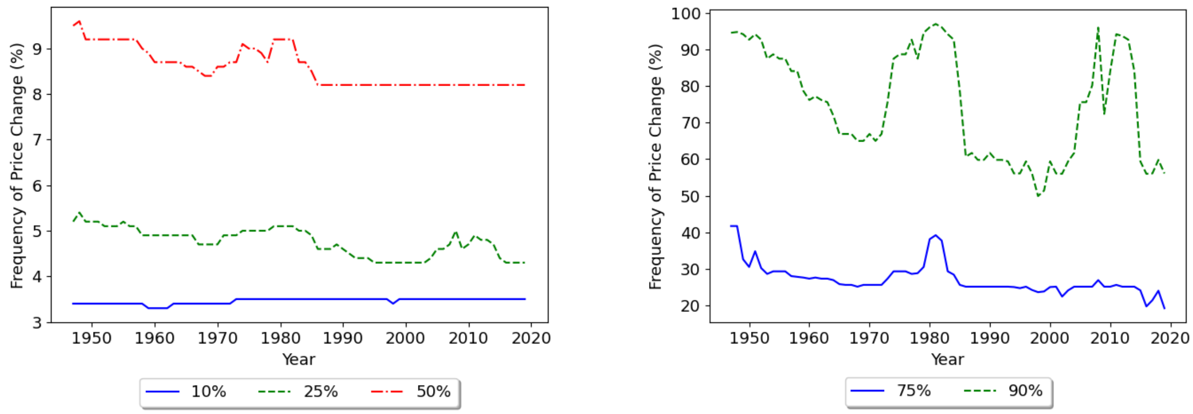
The figure shows percentiles of the frequency of price change distribution from 1947 through 2019 where industrial shares are measured using gross output rather than value-added GDP. The frequency of price change is the probability (in percentage terms) with which firms change their price each month. Sources: BEA, BLS, World KLEMS.

Table 19: Frequency of Price Change - Intermediate Inputs

Year	10	25	50	75	90
1947	3.4	5.2	9.5	41.7	94.6
1957	3.4	5.1	9.2	28.0	84.1
1967	3.4	4.7	8.5	25.6	66.9
1977	3.5	5.0	8.9	28.6	92.7
1987	3.5	4.6	8.2	25.1	61.7
1997	3.5	4.3	8.2	24.2	56.1
2007	3.5	4.7	8.2	25.1	80.2
2017	3.5	4.3	8.2	21.4	56.1
2019	3.5	4.3	8.2	19.2	56.1

The table shows percentiles of the frequency of price change distribution from 1947 through 2019 where the share of an industry is measured using the degree to which that industry's output is used as an intermediate input in other industries. This corresponds to Figure 15. The frequency of price change is the probability (in percentage terms) with which firms change their price each month. Sources: BEA, BLS, World KLEMS.

Figure 15: Frequency of Price Change - Intermediate Inputs



(a) For Low Percentiles (b) For High Percentiles

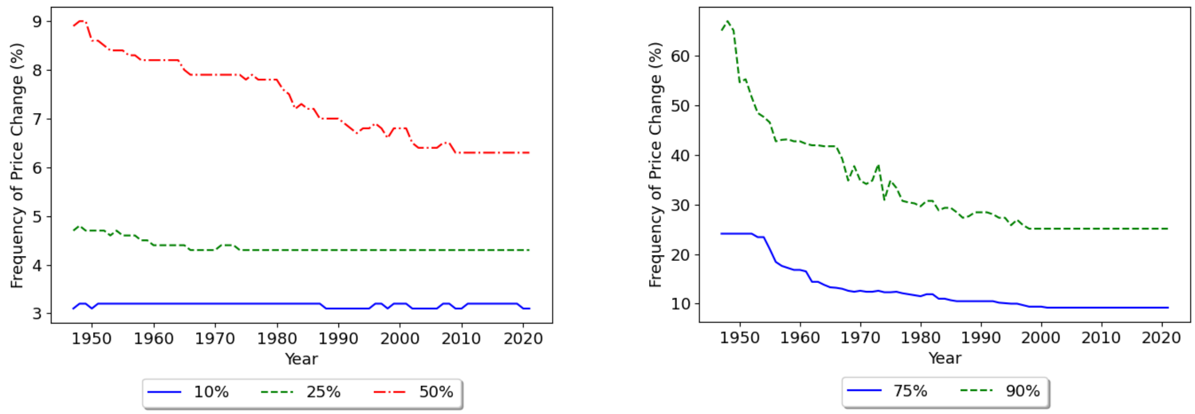
The figure shows percentiles of the frequency of price change distribution from 1947 through 2019 where the share of an industry is measured using the degree to which that industry's output is used as an intermediate input in other industries. The frequency of price change is the probability (in percentage terms) with which firms change their price each month. Sources: BEA, BLS, World KLEMS.

Table 20: Frequency of Price Change - Labor Compensation

Year	10	25	50	75	90
1947	3.1	4.7	8.9	24.1	65.0
1957	3.2	4.6	8.3	17.6	43.0
1967	3.2	4.3	7.9	13.0	39.2
1977	3.2	4.3	7.8	12.1	30.7
1987	3.2	4.3	7.0	10.5	27.3
1997	3.2	4.3	6.8	9.7	25.8
2007	3.2	4.3	6.5	9.2	25.1
2017	3.2	4.3	6.3	9.2	25.1
2019	3.2	4.3	6.3	9.2	25.1

The table shows percentiles of the frequency of price change distribution from 1947 through 2019 where the share of an industry is measured using the total labor compensation issued by that industry. This corresponds to Figure 16. The frequency of price change is the probability (in percentage terms) with which firms change their price each month. Sources: BEA, BLS, World KLEMS.

Figure 16: Frequency of Price Change - Labor Compensation

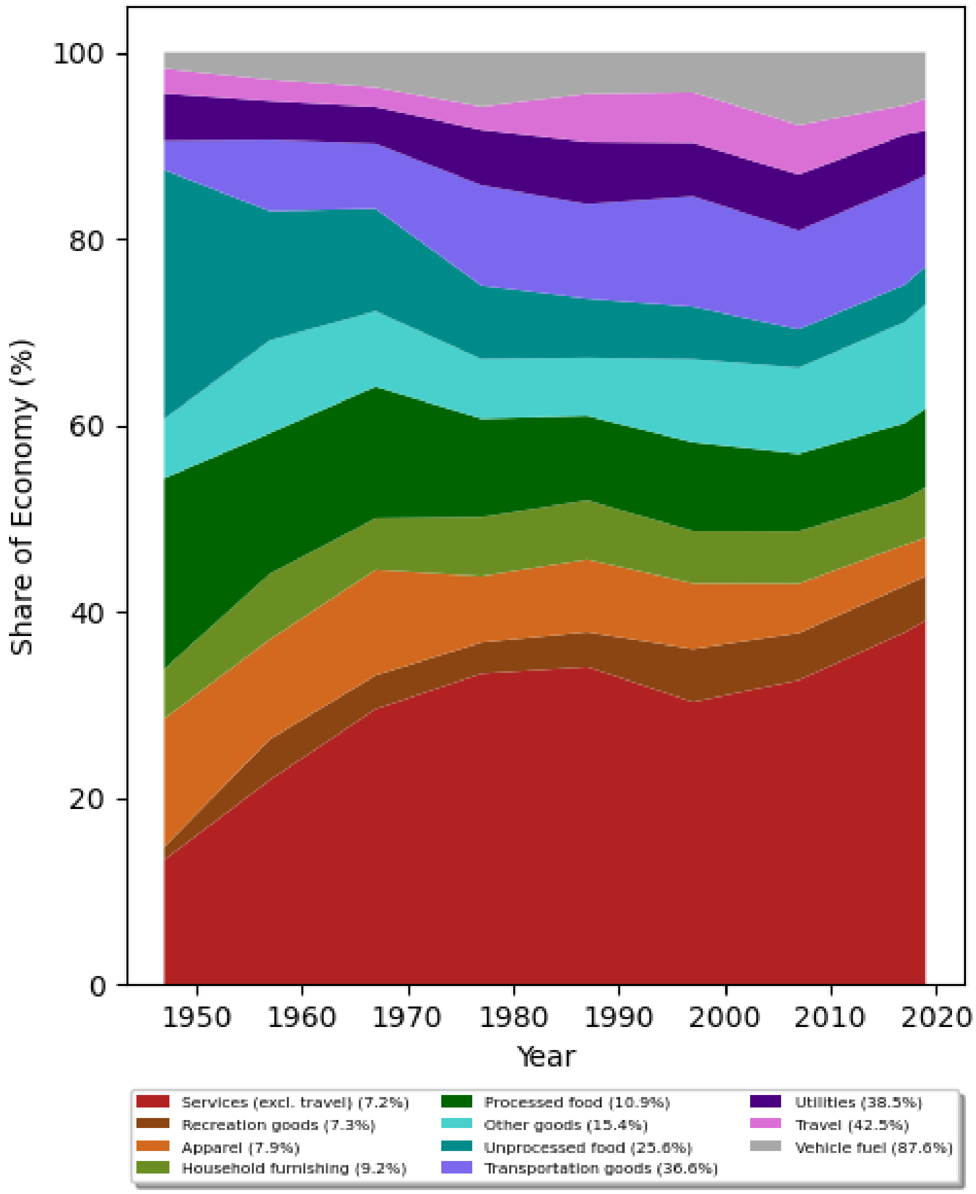


(a) For Low Percentiles

(b) For High Percentiles

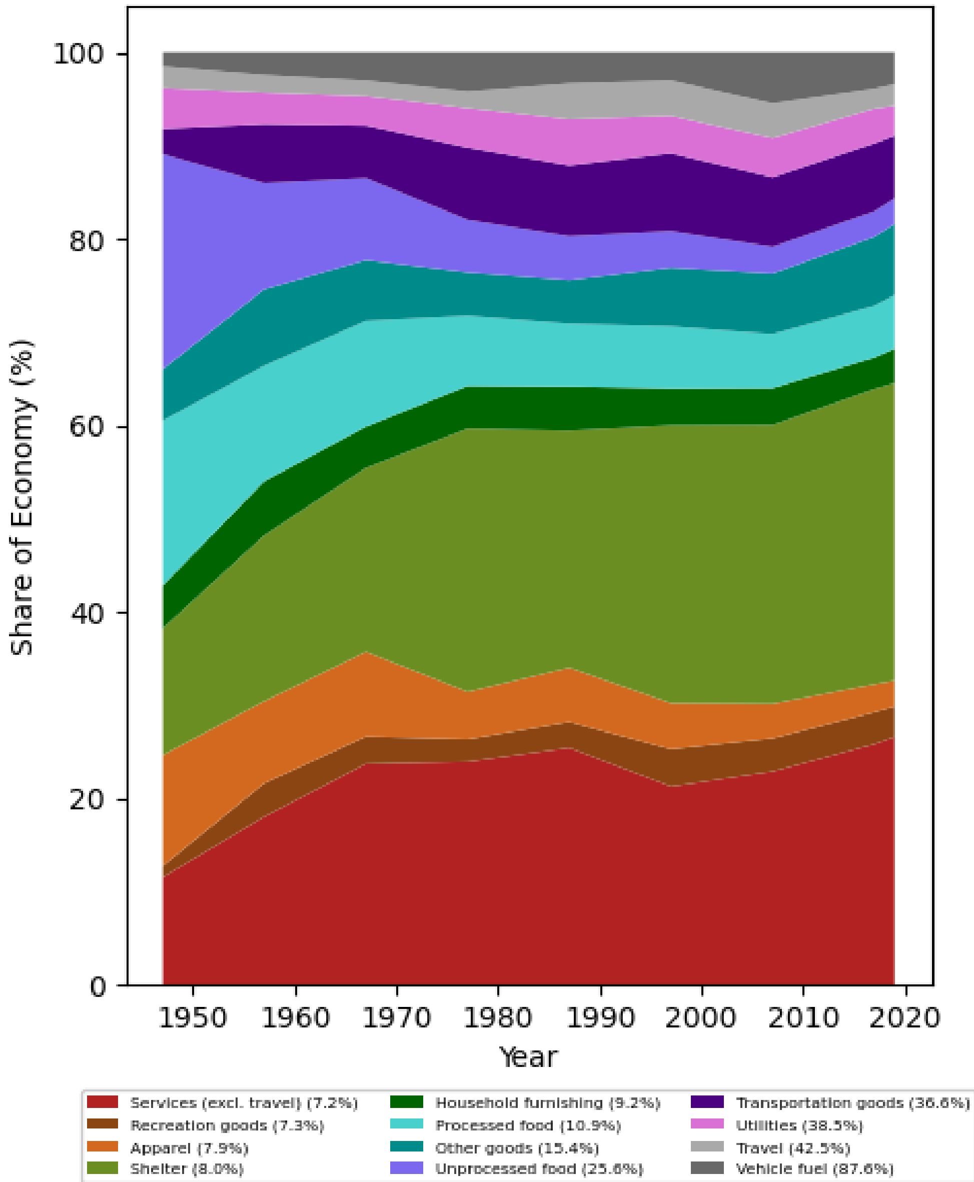
The figure shows percentiles of the frequency of price change distribution from 1947 through 2019 where the share of an industry is measured using the total labor compensation issued by that industry. The frequency of price change is the probability (in percentage terms) with which firms change their price each month. Sources: BEA, BLS, World KLEMS.

Figure 17: Distribution of the Frequency of Price Change Measured with Consumption Shares Including Shelter



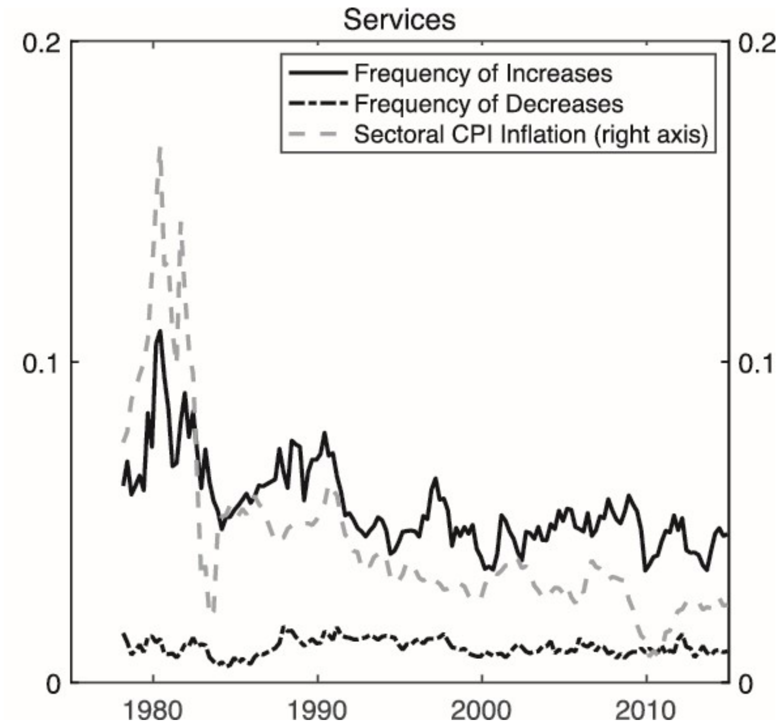
The figure shows percentiles of the frequency of price change distribution from 1947 through 2019. The industries are measured using consumption share data from the BLS starting in 1947, which is matched to data on the frequency of price change for the 11 industries in Table 5 of Nakamura and Steinsson (2008). The frequency of price change is the probability (in percentage terms) with which firms change their price each month. Sources: BEA, BLS, World KLEMS.

Figure 18: Distribution of the Frequency of Price Change Measured with Consumption Shares Including Shelter



Similar to Figure 17 except including shelter. Sources: BEA, BLS, World KLEMS.

Figure 19: Frequency of Price Change - Time-variation



The figure shows the frequency of price change (increases and decreases) for products in the service industry from 1978 through 2015. To construct the frequency series plotted in this figure, Nakamura et al. (2018) calculates the mean frequency of price increases and decreases in each ELI for each month. They then take the weighted median across ELIs for services separately and plot them. Sources: Nakamura et al. (2018).

C Robustness Check: Allowing for Products Weights within Industries to Vary by Year

In our empirical approach, we use an algorithm to compute the proportion of an industry, for which we have historical share data, sold by a given CPI/PPI product. As part of this algorithm, we fix the weight assigned to each product in the CPI and PPI, respectively, to its weight in a base year. We do this because the time-varying weight data we have lines up imperfectly with the products in Nakamura and Steinsson (2008) and because we lack time-varying weight data for the PPI before 1998. One concern with this static weighting is that it could introduce measurement error into our empirical analysis, especially if the forces that caused industrial composition changes in the US economy also changed the relative importance of CPI/PPI products in the respective index baskets. Fortunately, we can check this as yearly data for the economic weights of some of the products that we consider is available, although availability is limited to a smaller number of years than in our full sample. The time-varying weight data we have for PPI products much more closely (though still imperfectly) match the products in Nakamura and Steinsson (2008) from which we obtain our price rigidity statistics. Therefore, in this robustness check, we consider only those PPI products for which we have weights over time and which are available in Nakamura and Steinsson (2008). The weights data are available starting in 1998. We further restrict to categories for which weights data are available for the full 1998–2019 period.

Table 21 shows percentiles of the distribution of the frequency of price change computed using fixed weights (as in our main algorithm) and time-varying weights in Panel A and Panel B, respectively. We observe that the two distributions show very similar features. There is a rise in the frequency of price change across percentiles from 1998 through 2014 but then a decline in 2019. Therefore, we find that allowing time-varying weights does not appear to affect our results, at least for PPI products over the time period for which we have weight data. It may appear strange that the frequency of price change is increasing. However, this is because we dropped products for which we do not have weight data. We consider the full set of PPI products in Figure 13 and Table 17. With the full set of products, we do not find the increase in the frequency of price change that we observe in Table 21.

Table 21: Median Frequency of Price Change with Fixed (1998)-Weights versus Time-Varying Weights

Percentile	1998	2004	2009	2014	2019
Panel A: Weights Fixed to 1998 Weights					
10%	2.8	3.1	3.1	3.1	3.1
25%	4.2	4.7	4.7	5.1	4.8
50%	7.5	12.9	13.3	16.5	12.9
75%	27.3	34.8	42.7	48.7	34.1
90%	69.9	98.9	99.5	99.5	98.9
Panel B: Varying Weights					
10%	2.8	3.1	3.1	3.2	3.1
25%	4.2	4.7	4.9	5.1	5.0
50%	7.5	13.9	13.9	21.9	13.9
75%	27.3	46.6	46.6	51.6	37.7
90%	69.9	98.9	99.3	99.3	98.9

Sources: BEA, BLS, World KLEMS.

D Recursive Formulation of the Firm's Optimization Problem

A firm z in period t chooses $L_t(z)$ and $M_t(z)$ to minimize its total cost of production subject to its production function. That is,

$$\min_{L_t(z),M_t(z)} \left\{ W_t L_t(z) + P_t M_t(z) + \phi_t(z) \left[y_t(z) - A_t(z) L_t(z)^{1-s_m} M_t(z)^{s_m} \right] \right\}. \tag{18}$$

The first-order conditions of the firm's cost minimization problem are:

$$\begin{aligned} W_t &= \phi_t(z) A_t(z)(1-s_m) L_t(z)^{-s_m} M_t(z)^{s_m}, \\ P_t &= \phi_t(z) A_t(z) s_m L_t(z)^{1-s_m} M_t(z)^{s_m-1}, \end{aligned} \tag{19}$$

where $\phi_t(z)$ represents the marginal cost of firm z at time t. Putting these two conditions together yields the real wage as:

$$\frac{W_t}{P_t} = \frac{1-s_m}{s_m} \frac{M_t(z)}{L_t(z)}, \tag{20}$$

which implies:

$$L_t(z) = \frac{1-s_m}{s_m} \left(\frac{W_t}{P_t} \right)^{-1} M_t(z). \tag{21}$$

Combining equation 21 with the production function in equation 8 yields:

$$L_t(z) = \left(\frac{1-s_m}{s_m} \right)^{s_m} \left(\frac{W_t}{P_t} \right)^{-s_m} \frac{y_t(z)}{A_t(z)}. \tag{22}$$

Substituting equation 20 into the firm's real profits (equation 14 divided by P_t) yields:

$$\Pi_t^R(z) = \left(\frac{p_t(z)}{P_t} \right) y_t(z) - \frac{1}{1-s_m} \frac{W_t}{P_t} L_t(z) - \chi_j \frac{W_t}{P_t} I_t(z) - U. \tag{23}$$

Then substituting in the labor demand per equation 22 yields:

$$\Pi_t^R(z) = \left(\frac{p_t(z)}{P_t} \right) y_t(z) - (1-s_m)^{s_m-1} s_m^{-s_m} \left(\frac{W_t}{P_t} \right)^{1-s_m} \frac{y_t(z)}{A_t(z)} - \chi_j \frac{W_t}{P_t} I_t(z) - U. \tag{24}$$

Inputting the real wage from equation 7 and output demand from equation 11 yields:

$$\Pi_t^R(z) = \left(\frac{p_t(z)}{P_t}\right)^{1-\theta} Y_t - (1-s_m)^{s_m-1} s_m^{-s_m} \left(\omega L_t^{\psi} C_t^{\gamma}\right)^{1-s_m} \left(\frac{p_t(z)}{P_t}\right)^{-\theta} Y_t \frac{1}{A_t(z)} - \chi_j \omega L_t^{\psi} C_t^{\gamma} I_t(z) - U. \tag{25}$$

Moreover, under the assumption of linear disutility of labor ($\psi = 0$) and log utility in consumption ($\gamma = 1$), $\frac{W_t}{P_t} = \omega C_t$. Therefore, we can write the firm's real profits as:

$$\Pi_t^R(z) = \left(\frac{p_t(z)}{P_t}\right)^{1-\theta} C_t - (1-s_m)^{s_m-1} s_m^{-s_m} (\omega C_t)^{1-s_m} \left(\frac{p_t(z)}{P_t}\right)^{-\theta} Y_t \frac{1}{A_t(z)} - \chi_j \omega C_t I_t(z) - U. \tag{26}$$

Since $Y_t = C_t + \int_0^1 M_t(z) dz$, we have:

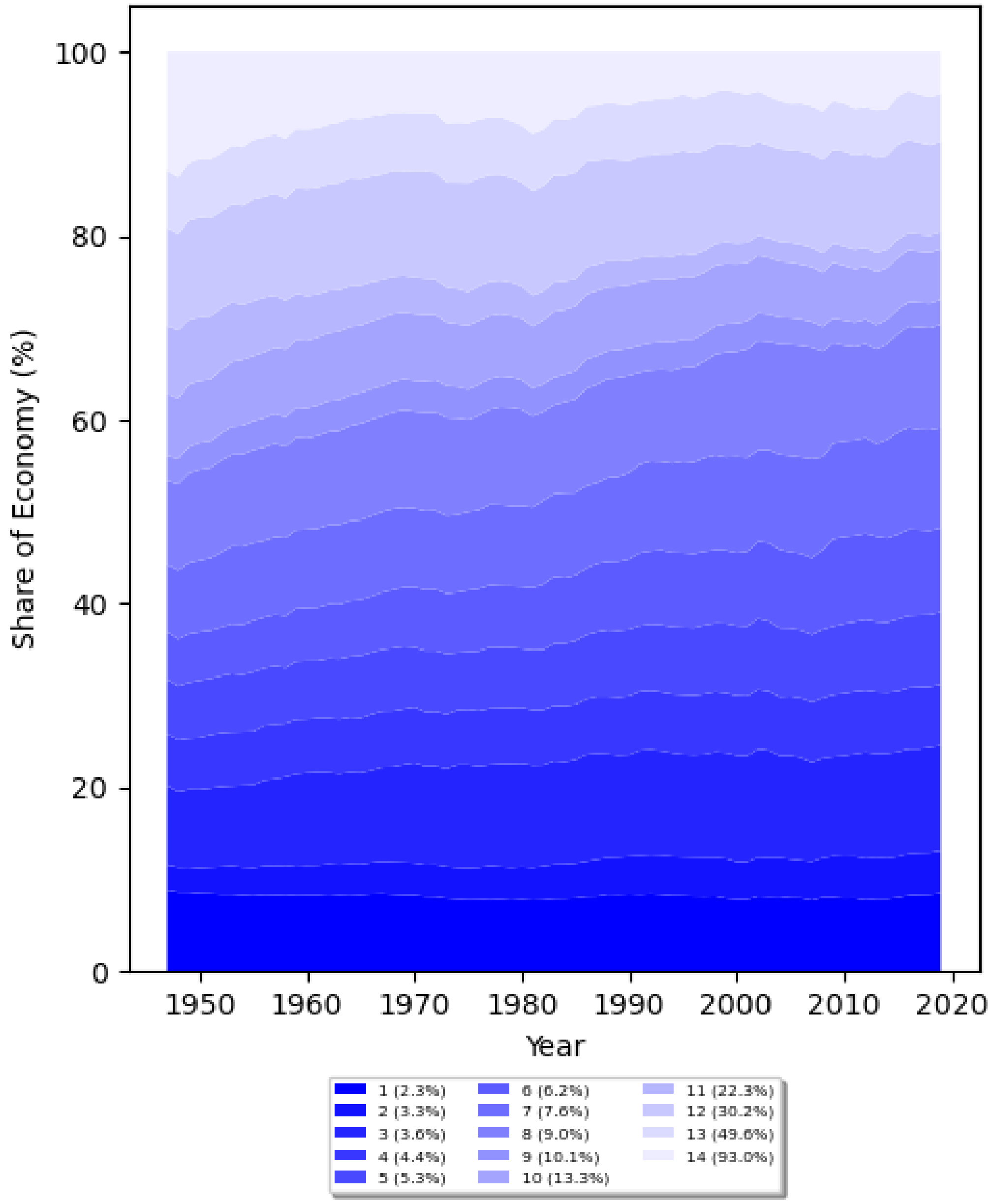
$$\begin{aligned}
Y_t &= C_t + \int_0^1 \left(\frac{y_t(z)}{A_t(z) L_t(z)^{1-s_m}}\right)^{\frac{1}{s_m}} dz \qquad \text{using equation 8} \\
&= C_t + \int_0^1 \left(\frac{y_t(z)}{A_t(z)\left(\left(\frac{1-s_m}{s_m}\right)^{s_m}\left(\frac{W_t}{P_t}\right)^{-s_m}\frac{y_t(z)}{A_t(z)}\right)^{1-s_m}}\right)^{\frac{1}{s_m}} dz \qquad \text{using equation 22} \\
&= C_t + \int_0^1 \left(\frac{y_t(z)^{s_m}}{A_t(z)^{s_m}\left(\left(\frac{1-s_m}{s_m}\right)^{s_m}\left(\frac{W_t}{P_t}\right)^{-s_m}\frac{1}{A_t(z)}\right)^{1-s_m}}\right)^{\frac{1}{s_m}} dz \qquad \text{using equation 22} \\
&= C_t + \frac{s_m}{1-s_m}\omega C_t \int_0^1 \left(\frac{y_t(z)^{s_m}}{A_t(z)^{s_m}\left(\frac{1}{A_t(z)}\right)^{1-s_m}}\right)^{\frac{1}{s_m}} dz \\
&= C_t \left[1 + \frac{s_m}{1-s_m}\omega \int_0^1 \left(\frac{y_t(z)^{s_m}}{A_t(z)^{s_m}\left(\frac{1}{A_t(z)}\right)^{1-s_m}}\right)^{\frac{1}{s_m}} dz\right].
\end{aligned}$$

Thus, we get $Y_t = constant \times C_t$. Finally, as $C_t = \frac{S_t}{P_t}$ per equation 16, we can write the firm's real profits just as a function of $A_t(z)$, $\frac{p_t(z)}{P_t}$, $\frac{S_t}{P_t}$, $\frac{p_{t-1}(z)}{P_t}$.

E Calibration Details

Figure 20 shows how the sectoral composition of the United States changed from 1947 to 2019. It shows each sector's share of the economy from 1947 to 2019 ordered from the lowest to the highest frequency of price change; that is, the sector with the lowest frequency of price change is at the bottom of the graph. Throughout the 1947–2019 period, the mass of sectors with a low frequency of price change has grown, while the mass of sectors with a high frequency of price change has shrunk. These evolution trends at the sector level are similar to the trends that we observed at the industry level in Figures 2 and 3.

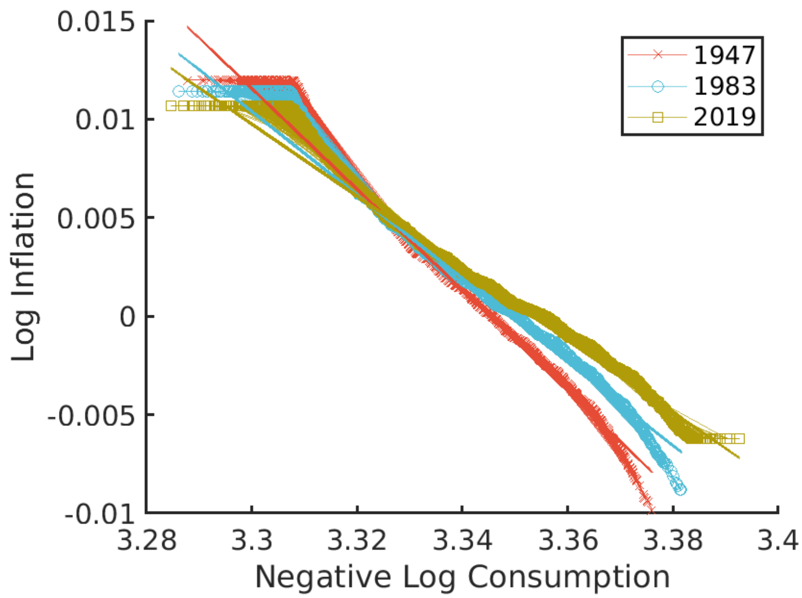
Figure 20: Sectoral Composition of the US: 1947–2019



The figure shows the model sectors' shares of the economy over time. The x-axis represents the year, and the y-axis represents the share of the sector in the model in a percentage. The sectors are sorted from lowest median frequency of price change (in 1983) to highest. The median frequency of price change for the sector is constructed across the distribution of frequencies of price changes of products in that sector, with the distribution based on the products' shares of the sector in 1983. Source: Authors' calculations.

F Flattening of the Phillips Curve: Full Simulation Result

Figure 21: Evolution of the Phillips Curve: 1947–2019



The figure shows the relationship between (log) inflation and negative of (log) consumption for three years in our data—1947, 1983, and 2019—while ignoring the simulation points that constitute the flat sections in the original Phillips curve shown in figure 21. The graph's color-symbols plot the nonlinear relationship for different years: olive for 2019, blue for 1983, and red for 1947. The graph's lines of the same color show the approximate linear relationship (estimated using a regression line through the nonlinear curve) for the corresponding year. Source: Authors' calculations.

G Evolution of the Phillips Curve through the Lens of the Single-Sector New Keynesian Model

In the main text, we used a calibrated multisector menu cost model to accurately capture the firms' pricing decisions. We believe that it also worthwhile to compute the change in the slope of the Phillips curve through the lens of the standard three-equation New Keynesian model. The (linearized) New Keynesian Phillips curve is given by:

$$\pi_t = \kappa mc_t + \beta \mathbb{E}_t \pi_{t+1},$$

where mc_t is the marginal cost at time t and is given by the difference between the real wage and the productivity, $w_t - a_t$. The real wage is, in turn, equal to the marginal product of labor $\gamma c_t + \eta l_t$, which can further be re-written in terms of output as $(\gamma + \eta)y_t$. Under our assumptions of log utility ($\gamma = 1$) and linear labor disutility ($\eta = 0$), we get $mc_t = y_t$. Therefore, we can re-write the Phillips curve as a relation between inflation and output:

$$\pi_t = \kappa y_t + \beta \mathbb{E}_t \pi_{t+1},$$

where κ is a composite parameter that depends on the Calvo price- flexibility parameter γ and the discount factor β, and determines the slope of the Phillips curve.

$$\kappa = \frac{\lambda\,[1-(1-\lambda)\beta]}{1-\lambda}$$

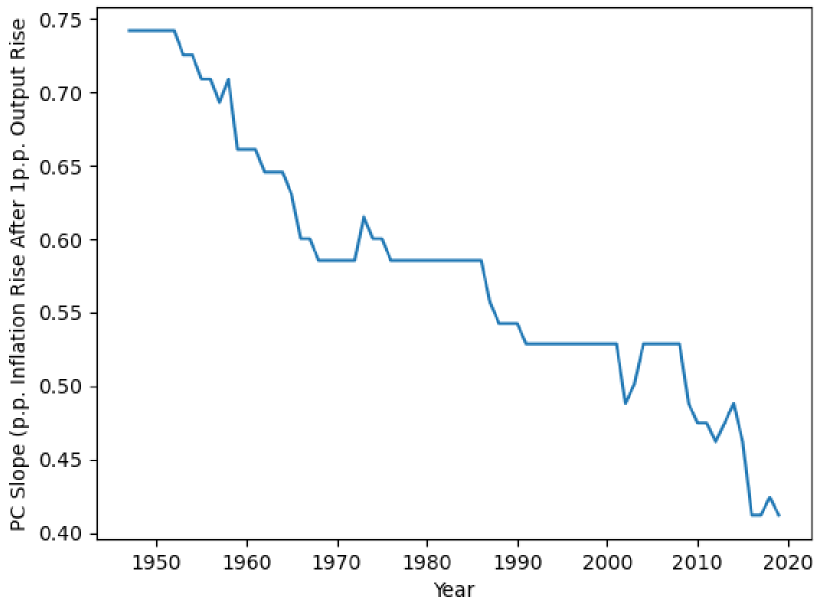
We set monthly $\beta = 0.96^{1/12}$. We set monthly γ for each year between 1947 through 2019 based on the respective median of the annual distributions of the (monthly) frequency of price change that we computed in section 3. This yields κ, which is the monthly slope of the Phillips curve. We then annualize κ to compute the corresponding slope statistic that we derived in the main text.

For example, the median frequency of price change was 8.2 percent in 1983. This means $\gamma = 0.082$, which yields $\kappa = 0.0076$. This implies that a 1 p.p. rise in y_t per month is associated with 0.0076 p.p. higher inflation per month. Therefore, a 1 p.p. rise in y_t for one year is associated with a 0.59 p.p. rise in inflation in one year.[45]

Figure 22 shows the evolution of the slope of the Phillips curve over our sample period based on the calibrated basic New Keynesian model. We find that changes in industrial composition have led to a decline in the slope from –0.74 in 1947 to –0.59 in 1983 to –0.41 in 2019. This amounts to a 44.5% flattening from 1947 to 2019.

[45]To see this, note that $\Delta\pi_0 = \kappa mc_0 + \kappa\beta mc_1 + \ldots + \kappa\beta^{11} mc_{11} = \kappa(1+\beta+\ldots+\beta^{11})$; $\Delta\pi_1 = \kappa(1+\beta+\ldots+\beta^{10})$; $\ldots\ \Delta\pi_{11} = \kappa$. Therefore, the total change in inflation is $77\kappa = 0.59$.

Figure 22: Evolution of the Phillips Curve in the Basic New Keynesian Model: 1947–2019



The figure shows the slope of the Phillips curve through the lens of the basic New Keynesian model for 1947 through 2019. Source: Authors' calculations.

H Discussion: Inflation rates during the recovery from the COVID-19 pandemic

In the latter half of 2021 and at the start of 2022 as the economy recovered from the COVID-19 pandemic, there was a steep rise in inflation. Inflation rose to 6.8 percent in November 2021 and continued to accelerate for several months, reaching 8.5 percent in March 2022, which was its highest rate since 1982. To the extent that this spike was driven by demand-side factors, including the distribution of fiscal stimulus checks during the pandemic, as well as the reopening of the economy and release of pent-up demand in the pandemic's aftermath, it may appear at odds with the idea that the Phillips curve has flattened, since a flatter Phillips curve implies a relatively lower response of inflation to demand shocks. Therefore, we now investigate the degree to which high inflation occurs in response to unexpected positive demand shocks in an economy where shifts in industrial composition have flattened the Phillips curve.

The nature of the aggregate demand shock that hit the economy in late 2021 through early

2022 is unclear. High inflation that persists for several months could result from a one-time large shock to aggregate demand that continues to have an impact on firms' price-setting several months after the shock first hits, or it could result from a series of shocks, either small or large, that hit the economy every month. Therefore, in our investigation we study the inflation response to nominal aggregate demand shocks of varying sizes and levels of persistence.

To do this, we first categorize the aggregate demand shocks, η_t, by size and then further bin them by persistence. We categorize a shock as "small" if it falls within 0.5 to 1.5 standard deviations (SD) around its mean (zero). We categorize a shock as "large" if it falls within 1.5 to 2.5 SD. Since we are interested in explaining a large rise in inflation, we consider only positive shocks to η_t. In the model, the shocks, η_t, are independently and identically distributed and are not persistent by definition. So we characterize the persistence of the i.i.d. shocks based on the number of consecutive periods in which the economy is hit by the same-sized shocks. For example, if a shock is small, we assign it a persistence of 1; we assign it a persistence of 2 if the current shock and the shock in the preceding period are small; we assign it a persistence of $= 3$ if the current shock and the shocks in the preceding two periods are small, and so on. We repeat the process for the large shocks.[46] In this way, we differentiate between small and large shocks and categorize these two shock sizes into persistence bins ranging from 1 through 6 for small shocks and 1 through 4 for large shocks. Once we have placed our simulation points into bins based on shock size and level of persistence, we compute the inflation for each bin by taking the mean of the simulated inflation numbers across the points within that bin and annualizing it. We repeat this exercise for all the years to enable a comparison of the inflation response to demand shocks across the years as the industrial composition of the United States and consequently the slope of the Phillips curve changed. The results of this exercise are shown in figure 23.

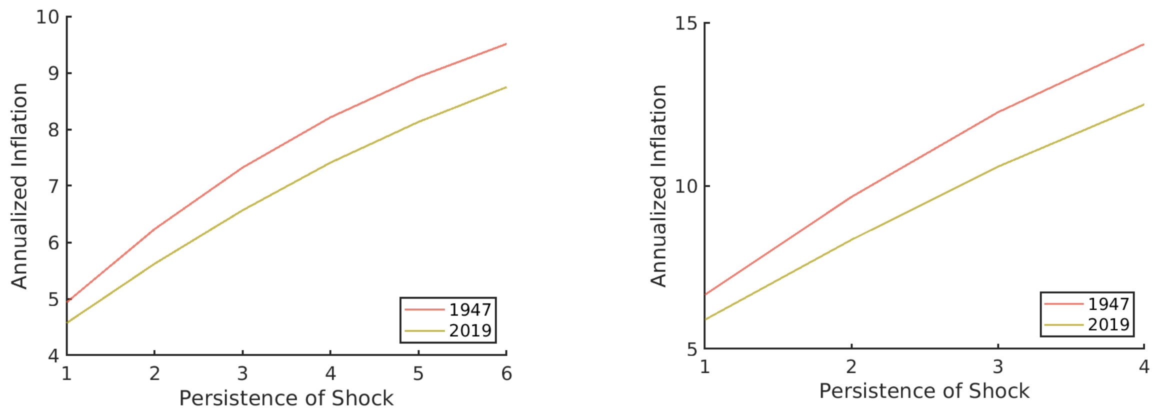
We find, rather unsurprisingly, that across all the years, conditional on shock persistence, large shocks to aggregate nominal demand imply larger inflation responses compared with small shocks. More interestingly, conditional on the size of the shock, more persistent shocks to aggregate nominal demand imply larger responses compared with less persistent shocks. Numerically, for a small shock, the annualized inflation response in 2019 ranges from 4.6 percent to 8.7 percent depending on the persistence of the shock. The corresponding range of responses in 2019 for a large shock is 5.9 percent to 12.5 percent . Therefore, despite a flatter Phillips curve in 2019, significant inflation still could have resulted from an aggregate demand shock that was both small and persistent, an aggregate demand shock that was

[46] Note that by this way of defining persistence, a shock that belongs in higher-persistence bins also belongs in lower-persistence bins.

both large and persistent, or a one-time large aggregate demand shock. Importantly also, while inflation response to any given shock would have been larger in 1947 due to lower aggregate price stickiness compared with 2019, the differences between the years appear to be small (never more than two percentage points).

This exercise sheds light on the observed spike in inflation in the aftermath of the COVID-19 pandemic. It suggests that a high-inflation scenario, as was observed in the first quarter of 2022, is plausible in the face of unexpected nominal demand shocks that are either large or persistent or both, even with a flatter Phillips curve, as the economy now has.

Figure 23: Inflation Responses to Small versus Large Shocks of Varying Levels of Persistence



(a) For Small Shocks

(b) For Large Shocks

The figure shows the response of annualized inflation to nominal aggregate demand shocks of varying sizes and levels of persistence. Panel (a) shows the response for "small" shocks, which are defined as shocks within +0.5 to +1.5 SD. Panel (b) shows the response for "large" shocks, which are defined as shocks within +1.5 to +2.5 SD. Persistence denotes the number of consecutive periods in which the shock is small (large) in panel (a) [(b)]. For example, the bin of persistence$=2$ includes the simulation points/periods for which the shock in that period and in the preceding period was small. By this definition of persistence, simulation points that belong in higher-persistence bins are also members of lower-persistence bins. The annualized inflation on the y-axis is the annualized mean inflation among all simulation points that fall in the particular shock-persistence bin on the x-axis.