The Elusive Costs of Inflation: Price Dispersion during the U.S. Great Inflation

Emi Nakamura
Columbia University

Jón Steinsson
Columbia University

Patrick Sun
FCC

Daniel Villar *
Federal Reserve Board

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Abstract

A key policy question is: How high an inflation rate should central banks target? This depends crucially on the costs of inflation. An important concern is that high inflation will lead to inefficient price dispersion. Workhorse New Keynesian models imply that this cost of inflation is very large. An increase in steady state inflation from 0% to 10% yields a welfare loss that is an order of magnitude greater than the welfare loss from business cycle fluctuations in output in these models. We assess this prediction empirically using a new dataset on price behavior during the Great Inflation of the late 1970's and early 1980's in the United States. If price dispersion increases rapidly with inflation, we should see the absolute size of price changes increasing with inflation: price changes should become larger as prices drift further from their optimal level at higher inflation rates. We find no evidence that the absolute size of price changes rose during the Great Inflation. This suggests that the standard New Keynesian analysis of the welfare costs of inflation is wrong and its implications for the optimal inflation rate need to be reassessed. We also find that (non-sale) prices have not become more flexible over the past 40 years.

JEL Classification: E31, E50

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1 Introduction

Recent years have seen a resurgence of interest in the question of the optimal level of inflation. In the years before the Great Recession, there was a growing consensus emerging among policymakers that good policy consisted of targeting an inflation rate close to zero. One manifestation of this was that many countries adopted explicit inflation targets concentrated around 2% per year. Within academia, prominent studies argued for still lower rates of inflation even after having explicitly taken account of the zero lower bound (ZLB) on nominal interest rates (Schmitt-Grohe and Uribe, 2011; Coibion et al., 2012). The Great Recession has led to a reconsideration of this consensus view with an increasing number of economists arguing for targeting a higher inflation rate of say 4% per year (see, e.g., Blanchard et al., 2010; Ball, 2014; Krugman, 2014; Blanco, 2015b).

An important concern with targeting higher inflation is that this will increase price dispersion and thereby distort the allocative role of the price system. Intuitively, in a high inflation environment, relative prices will fluctuate inefficiently as prices drift away from their optimal value during intervals between price adjustment. As a consequence relative prices will no longer give correct signals regarding relative costs of production, leading production efficiency to be compromised.

In standard New Keynesian models—the types of models used in most formal analysis of the optimal level of inflation—these costs are very large even for moderate levels of inflation. Calibrating such a model in a relatively standard way, we show that the consumption equivalent welfare loss of moving from 0% inflation to 12% inflation is roughly 10%. For comparison, the welfare costs of business cycle fluctuations in output—even including large recessions like the Great Depression and Great Recession—are an order of magnitude smaller in these same models.[1] No wonder these models strongly favor virtual price stability.

Measuring the sensitivity of price dispersion to changes in inflation is challenging for several reasons. One challenge is the small amount of variation we have seen in the inflation rate in the U.S. over the last few decades. Existing BLS micro-data on U.S. consumer prices have been influential in establishing basic facts about the frequency and size of price changes (Bils and Klenow,

[1]The models used to analyze the costs of welfare in the New Keynesian literature typically assume a representative agent with constant relative risk aversion preferences and output fluctuations that are trend stationary. In this case, Lucas (2003) shows that the consumption equivalent welfare loss of business cycle fluctuations in consumption over the period 1947-2001 are 0.05% if consumers are assumed to have log-utility. Redoing Lucas' calculation with a coefficient of relative risk aversion of 2 and considering fluctuations in annual per capita consumption around a linear trend over the period 1920-2009 implies a welfare loss of 0.4%. A substantial literature has since argued that Lucas' calculation substantially understates the true costs of business cycle fluctuations (see, e.g., Barro, 2009; Krusell et al., 2009).

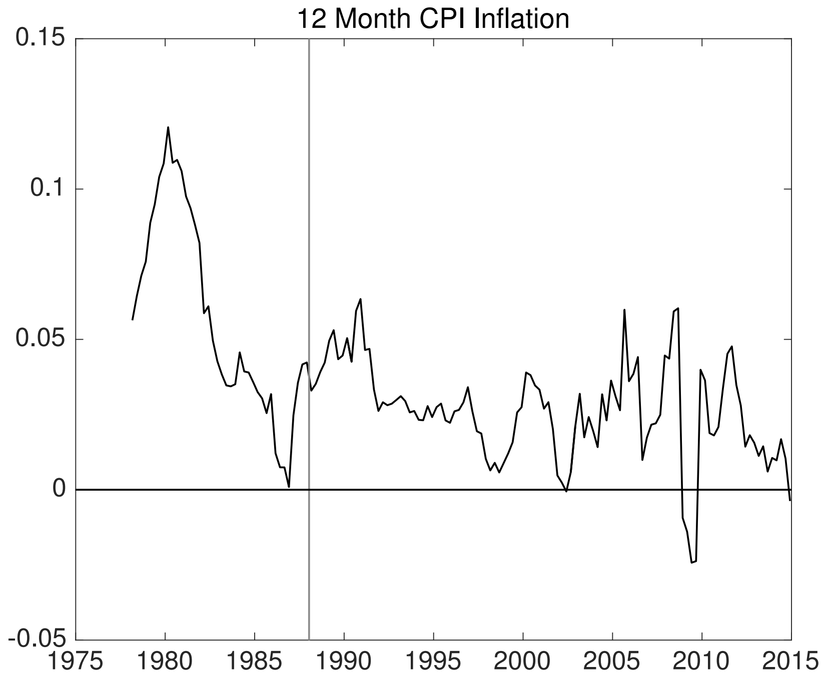

Figure 1: CPI Inflation in the U.S. (excluding shelter)

2004; Nakamura and Steinsson, 2008; Klenow and Kryvtsov, 2008). These data, however, have the substantial disadvantage that they span only the post-1987 Greenspan-Bernanke period of U.S. monetary history, when inflation was low and stable. This seriously limits their usefulness in studying how variation in inflation affects the economy.

To overcome this challenge, we have extended the BLS micro-dataset on U.S. consumer prices back to 1977. This allows us to analyze a period when inflation in the U.S. rose sharply—peaking at roughly 12% per year in 1980—and was then brought down to a lower level in dramatic fashion by the Federal Reserve under the leadership of Paul Volcker (see Figure 1). We constructed these new data from original microfilm cartridges found at the BLS by first scanning them and then converting them to a machine-readable dataset using custom optical character recognition software. This effort took several years to complete partly because the data were never allowed to leave the BLS building in Washington DC.

A second challenge to measuring the sensitivity of price dispersion to changes in inflation is the presence of a large amount of unobserved product heterogeneity. Much of the cross-sectional dispersion in prices—even within narrowly defined product categories—likely results from heterogeneity in product size and quality (e.g., a can of soda versus a 2 liter bottle, organic versus non-organic milk, Apple's iPhone 6S versus LG's G4 smartphone). The simplest way to empirically assess price dispersion is to calculate the standard deviation of prices within a narrow category. But this approach will lump together desired price dispersion resulting from product heterogeneity and inefficient price dispersion resulting from price rigidity. In fact, the amount of desired price dispersion within even narrow product categories is likely to dwarf inefficient price dispersion at moderate levels of inflation. This situation is further complicated by the fact that the recent literature has convincingly argued that desired real prices of a product vary a great deal over time (Golosov and Lucas, 2007). This means that simple reduced-form approaches to "differencing out" product heterogeneity—such as looking at the deviations of a product's price from its long-run mean real level—will not work well.[2]

Earlier research seeking to study the relationship between price dispersion and inflation faced this same challenge (see, e.g., Van Hoomissen, 1988; Lach and Tsiddon, 1992). It concluded that studying price dispersion directly was not viable and focused instead on price *change* dispersion.[3] These researchers argued that price change dispersion is an acceptable proxy for price dispersion in some simple menu cost models. This is not, however, the case even qualitatively in the more empirically realistic menu cost models used today. In these models, price change dispersion actually falls with inflation at low levels of inflation while price dispersion is roughly flat.[4]

To overcome this challenge, we assess the sensitivity of inefficient price dispersion to changes in inflation by looking at how the absolute size of price changes varies with inflation. Intuitively, if inflation leads prices to drift further away from their optimal level, we should see prices adjusting by larger amounts when they adjust. For this reason, if inefficient price dispersion rose during the Great Inflation period, a tell-tale sign of this should be that the absolute size of price changes should have risen during that period as well. We show that this intuition works in the Calvo model and in a Golosov-Lucas style menu cost model (i.e., one with large idiosyncratic shocks). In the Calvo model, the average absolute size of price changes rises rapidly with inflation as does

[2]Golosov and Lucas (2007) point out that large idiosyncratic shocks to desired prices are needed to explain the large frequency and size of price changes at low levels of inflation. We illustrate in section 4.1 that this makes reduced-form measurement of inefficient price dispersion challenging.

[3]Lach and Tsiddon (1992) state that they were thwarted in looking directly at price dispersion. Though they do not explain exactly why, they say: "the problems we run into while analyzing the relationship between this measure of price dispersion and inflation convinced us that we need a more structured and empirically oriented model to tackle this issue. Hence we do not present results on the effects of inflation on the cross-sectional dispersion of price levels."

[4]The intuition for this result is simple. At low inflation rates, a significant fraction of price changes are price decreases. This leads to a widely dispersed distribution of price changes (increases and decreases). As inflation increases, the frequency of price decreases falls and the price change distribution narrows to include mostly price increases. This reduces the cross-sectional variance of price changes.

inefficient price dispersion. In the menu cost model, however, the average absolute size of price changes and inefficient price dispersion are virtually flat over the range of inflation rates relevant for our empirical work.[5] Intuitively, in the menu cost model, prices never drift too far from their optimal level since firms find it optimal to pay the (relatively small) menu cost before this happens. This greatly limits the extent to which price dispersion rises with inflation in the menu cost model and, as a result, the welfare loss from increasing inflation is small in this model, a point emphasized by Burstein and Hellwig (2008).

We show that, in the data, the mean absolute size of price changes in the U.S. is essentially flat over our entire sample period. The standard deviation of the absolute size of price changes is also essentially flat. There is, thus, no evidence that prices deviated more from their optimal level during the Great Inflation period when inflation was running at higher than 10% per year than during the more recent period when inflation has been close to 2% per year.

We conclude from this that the main costs of inflation in the New Keynesian model are completely elusive in the data. This implies that the strong conclusions about optimality of low inflation rates reached by researchers using models of this kind need to be reassessed. It may well be that inflation rates above 2% have other important costs. A strong consensus for low inflation being optimal must rely on these other costs outweighing the benefits of higher inflation.

Rather than seeing an increase in the absolute size of price changes during the Great Inflation, we see a substantial increase in the frequency of price change. The behavior of both the absolute size and frequency of price change as inflation varies in our sample line up much better with the predictions of menu cost models than they do with the predictions of the Calvo model. In this regard, our results reinforce results based on micro-data from several other countries (see, e.g., Gagnon, 2009; Alvarez et al., 2016).

A second dramatic result of our analysis is that, despite all of the technological change that has occurred over the past four decades, regular prices (excluding temporary sales) do not seem to have become more flexible over this period, controlling for inflation. We show that a simple menu cost model with a fixed menu cost over the entire sample period can match the empirical relationship between the frequency of price change and inflation. Menu costs are, of course, a

[5]This contrasts with earlier menu cost models that abstracted from large idiosyncratic shocks. In those models, the response of the absolute size of price changes to inflation is more substantial (Barro, 1972; Sheshinski and Weiss, 1977). The reason for the difference is that the size of price changes is determined primarily by the large idiosyncratic shocks in our menu cost model and is therefore not very sensitive to inflation when inflation is low.

veil for a variety of deeper frictions in the price adjustment process arising from technological, managerial, or customer-related factors. Whatever these costs are, they do not appear to be going away over time.[6]

In sharp contrast, we show that the frequency of temporary sales has increased substantially over the past four decades. Temporary sales occur only in a subset of sectors. But their frequency has increased substantially in all of these sectors. Whether this has important implications for aggregate price flexibility is a question of active research over the past decade. The empirical literature has emphasized that temporary sales have quite different empirical properties from those of regular prices. Sales are much more transitory than other price changes, and less responsive to macroeconomic conditions. These characteristics substantially limit the contribution of temporary sales to aggregate price flexibility.[7] Moreover, this growth in temporary sales leaves the large and growing "gorilla in the room" sector—the service sector—untouched.

Relatively little work has been done on the sensitivity of price dispersion to changes in inflation in the United States. Reinsdorf (1994) uses BLS micro data for the period 1980-1982 (a subset of our data) and finds that price dispersion rose when inflation fell. Sheremirov (2015) uses scanner price data for the relatively low inflation period of 2002-2012. He finds that price dispersion rises with inflation. Alvarez et al. (2016) study the relationship between price dispersion and inflation during the Argentinian hyperinflation in 1989-1990. They find that the elasticity of price dispersion with inflation is roughly 1/3 at high inflation rates, in line with a simple menu cost model.[8]

The stability of the absolute size of price changes at different levels of inflation that we find in our data is consistent with earlier work. Cecchetti (1986) analyzes magazine prices at news stands and finds that the absolute size of price changes is stable over his sample period of 1953 to 1979. Gagnon (2009) finds that the absolute size of price changes varies little with inflation in Mexico during a large bout of inflation in the mid 1990's. Wulfsberg (2016) similarly finds that the absolute size of price changes varies very little in Norway over the Great Inflation period. Using scraped

[6] When firms are asked why they don't change their prices, they often say that the reason is "implicit contracts" with customers (Blinder et al., 1998). There is no reason to think that customer-related pricing frictions of this kind would be going away over time. Nakamura and Steinsson (2011) provide a recent formalization of how "customer markets" can yield price rigidity.

[7] These arguments are made in Nakamura and Steinsson (2008), Guimaraes and Sheedy (2011), Kehoe and Midrigan (2015), Anderson et al. (2015). See also Nakamura and Steinsson (2013) for a discussion of these ideas.

[8] An early literature studied the relationship between inflation and the dispersion of sectoral inflation rates (Mills, 1927; Glejser, 1965; Vining and Elwertowski, 1976; Parks, 1978; Fischer, 1981; Debelle and Lamont, 1997). However, such measures are very sensitive to sectoral shocks such as oil price shocks (Bomberger and Makinen, 1993).

data from the internet, Cavallo (2015) finds that the absolute size of price changes does not vary much across countries with very different levels of inflation.

The paper proceeds as follows. Section 2 discusses the welfare loss resulting from inflation in different models with price rigidity. Section 3 describes the construction of our new micro-dataset on consumer prices. Section 4 presents evidence based on this data that inefficient price dispersion was no higher when inflation was high in the late 1970's and early 1980's than it has been since then. Section 5 discussed the evolution of the frequency of price change over our sample period. Section 6 discusses our results on the evolution of price flexibility. Section 7 concludes.

2 Costs of Inflation in Sticky Price Models

To understand what drives the large costs of inflation in standard sticky price models, it is useful to lay out a simple model of the type used in the literature. The model economy is populated by households, firms, and a government. Consider first the households. There are a continuum of identical households that seek to maximize discounted expected utility given by

$$E_t \sum_{j=0}^{\infty} \beta^j \left[\log C_{t+j} - L_{t+j}\right], \tag{1}$$

where E_t denotes the expectations operator conditional on information known at time t, C_t denotes household consumption of a composite consumption good, and L_t denotes household supply of labor. Households discount future utility by a factor β per period. The composite consumption good C_t is an index of household consumption of individual goods produced in the economy given by

$$C_t = \left[\int_0^1 c_{it}^{\frac{\theta-1}{\theta}}\, di\right]^{\frac{\theta}{\theta-1}}, \tag{2}$$

where c_{it} denotes consumption of individual product i. The parameter $\theta > 1$ denotes the elasticity of substitution between different individual products.

Households earn income from two sources: their labor and ownership of the firms in the economy. The household's budget constraint is therefore

$$P_t C_t + Q_{it} B_{it} \leq W_t L_t + (D_{it} + Q_{it}) B_{it-1}, \tag{3}$$

where P_t denotes the aggregate price index, i.e., the minimum cost of purchasing a unit of C_t, W_t denotes the wage rate, D_{it}, Q_{it}, and B_{it} denote the dividend, price, and quantity purchased and sold of asset i. The assets in the economy include ownership claims to the firms in the economy and may include other assets such as a risk-free nominal bond and Arrow securities although these will not play any role in our analysis. To rule out "Ponzi schemes", we assume that household financial wealth must always be large enough that future income suffices to avert default.

Households take the prices of the individual goods p_{it} as given and optimally choose to minimize the cost of attaining the level of consumption C_t. This implies that their demand for individual product i is given by

$$c_{it} = \left(\frac{p_{it}}{P_t}\right)^{-\theta} C_t, \tag{4}$$

where

$$P_t = \left[\int_0^1 p_{it}^{1-\theta} di\right]^{\frac{1}{1-\theta}}. \tag{5}$$

Optimal choice of labor by the household taking the wage W_t as given yields a labor supply equation

$$\frac{W_t}{P_t} = C_t. \tag{6}$$

Household optimization also yields expressions for the household's valuation of all assets that exist in the economy. For the purpose of calculating the equilibrium in our model, it will be useful to have an expression for the household's valuation at time t of an uncertain dividend payment from firm i at time $t+j$, i.e., a j-period "dividend strip" for firm i. Let's denote the value of this dividend strip as V_{it}^j. Its value is

$$V_{it}^j = E_t\left[\beta^j \left(\frac{C_{t+j}}{C_t}\right)^{-1} D_{t+j}\right]. \tag{7}$$

Other conditions for household optimization do not play a role in determining the equilibrium.

There exists a continuum of firms in the economy that each produce a distinct individual product using the production function

$$y_{it} = A_{it} L_{it}. \tag{8}$$

Here A_{it} denotes the productivity level of firm i and L_{it} is the amount of labor demanded by firm i. The logarithm of firm productivity varies over time according to the following AR(1) process

$$\log A_{it} = \rho \log A_{it-1} + \epsilon_t, \tag{9}$$

where $\epsilon_t \sim \mathrm{N}(0, \sigma_\epsilon^2)$ are independent over time and across firms.

Firms commit to meet demand for their products at the price they post. They hire labor on the economy-wide labor market at wage rate W_t in order to satisfy demand. The marginal cost of firm i is $MC_{it} = W_t/A_{it}$. The firms are monopoly suppliers of the goods they produce. Their main decision is how to price these products. We assume that changing prices is costly and consider several different assumptions about these costs below.

Finally, to keep our model as simple as possible so that we can focus on the driving forces underlying costs of inflation in a sticky price setting, we assume that the monetary authority is able to control nominal output $S_t = P_t C_t$. Specifically, the monetary authority acts so as to make nominal output follow a random walk with drift in logs:

$$\log S_t = \mu + \log S_{t-1} + \eta_t \tag{10}$$

where $\eta_t \sim \mathrm{N}(0, \sigma_\eta^2)$ are independent over time. We will refer to S_t either as nominal output or as nominal aggregate demand.

2.1 The Flexible Price Benchmark

Let's begin by considering the equilibrium of this economy when prices are completely flexible. In this case, the firms will set the price of the good they produce equal to a markup over marginal cost

$$p_{it} = \frac{\theta}{\theta - 1} \frac{W_t}{A_{it}}, \tag{11}$$

This price setting equation can then be used to show that at the aggregate level

$$P_t = \frac{\theta}{\theta - 1} \frac{W_t}{A_f}, \tag{12}$$

where

$$A_f = \left[\int_0^1 A_{it}^{\theta - 1} di \right]^{\frac{1}{\theta - 1}}. \tag{13}$$

We refer to A_f as flexible price aggregate labor productivity.[9] The production function of this simple economy also aggregates easily. Using firm i's production function—equation (8)—the demand curve for firm i's output—equation (4)—the price setting equation for firm i—equation (11)—and integrating over i yields the following aggregate production function

$$Y_t = A_f L_t. \tag{14}$$

[9]Since we abstract from aggregate productivity shocks, if the cross-sectional distribution of idiosyncratic firm productivity A_{it} starts off at its ergodic distribution, the integral on the right-hand-side of equation (13) will remain constant.

where Y_t denotes aggregate output (which is equal to aggregate consumption $Y_t = C_t$). See Appendix A for derivations of equations (11)-(14).

We can now see that in this flexible price version of our model, the equilibrium values of output, labor, and real wages are determined by the following three simple equations:

$$\text{Labor Supply:} \qquad \frac{W_t}{P_t} = Y_t \tag{15a}$$

$$\text{Production Function:} \qquad Y_t = A_f L_t \tag{15b}$$

$$\text{Markup:} \qquad P_t = \Omega_f \frac{W_t}{A_f}. \tag{15c}$$

where $\Omega_f = \theta/(\theta - 1)$ denotes the amount by which firms choose to markup their products' prices over marginal costs when prices are fully flexible. Notice that these three equations only determine W_t/P_t, not the level of P_t and W_t individually. To pin down the level of nominal prices and wages, one must add $S_t = P_t Y_t$ to the system.

Using equations (15a)-(15c) to solve for output and labor supply yields

$$Y_t = \Omega_f^{-1} A_f \tag{16a}$$

$$L_t = \Omega_f^{-1}. \tag{16b}$$

Notice that this solution is independent of the rate of inflation and also independent of the history of shocks to nominal aggregate demand. The only distortion that moves this economy away from a first-best outcome is the monopoly power of the firms. This distortion leads the firms to set prices above marginal costs. As a consequence, output is inefficiently low.[10]

2.2 Equilibrium with Sticky Prices

When prices are sticky, the determination of equilibrium is more complicated and will depend on the exact nature of the price adjustment costs. We will consider several different assumptions about the nature of price adjustment costs including the case of a constant fixed cost (the menu cost model) and a case where the cost is zero with some probability in each period and infinite with a complementary probability (the Calvo (1983) model). We assume that firms maximize the value of their stochastic stream of dividends. The methods we use to solve for the equilibrium in these models are described in detail in Nakamura and Steinsson (2010).

[10] In a fully competitive version of the economy described above—i.e., one in which the markets for all the goods are competitive—all prices would be set equal to marginal cost and the markup Ω_f would therefore be one. Output would therefore be higher. We know from the first welfare theorem that this is the efficient level of output.

To help build understanding about the costs of inflation that result from sticky prices, it is useful to compare the equilibrium in the sticky price case with the flexible price equilibrium.[11] To this end, we consider an analogous set of equations to equations (15) for the sticky price case:

$$\text{Labor Supply:} \qquad \frac{W_t}{P_t} = Y_t \tag{17a}$$

$$\text{Production Function:} \qquad Y_t = A_t(\bar{\pi})(L_t - L_t^{pc}) \tag{17b}$$

$$\text{Price Setting:} \qquad P_t = \Omega_t(\bar{\pi})\frac{W_t}{A_t(\bar{\pi})}. \tag{17c}$$

The same labor supply equation continues to hold in the sticky price case. The aggregate production function—equation (17b)—however, differs from its flexible price analog—equation (15b)—in two ways. First, some labor is needed to change prices and does not produce output. We use L_t^{pc} to denote this extra labor. This is one source of costs of price rigidity. Second, aggregate labor productivity is lower in the sticky price economy than under flexible prices because in the sticky price model the relative prices of different goods do not accurately reflect the goods' relative marginal cost of production. In Appendix A we show that the value of aggregate labor productivity when prices are sticky is

$$A_t(\bar{\pi}) = \left[\int_0^1 \left(\frac{p_{it}}{P_t}\right)^{-\theta} A_{it}^{-1} di\right]^{-1}. \tag{18}$$

Note that aggregate labor productivity is not only a function of the physical productivity of the individual firms, but also a function of the relative prices of the goods they sell. This occurs because we use a utility based definition of aggregate output (see equation (2) and note that $Y_t = C_t$) and the marginal utility households derive from consumption of a particular product falls as they consume more of that product relative to other products. Consider for simplicity a case where all products have the same physical productivity. In this case, products that have low relative prices—and are therefore consumed in greater quantities—will contribute less to aggregate output on the margin than products with high relative prices. This will lower aggregate productivity of labor.[12] More generally, the more intensive consumption of the low priced goods will lower aggregate productivity of labor, unless their lower relative prices are offset by higher physical productivity.

When prices are sticky, the relative price of a particular product drifts downward as time passes between adjustments. This is one source of divergence between relative prices and relative

[11] This exposition builds on related analysis in Blanco (2015a) as well as earlier work in Burstein and Hellwig (2009).

[12] In the special case in which all firms have equal productivity, the variance of prices is a second order approximation for aggregate labor productivity.

productivity that results in lower aggregate labor productivity. This drift is more pronounced the higher is the level of inflation. For this reason, aggregate labor productivity is a decreasing function of the average level of inflation. To emphasize this, we make explicit the dependence of A_t on $\bar{\pi}$ by writing $A_t(\bar{\pi})$.

Equation (17c) is most usefully thought of as defining $\Omega_t(\bar{\pi})$. We will refer to $\Omega_t(\bar{\pi})$ as the aggregate markup in the sticky price case. Variation in $\Omega_t(\bar{\pi})$ reflects the degree to which the price level rises more or less rapidly than $A_t(\bar{\pi})$ falls as inflation changes.[13]

Manipulating equations (17) yields

$$Y_t = \Omega_t(\bar{\pi})^{-1} A_t(\bar{\pi}) \tag{19a}$$

$$L_t = \Omega_t(\bar{\pi})^{-1} + L_t^{pc} \tag{19b}$$

This shows that output under sticky prices will differ from its level under flexible prices for two reasons: 1) aggregate labor productivity will be lower, 2) the aggregate markup may be different; and aggregate labor supply will also differ from its level under flexible prices for two reasons: 1) Some labor is needed to change prices, 2) the aggregate markup may be different.

Welfare in the economy, in turn, depends on output and labor through equation (1). As is common in the literature, we will report welfare differences across models and levels of inflation in terms of consumption equivalent welfare changes. I.e., when comparing welfare in model economy A with welfare in model economy B we will solve for the value of Λ that yields

$$E\left[\log\left((1+\Lambda)C_t^A\right) - L^A\right] = E\left[\log\left(C_t^B\right) - L^B\right]. \tag{20}$$

The value Λ then measures the percentage change in consumption needed to make households in economy A equally well off as households in economy B.

2.3 Model Calibration

Below, we calculate equilibrium outcomes for a menu cost model and a Calvo model and compare them to the flexible price benchmark. These models are calibrated as follows. A unit of time is meant to correspond to a month. We set the subjective discount factor to $\beta = 0.96^{1/12}$. The baseline value that we use for the elasticity of substitution between intermediate goods is $\theta = 4$.

[13] It should be noted that $\Omega_t(\bar{\pi})$ does not measure how the average markup of firms over *physical* marginal costs change as inflation changes since $A_t(\bar{\pi})$ is not a measure of physical productivity but rather is also affected by the distribution of relative prices.

This value is roughly in line with estimates of the elasticity of demand for individual products in the industrial organization and international trade literatures (Berry et al., 1995; Nevo, 2001; Broda and Weinstein, 2006). This is, however, at the low end of values for θ that have been used in the macroeconomics literature on the welfare costs of inflation. We will also present results for $\theta = 7$, which is the value used by Coibion et al. (2012).

In the menu cost model, we calibrate the level of the menu cost and the standard deviation of the idiosyncratic shocks to match the median frequency of price change of 10.1% per month and the median absolute size of price changes of 7.5% over the (relatively low inflation) period 1988-2014.[14] The resulting parameter values are $K = 0.019$ for the menu cost and $\sigma_\epsilon = 0.037$ for the standard deviation of the idiosyncratic shocks.[15] In the Calvo model, we set the frequency of price change equal to the median frequency of price change in the data and the standard deviation of the idiosyncratic shocks to the same value as in the menu cost model. In both models, we assume that the first-order autoregressive parameter of the process for idiosyncratic productivity is $\rho = 0.7$, the same value as in Nakamura and Steinsson (2010).

We calibrate the standard deviation of shocks to nominal aggregate demand to be $\sigma_\eta = 0.0039$ based on the standard deviation of changes in U.S. nominal GDP over the period 1988-2014. We present results for a range of values of average change in nominal aggregate demand (i.e., a range of values for average inflation).

2.4 Numerical Results on the Costs of Inflation

Figure 2 plots the consumption equivalent welfare loss experienced by households when prices are sticky as a function of the inflation rate. The welfare loss is calculated relative to welfare in an economy with flexible prices. The difference in results between the menu cost model and the Calvo model is striking. For the menu cost model, the welfare loss is small and virtually completely constant at about 0.4% as a function of inflation. This is true both when $\theta = 4$ and $\theta = 7$.[16] For

[14] More specifically, we first calculate the average frequency and absolute size of price changes within ELIs (see section 3 for a discussion of what an ELI is) in each year. We then take a median across ELIs in each year. We then take an average of these medians over years.

[15] This menu cost implies that 0.019 units of labor are needed to change a price. For comparison, the non-stochastic steady state level of labor each month is $\Omega_f^{-1} = 0.75$.

[16] These costs include the menu costs themselves, i.e., the physical cost of changing prices. However, these physical costs are small for the reasons emphasized in Mankiw (1985) and Akerlof and Yellen (1985). The physical costs of price change rise slightly as inflation rises since the frequency of price change rises. However, this small effect is offset by a slight fall in price dispersion as prices bunch in the lower half of the inaction region (i.e., in the part below the reset price) as inflation rises above zero. At higher levels of inflation, price dispersion rises and the costs of inflation

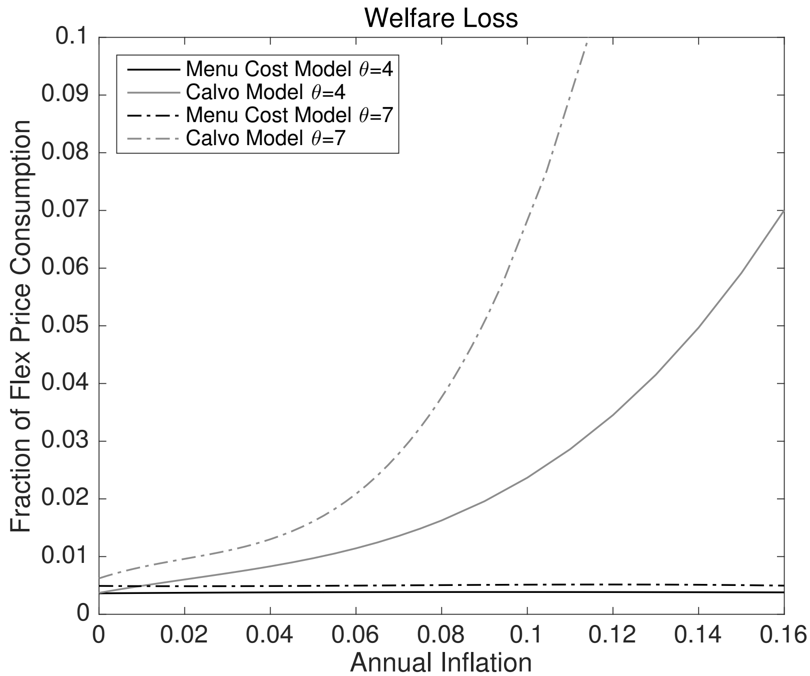

Figure 2: Welfare Loss

Note: The figure plots the consumption equivalent loss of welfare in each model as a function of the inflation rate relative to welfare when prices are completely flexible.

the Calvo model, however, the costs of price rigidity rise sharply with inflation. Consider first our baseline case of $\theta = 4$. When inflation is zero, these costs are similar in magnitude to those in the menu cost model. When inflation is 10% per year, these costs have risen to 2.4%; and when inflation is 16% per year, these costs are a staggering 7% per year. With $\theta = 7$, these welfare losses rise even faster. In this case, the welfare loss hits 10% when inflation is roughly 12%.

Clearly, the exact nature of price rigidities matter a great deal when assessing the costs of inflation. The reason for this is that the welfare costs of inaction are highly convex in the difference between a firm's price and its static optimal price. In the menu cost model, firms always have the option to pay the (relatively small) menu cost and therefore never allow their price to drift far from its optimal level. In the Calvo model, however, some firms are stuck with a price that is very far from its optimal lever and this generates large welfare losses.

It is interesting to consider the extent to which the difference between the Calvo model and the menu cost model arises because the frequency of price change is allowed to vary in the menu cost model versus because the menu cost model induces a different selection of firms to change their

rise.

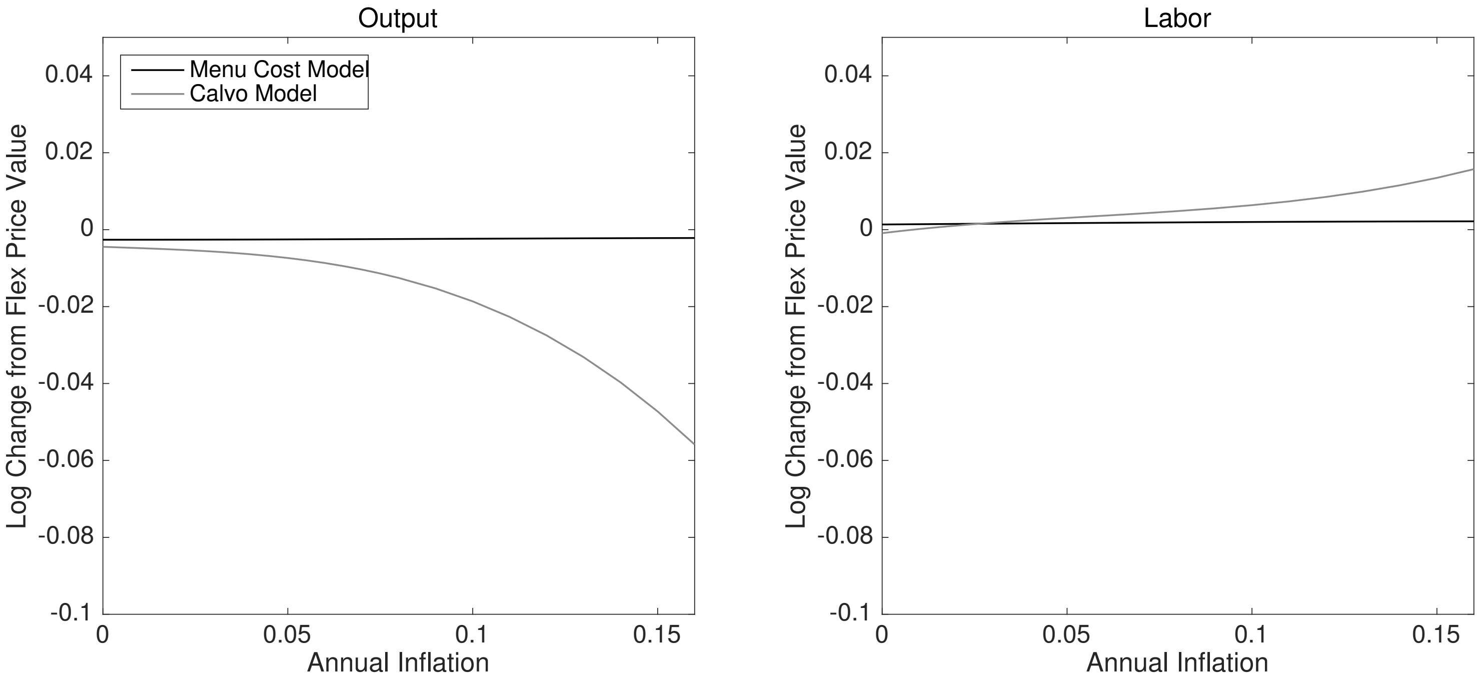

Figure 3: Output and Labor Supply

Note: The left panel plots average output and the right panel plots average labor supply. In each case, these variables are plotted as a function of inflation relative to their level when prices are flexible.

prices conditional on the frequency of price change. To this end, Figure A.5 in the appendix adds results for a version of the Calvo model with a frequency of price change that varies with inflation and is chosen to equal the frequency of price change in the menu cost model at each level of inflation. This model generates welfare losses that are substantially smaller than the Calvo model with a fixed frequency of price change but quite a bit larger than the menu cost model. These results show that both variation in the frequency and differences in selection contribute substantially to the difference between the Calvo model and the menu cost model.[17]

To gain further insight, Figure 3 plots the level of output and labor supply in the menu cost model and Calvo model as a function of inflation (again relative to the level of these variables when prices are flexible). This figure shows that in the Calvo model, an increase in inflation from 0% to 10% leads to a fall in output of about 1.5%. But the amount of labor needed to produce this lower output is actually greater by 0.7% due to a fall in labor productivity. As with welfare, these changes in output and labor supply grow increasingly rapidly as inflation rises above 10%.

Figure 4 plots labor productivity directly as well as the aggregate markup (again relative to

[17]Figures A.6 - A.8 present results on the absolute size and frequency of price change for this version of the Calvo model with a varying frequency of price change in addition to the other models considered in the paper.

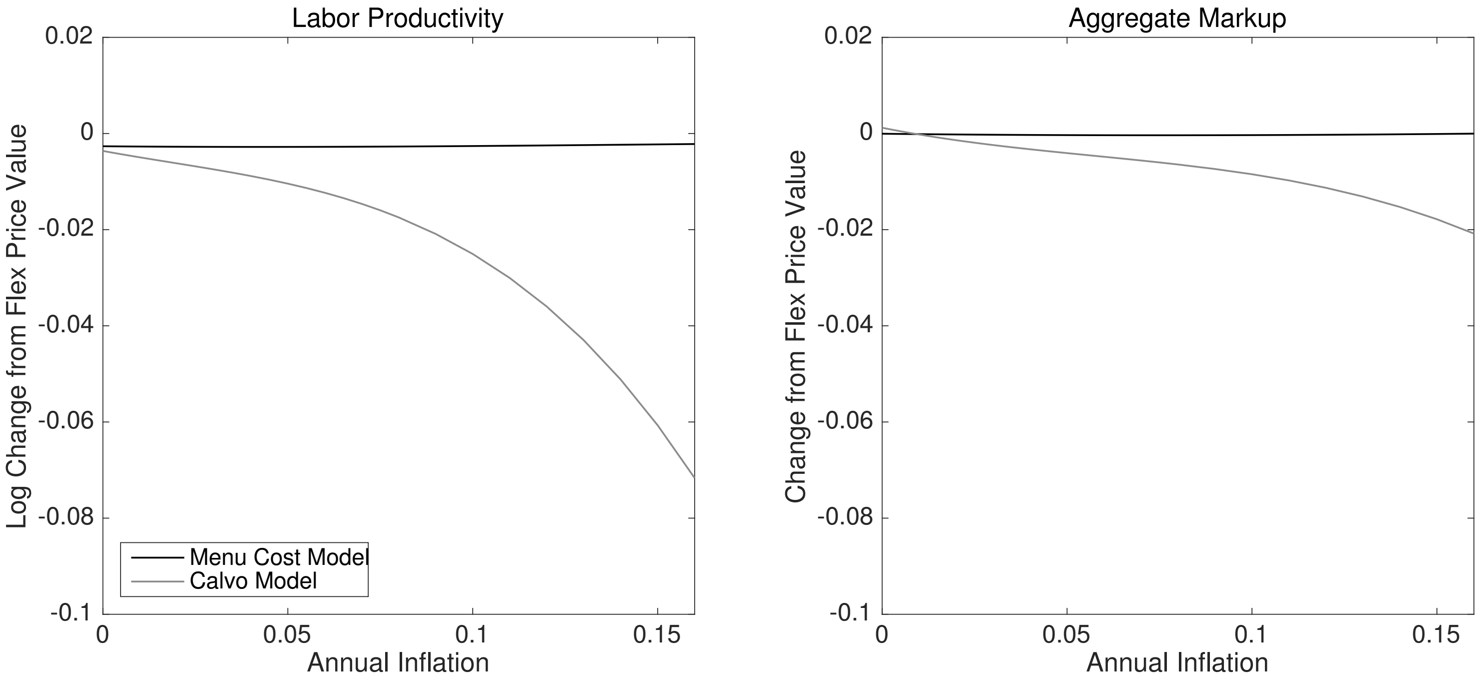

Figure 4: Labor Productivity and Aggregate Markup

Note: The left panel plots average labor productivity and the right panel plots the aggregate markup. In each case, these variables are plotted as a function of inflation relative to their level when prices are flexible.

the level of these variables when prices are flexible). From this figure we see that the welfare loss that results from a higher rate of inflation in the Calvo model comes entirely from a sharp fall in labor productivity. Labor productivity falls by 2.1% when inflation rises from 0% to 10%. The other two potential sources of welfare losses discussed in section 2.2 are non-existent or actually increase welfare in the Calvo model. First, in the Calvo model, firms face no direct costs when they change their prices. Second, the aggregate markup actually falls when inflation rises (by roughly 0.9 percentage points, when inflation rises from 0% to 10%).[18] In other words, the price level relative to the wage rate does not rise quite as rapidly as labor productivity falls implying the output does not fall as rapidly as labor productivity.[19]

At an intuitive level, the loss of labor productivity in the Calvo model when inflation rises is due to an increase in inefficient price dispersion. In fact, these two concepts are equal up to a second order approximation when we abstract from idiosyncratic productivity shocks. To drive home this

[18]Recall that our measure of the aggregate markup is different from the average of firms' markups over physical marginal cost (since our measure of aggregate productivity is utility based). The average markup over physical marginal costs actually rises with inflation in the Calvo model (King and Wolman, 1996).

[19]In the menu cost model we analyze, the aggregate markup does not change much with inflation over the range we consider. Benabou (1992) studies a menu cost model with consumer search in which the higher price dispersion resulting from inflation leads to more search, which in turn makes markets more competitive an lowers markups.

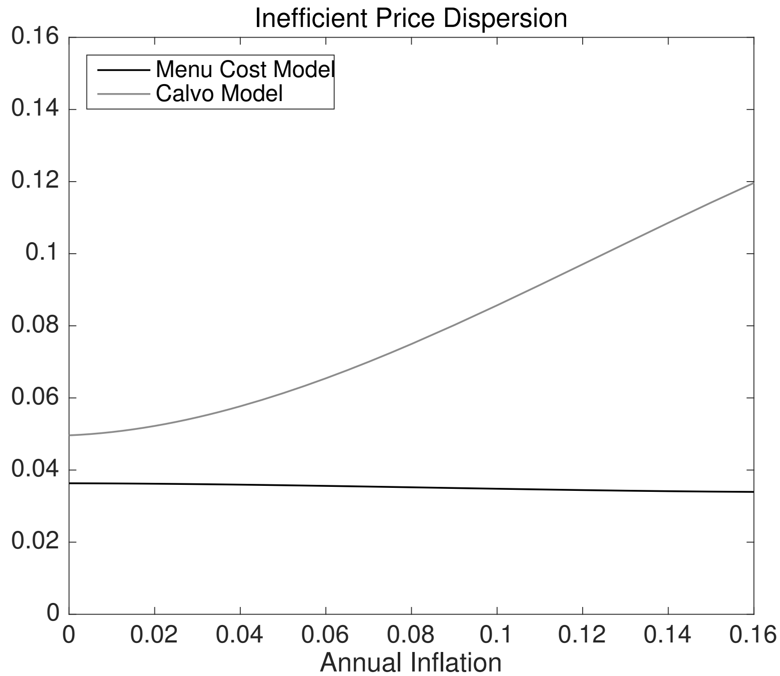

Figure 5: Inefficient Price Dispersion

Note: The measure of inefficient price dispersion that we plot here is the standard deviation across firms of the firm's price relative to the price it would charge if it had flexible prices.

point, Figure 5 plots inefficient price dispersion in the Calvo model and the menu cost model as a function of inflation. We see that the pattern for inefficient price dispersion is very similar to the pattern for labor productivity (and the overall welfare loss). This is useful in terms of providing us with guidance regarding what statistics we should calculate to shed empirical light on the costs of inflation.

3 New Micro-Data on Consumer Prices during the Great Inflation

Our analysis is based on a new dataset that we have developed with the help and support of staff at the Bureau of Labor Statistics.[20] The dataset contains the individual price quotes underlying the U.S. Consumer Price Index for the period from May 1977 to October 1986 and May 1987 to December 1987. Prior to our project, the BLS CPI Research Database contained data starting only in 1988. It therefore had the important disadvantage that it did not cover the most eventful period in post-WWII U.S. monetary history: the "Great Inflation" of the late 1970's and early 1980's.

[20] We owe a huge debt to Daniel Ginsberg, John Greenlees, Michael Horrigan, Robert McClelland, John Molino, Ted To and numerous others at the Bureau of Labor Statistics whose efforts were crucial in making this project possible.

The construction of the dataset involved two main phases. First, we worked with the BLS staff to scan the physical microfilm cartridges to convert them to digital images. This step was difficult because the microfilm cartridges were sufficiently old that modern scanners could not read them. Fortunately, we were able to find a company that was willing and able to retrofit a modern microfilm reader to read these outdated cartridges.

The process of scanning the microfilm cartridges left us with roughly 1 million images of "Price Trend Listings" that needed to be converted to machine-readable form. The BLS' high standards of confidentiality imply that all processing of the data must be done on-site at the BLS in Washington DC. This made it infeasible to outsource this step to a professional data-entry firm for manual data entry. The alternative available to use was to use optical character recognition (OCR) software for this conversion process. This was challenging because leading commercial software solutions turned out to be both prohibitively expensive and too slow. After considerable search, we, however, found a firm that was able to create custom software that ensured high quality and high enough speed to convert the large number of images we had.[21]

The raw microfilm cartridges we found at the BLS contain images of Price Trend Listings, starting in May 1977 and ending in October 1986. Each Price Trend Listing contains prices for the previous 12 months for a given product—a feature of the data that we make considerable use of in checking for errors, as we describe below. All cartridges from the period 1977-1981 we scanned, while cartridges from every other month for the period 1982-1986 were scanned. This choice was motivated by the higher quality of the images on the more recent cartridges. It is possible that even older CPI micro-data exists at the BLS. However, the CPI underwent a major revision in 1978. We conjecture that data collection was revised as a part of this revision and the May 1977 start date of our data is the start date of the new data collection system put in place at this time. We obtained separate, already digitized data on prices for the months of May to December in 1987. This left us with a short gap in coverage for the period November 1986 to April 1987.

The information contained on the Price Trend Listing images includes 1) an internal BLS category label called an Entry Level Item or ELI, 2) a location (city) identifier, 3) an outlet identifier, 4) a product identifier, 5) the product's price, 6) the percentage change in the product's price between collection periods, 7) a "sales flag" indicating whether the product's price was temporarily

[21] In overcoming these practical obstacles, we benefited greatly from Patrick's tireless work and ingenuity. The rest of us are very grateful for his efforts in this regard.

marked down at the time of collection, 8) an "imputation flag" indicating whether the price listed is truly a collected price or was imputed by the BLS, and 9) several additional flags that we do not use. From this we see that each product in the dataset is identified at a very detailed level—for example, a 2-Liter Diet Coke at a particular Safeway store in Chicago.

BLS employees collect the data by visiting outlets on a monthly or in some cases bi-monthly basis. Somewhere between 80,000 and 100,000 observations are collected per month. Prices of all items are collected monthly in the three most populous locations (New York, Los Angeles, and Chicago). Prices of food and energy are collected monthly in all other locations as well. Prices of other items are collected bimonthly. We focus on the monthly data in our analysis.

Fortunately, there are numerous redundancies in the raw data that allow us to check for errors in our OCR procedure. The first form of redundancy arises from the fact that prices for a particular product in a particular month appear on multiple Price Trend Listings because the Price Trend Listings include 12 months of previous prices, as we note above. We can use this redundancy to verify that the price observations obtained from different Price Trend Listings are, in fact, the same. The second form of redundancy arises because each Price Trend Listing includes both the price and a percentage change variable. We can therefore verify that the percentage change in prices obtained when we calculate this directly based on the converted prices is the same as the one reported in the percentage change variable. We describe both of these procedures in detail in Appendix B. We err on the side of caution: all of the price observations included in our final dataset have been "accepted" by either of the procedures described above.

The order of the Price Trend Listings allows us to check for errors in the OCR conversion of the product label and category variables. Each microfilm cartridge corresponds to a particular "collection period" when the prices were collected. On each cartridge, images are sorted first by product category (ELI), then by outlet, then by quote (a specific product, such as a 2-Liter Diet Coke), and finally by the version (used when a product is replaced by other very similar product). The order of the Price Trend Listings means that if our OCR procedure fails to convert a particular ELI value, we can easily fill it in using the surrounding values of ELI's. We use a similar procedure to fill in missing values of the outlet, quote and version variables. The algorithm we use for this is described in Appendix B. Errors in converting the product identifiers will lead to a spuriously large number of products. Appendix B discusses this in more detail and describes a procedure we use to verify that this does not bias our results.

Finally, our process for converting the sales and imputation flag variables makes use of the limited set of values taken by these values (e.g., "I" stands for imputation). We also make use of the fact that, like in the case of prices, the flags for a given product-month appear on multiple Price Trend Listings. We discuss these procedures in greater detail in Appendix B.

The BLS has changed the organization of the consumer price micro-data two times since 1978. The first change occurred in 1987 and the second, more substantial change, occurred in 1998. We have created a concordance to harmonize the ELI categories across these different time periods. To do this, we first used the category descriptions to match the ELI categories used in the 1977-1986 and the ones used in 1987-1997. We then used the descriptions available in the BLS' documentation for the CPI Research Database to match the ELI's for 1987-1997 and 1998 onwards. A detailed set of concordances is available on our websites.

We will hand over the new dataset we have constructed to the BLS so that they can make it available to researchers in the same way the existing BLS CPI Research Database is available. The data we will make available will include the original scanned images (in PDF format), the raw dataset that resulted from our OCR conversion (with all the redundancies discussed above), and the final dataset we constructed using the procedures discussed above and in Appendix B. The availability of all three of these versions of the data will therefore allow future researchers to improve on our data construction effort (both the OCR conversion and the accuracy verification of the OCR output).

In our analysis of this data, we drop all imputed prices. Whenever we observe a price change that is larger than one log point ($\log(p_t/p_{t-1}) > 1$), we set the price change variable and price change indicator to missing (i.e., we drop these large price changes). Only 0.04% of observations are dropped because they are large. We frequently calculate weighted means and medians of various statistics across ELIs by year. In all cases, we hold fixed the expenditure weights at their value in 2000. While the accuracy of our data conversion methods seems high for most of our sample, we are not fully confident in the quality of the resulting data at the very beginning of our sample. For this reason, we drop the data from 1977. Our sample period is therefore 1978 to 2014.

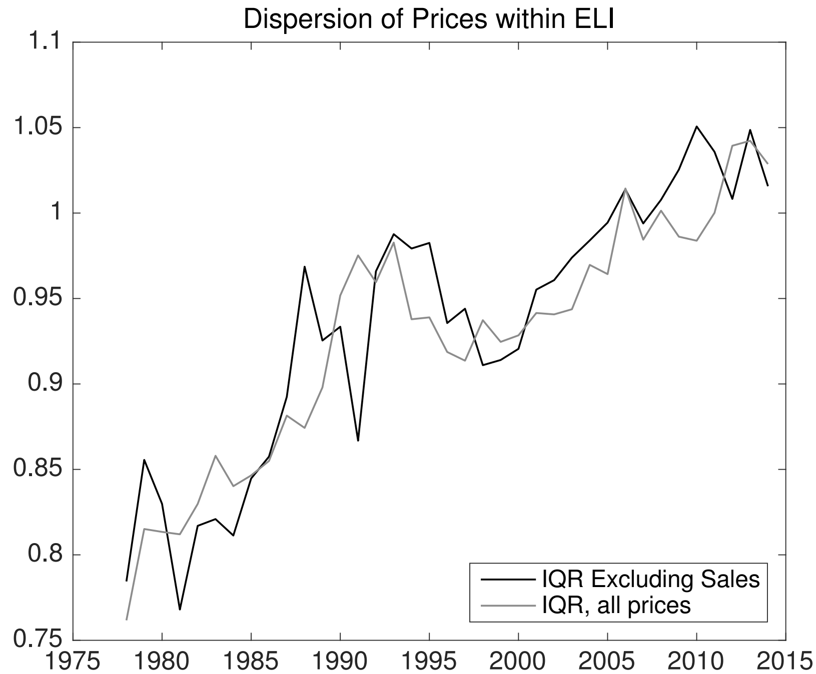

Figure 6: Dispersion of Log Prices within ELI

Note: To construct the series plotted in this figure, we first calculate the interquartile range of log prices in each ELI for each year. We then take the weighted median across ELI's. We do this both for prices including and excluding temporary sales.

4 Price Dispersion and the Size of Price Changes

We have seen in section 2 that the costs of inflation in sticky price models are largely due to increases in inefficient price dispersion. Figure 6 plots the evolution of a simple measure of price dispersion for U.S. consumer prices over the period 1978-2014. We first calculate the interquartile range of prices within Entry Level Items (ELI's)—narrow product categories defined by the BLS such as "salad dressing"—for each year. We then take the expenditure weighted median across ELI's. We calculate this measure of price dispersion both including and excluding temporary sales.

Figure 6 shows that this simple measure of price dispersion has increased steadily over the past 40 years. This is driven by dramatic increases in price dispersion within ELI for unprocessed food, processed food, and travel services. This increase in dispersion is, of course, the opposite result from what one might have expected given that inflation has fallen sharply over this period (see Figure 1). As we discuss in the introduction, a key empirical challenge is that much of the cross-sectional dispersion in prices—even within narrowly defined product categories—likely results from heterogeneity in product size and quality. The observed increase in the cross-sectional dispersion in prices may therefore come from an increase in product heterogeneity as opposed to time variation in inefficient price dispersion. The pattern revealed in Figure 6 suggests that a large increase in product variety over the past 40 year—for example among food products—has lead to an increase in price dispersion within ELI that has been large enough to dwarf any (relatively small) changes in price dispersion associated with price rigidity.[22]

4.1 Fixed-Effects Price Gap

The notion that raw price dispersion is dominated by product heterogeneity even within narrow categories suggests that "differencing out" fixed product characteristics may yield a good measure of inefficient price dispersion. One approach to doing this is to look at the deviation of observed prices from their long-run mean real level.[23] Consider the following statistic, which we refer to as the "fixed-effects price gap":

$$x_{ijt} = \log p_{ijt} - \log P_{jt} - \sum_{\tau=t_0^{ij}}^{T^{ij}} [\log p_{ij\tau} - \log P_{j\tau}]. \tag{21}$$

Here p_{ijt} is the price of product i in product category j at time t, P_{jt} is a price index for product category j, and t_0^{ij} and T^{ij} are the first and last periods for which we observe a price for product ij, respectively. The statistic x_{ijt} therefore measures the real price of product ij relative to its mean over the entire period for which we observe a price for this product.

If products' desired real prices were fixed over time (and each product observed for long enough in our data), then the fixed-effects price gap would difference out heterogeneity in desired prices within product category and allow us to construct a direct measure of inefficient price dispersion. The problem is that the recent literature has convincingly argued that desired real prices are far from being fixed over time. Price changes are too large, and are too often decreases, to be accounted for by aggregate shocks alone. Golosov and Lucas (2007) argue that these basic empirical features of the price data strongly suggest the presence of large idiosyncratic shocks to desired prices.[24]

To illustrate this problem, we simulate data from the menu cost model we describe in section 2. Recall that our objective is to find an empirical proxy for the true gap between a product's price and its unobserved desired price. Let's call this the "true price gap." Figure 7 presents a

[22] Another possible source of the increase in cross-sectional price dispersion is greater dispersion of desired markups. Price dispersion of this kind is desired from the firms' perspective but may reduce aggregate welfare.

[23] We are grateful to a referee for suggesting this procedure.

[24] It is not possible to get away from this idiosyncratic variation in prices simply by looking within categories. There is a large amount of idiosyncratic variation in the size and timing of price changes, even within ELI's.

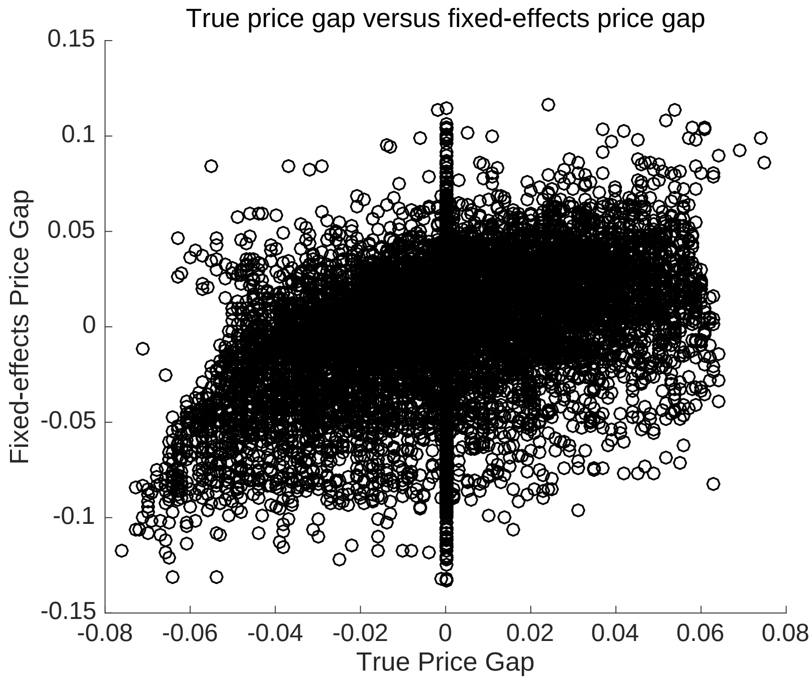

Figure 7: Fixed Effects Price Gap Vs. True Price Gap in the Menu Cost Model

scatter plot of the relationship between the fixed-effects price gap and the true price gap based on a simulation of our menu cost model.[25] Clearly, the fixed-effects price gap is only weakly correlated with the true price gap in our menu cost model. This arises because idiosyncratic shocks lead to large fluctuations in desired real prices. Moreover, there is a "selection effect": the fixed-effects price gap shows a large gap for products that have not adjusted their prices for a long time. However, when idiosyncratic variation in desired real prices is large, the fact that a product's price has not been adjusted for a long time contains information about the products optimal price. Products whose prices haven't adjusted in a long time are products whose real desired prices are falling for unobserved, idiosyncratic reasons.

4.2 Absolute Size of Price Changes

To overcome the difficulties discussed above, we propose to focus on the times when prices change. At these times, a substantial amount of information is revealed about the product's desired price and the distance a product's price has drifted from its desired price. Intuitively, if higher inflation

[25]We assume that there is a constant hazard rate that products will exit the dataset. When a product exits the dataset, a new product replaces the old product and enters the dataset with a newly reoptimized price. The hazard rate of product substitution in the simulation is set equal to the frequency of product substitutions estimated in Nakamura and Steinsson (2008).

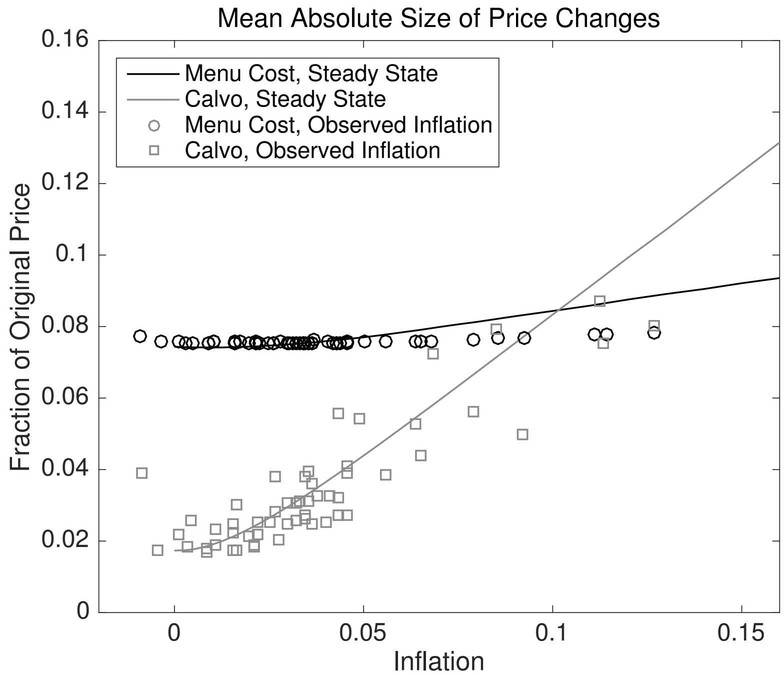

Figure 8: Absolute Size of Price Changes in Sticky Price Models

Note: The lines plot the mean absolute size of price changes as we vary the steady state level of inflation in the menu cost and Calvo models. The circles and squares plot the mean absolute size of price changes in the menu cost model and Calvo model, respectively, from a monthly simulation using the actual inflation rate from 1978 to 2014. Each point is the average from a particular year in the simulation.

truly leads prices to drift further from their efficient levels due to price rigidity, we should observe larger price changes when firms finally adjust their prices. This idea suggests that the absolute size of price changes may be a good proxy for inefficient price dispersion. Importantly, this "revealed preference" argument circumvents both the problem of product heterogeneity and the problem of idiosyncratic variation in desired prices.

Figure 8 compares the relationship between inflation and the average absolute size of price changes in the Calvo model and in the menu cost model. We do this in two ways. First, we plot the steady state average absolute size of price changes for different steady state values of inflation. These are the two lines in the figure. For the Calvo model, the average absolute size of price changes rises sharply with inflation, while this is not the case in the menu cost model. Recall that this is exactly the pattern that holds for inefficient price dispersion. This illustrates that studying the absolute size of price changes provides an indirect, yet powerful, way to measure the extent to which inefficient price dispersion rises with inflation.

A concern with the steady state calculation that underlies the two lines in Figure 8 is that the Great Inflation was a somewhat transitory event. Perhaps inflation was not high for long enough during the Great Inflation to create the degree of price dispersion needed to substantially raise the average absolute size of price changes. We can address this concern by simulating the response of the average absolute size of price change to the actual evolution of inflation in the U.S. in the two models over our sample period. These are the two sets of points in the figure. Each point gives the average absolute size of price changes and the average inflation in a particular year between 1978 and 2014.[26] This exercise, while somewhat noisier, gives results very similar to the steady state calculation discussed above.

Figure 9 plots the evolution of the absolute size of price changes over the period 1978-2014. We first calculate the mean absolute size of price changes within ELI by year and then take an expenditure weighted median across ELIs for each year. We again report results both including and excluding temporary sales. Even though the inflation rate has fallen sharply over our sample period, the absolute size of price changes has remained essentially unchanged over this time period at roughly 8%. If anything, there is actually a slight upward trend over the sample period. The evolution of the absolute size of price changes, therefore, provides no evidence that prices strayed farther from their efficient levels during the Great Inflation than in the low-inflation Greenspan-Bernanke period.[27]

The welfare costs of price rigidity depend non-linearly on the extent to which individual prices differ from their efficient level. Prices that are very far from optimal contribute disproportionately to welfare losses. The random nature of the timing of price adjustment in the Calvo model implies that as inflation rises the distribution of relative prices becomes highly dispersed. The distribution of relative prices has a long left tail with some firms having wildly inappropriate prices because they have not been able to change their price for a long period. When these prices finally change, they change by large amounts. In contrast, in the menu cost model, the absolute size of firms' price changes is small because all price changes are clustered around the sS bounds.

Conditional on the average absolute size of price changes, the standard deviation of the absolute

[26]The simulations are done at a monthly frequency and the results then time-averaged to annual observations. We start the simulation in January 1960 to make sure that the distribution of relative prices in 1978 reflects the actual U.S. inflation history leading up to that point. In these simulations, we assume for simplicity that the real wage is constant and feed in the observed inflation rate (i.e., we use a partial equilibrium version of the model). The perceived law of motion for the price level is a random walk with drift. We calibrate the perceived average drift and perceived standard deviation of monthly changes in the price level to their sample analogues over the period 1960 to 2014.

[27]Figure A.1 in the appendix shows that the average size is flat (or slightly upward sloping) within sector for six of the most important sectors in our data. Figure A.2 shows that there is nothing special about the median across ELIs. The 10th, 25th, 75th and 90th quantiles tell essentially the same story. Figure A.3 shows the absolute size of price increases and decreases at a quarterly frequency.

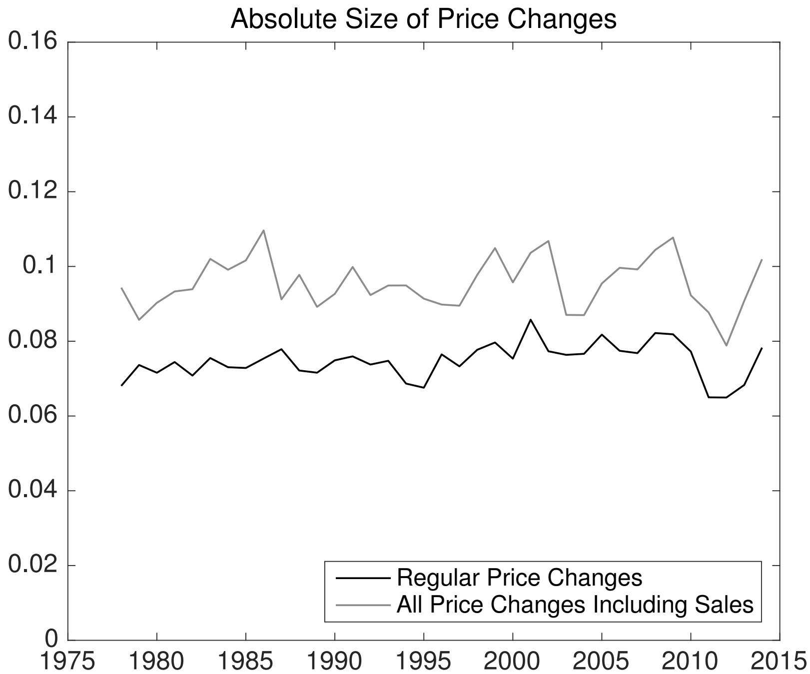

Figure 9: Absolute Size of Price Changes in U.S. Data

Note: To construct the series plotted in this figure, we first calculate the mean absolute size of price changes in each ELI for each year. We then take the weighted median across ELI's. We do this both for prices including and excluding temporary sales.

size of price changes provides information about the dispersion of the distribution of relative price changes and, in particular, information about how many firms have wildly inappropriate prices. Figure 10 plots the standard deviation of the absolute size of price changes as a function of inflation in the Calvo model and in the menu cost model (using the same two methods as we do for the mean absolute size of price changes in Figure 8). We see that the standard deviation of the absolute size of price changes rises by more than a factor of six in the Calvo model, as the inflation rate rises from 0 to 16% per year. In contrast, this measure rises only slightly in the menu cost model.

Figure 11 reports the standard deviation of the absolute size of price changes in the data over our sample period of 1978-2014. Like with the average absolute size statistic, we first calculate the standard deviation of the absolute size of price changes within ELI for each year and then take a weighted median across ELI's for each year. This statistic turns out to be quite stable over time in the data. It varies between roughly 4.5% and 6% for the majority of the sample period. If anything, it displays a slight upward trend. This statistic, again, provides us with no evidence that the distribution of relative prices became more dispersed during the Great Inflation.[28]

[28]The standard deviation of the absolute size of price changes is larger in the data than in the model. This likely reflects cross-sectional variation in menu costs that we have abstracted from in our model.

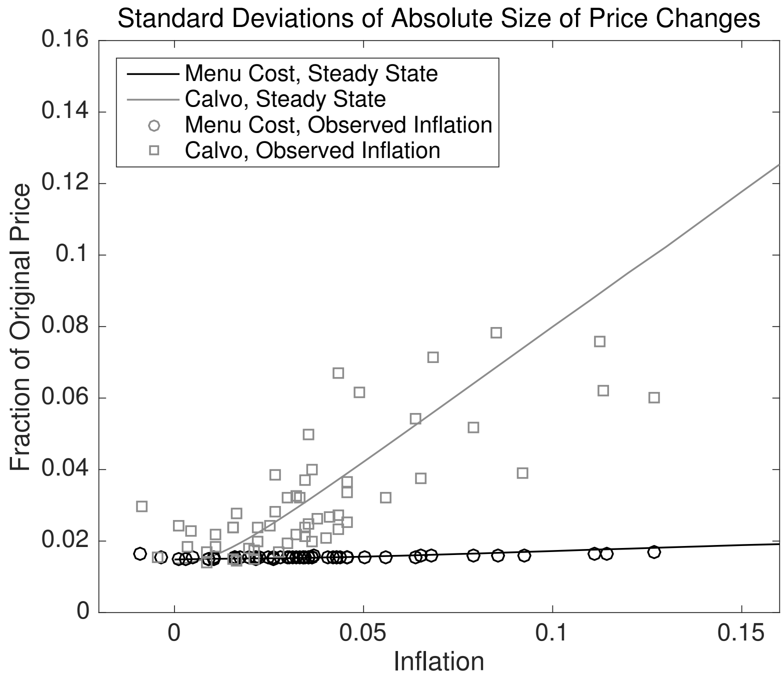

Figure 10: Standard Deviation of Absolute Size of Price Changes

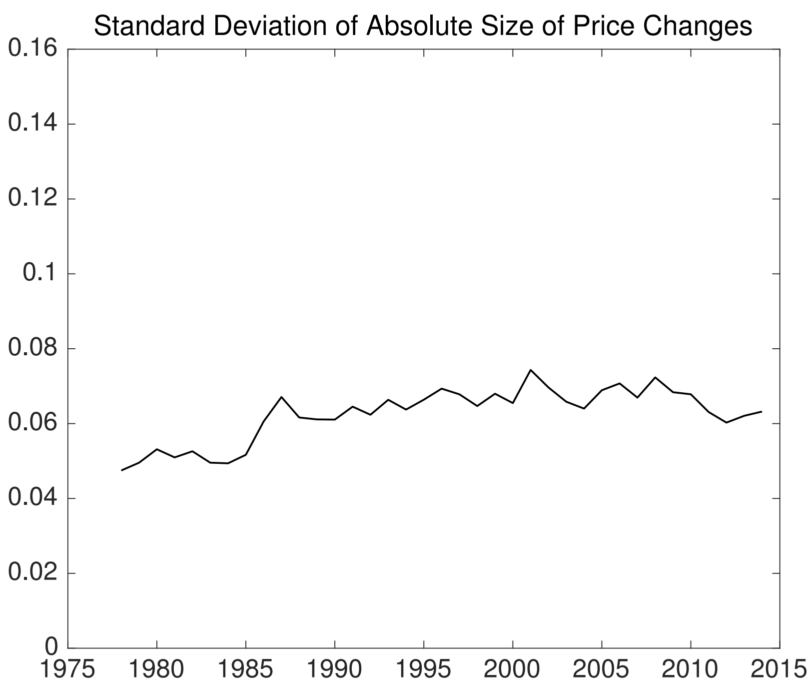

Figure 11: Standard Deviation of Absolute Size of Price Changes in U.S. Data

Note: To construct the series plotted in this figure, we first calculate the standard deviation of the absolute size of price changes in each ELI for each year. We then take the weighted median across ELI's.

We can similarly analyze the behavior of the fixed-effects price gap discussed in section 4.1 in the Calvo and menu cost models and in the data. Even thought the fixed-effects price gap does not provide a reduced form measure of price dispersion, it's evolution over time may still provide useful information through the lens of the structural models. The two lines in Figure 12 plot the interquartile range of the fixed-effect price gap for different levels of average inflation in the menu cost model and the Calvo model. Even though the fixed-effects price gap is only weakly correlated with the true price gap (Figure 7), the interquartile range of this statistic does rise more quickly with inflation in the Calvo model than the menu cost model. However, this statistic turns out to be quite noisy in the data, perhaps because measures of dispersion are harder to estimate than means. The circles in Figure 12 are a scatter plot of the interquartile range of the fixed-effects price gap versus the inflation rate across years in our sample after adjusting for breaks associated with reclassification of the ELI product groups in 1988 and 1998.[29] The large amount of noise in the fixed-effects price gap in the data limits the informativeness of this statistic in distinguishing between models in which inflation is costly and those in which it is not.

5 Frequency of Price Change

Thus far in the paper, we have focused on the size of price changes because of its relation to price dispersion and welfare. The frequency of price change is in some sense the flip side of the coin. If inflation rises but the size of price changes don't, the frequency of price change must be changing.[30] Earlier research by Klenow and Kryvtsov (2008) and Nakamura and Steinsson (2008) has studied the time series behavior of the frequency of price change and its relationship to inflation in the U.S. using data on prices since 1988. The inference one can draw from these papers is, however, limited by the fact that inflation in the U.S. has been low and stable over the post-1988 period. The data

[29] We use price indexes at the major group level to construct the fixed-effects price gap in the data. We first calculate the fixed-effects price gap at the product-month level and then calculate the interquartile range of this statistic at the ELI-year level. As we discuss in section 3, the BLS updated the ELI product group classification in 1988 and in 1998. This reclassification leads to obvious breaks in the interquartile range of the fixed-effects price gap in several major groups. To adjust for this, we run a regression of the interquartile range of the fixed-effects price gap at the ELI-year level on major group inflation, major group dummies, dummies for pre-1988 and post-1998, and the pre-1988 and post-1998 dummies interacted with the major group dummies. We then filter out the pre-1988 and post-1998 dummies as well as their interaction with the major group dummies. After we have done this filtering, we take a weighted median across ELI within year and plot the resulting statistics against the inflation rate in that year.

[30] A subtlety here is that at low levels of inflation the frequency and absolute size of price changes can be relatively constant as inflation rises if the fraction of price changes that are increases is rising with inflation. In this case, the behavior of the average size and the average absolute size can be quite different. At higher levels of inflation, most price changes are increases and this distinction is less important (Gagnon, 2009).

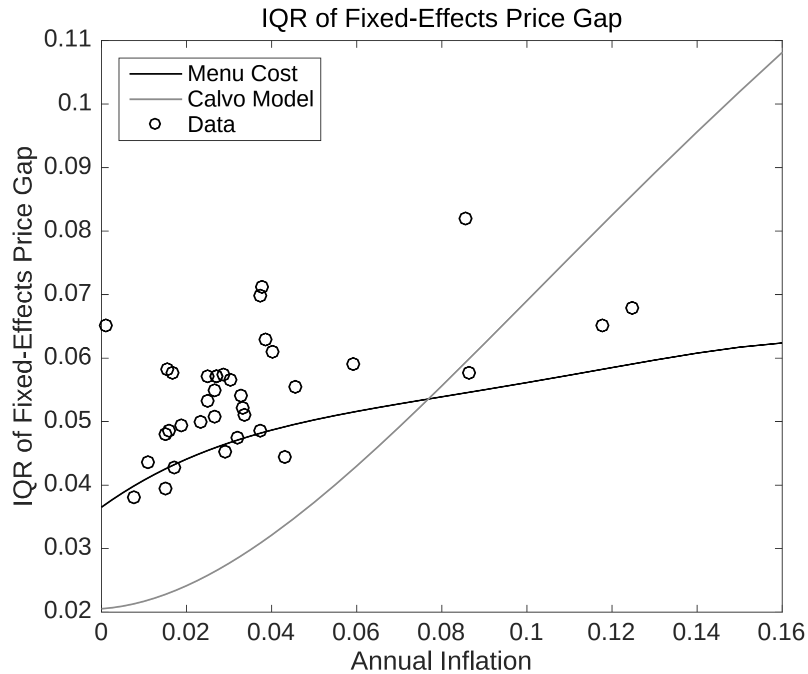

Figure 12: Fixed-Effects Price Gap in the Models and the Data

Note: The lines plot the interquartile range of the fixed-effects price gap in the menu cost and Calvo models for different levels of steady state inflation. The circles are a scatter plot of the the interquartile range of the fixed-effects price gap versus the inflation rate across years in our sample after adjusting for breaks associated with reclassification of the ELI product groups in 1988 and 1998.

from the Great Inflation that we analyze in this paper have much more power to distinguish among different pricing theories.[31]

Figure 13 plots the relationship between the frequency of price change and inflation in the menu cost model and the Calvo model. As with the size statistics discussed in section 4, we calculate this relationship for different steady state levels of inflation (the lines in the figure) and for a simulation based on the actual history of inflation in the U.S. over the period 1978 to 2014 (the points in the figure). Not surprisingly, the menu cost model implies that the frequency of price change rises with inflation. When inflation rises from 0% to 16%, the frequency of price change rises by more than half, going from 10% to 16%. In contrast, the frequency of price change is constant in the Calvo model by assumption.

Figure 14 plots the frequency of price change for consumer prices in the U.S. over our sample period of 1978-2014 along with the CPI inflation rate. To construct this series, we first calculate

[31] Important evidence on this topic is also available from a number of other (mostly middle income) countries with more volatile inflation rates. See, in particular, Gagnon (2009) and Alvarez et al. (2016) for evidence from Mexico and Argentina, respectively, and Wulfsberg (2016) for evidence from Norway. Nakamura and Steinsson (2013) discuss this literature in more detail.

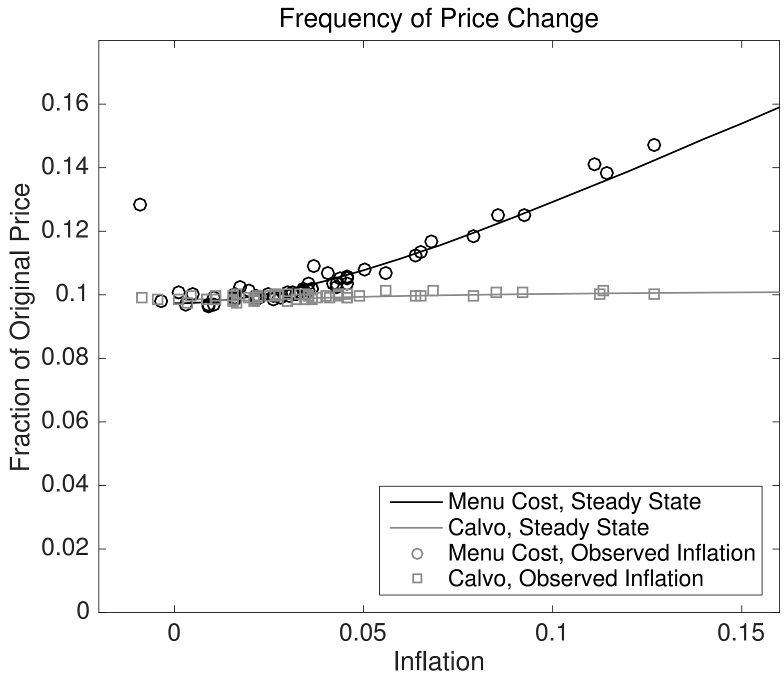

Figure 13: Frequency of Price Changes in Sticky Price Models

Note: The lines plot the frequency of price change as we vary the steady state level of inflation in the menu cost and Calvo models. The circles and squares plot the frequency of price change in the menu cost model and Calvo model, respectively, from a monthly simulation using the actual inflation rate from 1978 to 2014. Each point is the average from a particular year in the simulation.

the mean frequency of price change by ELI for each year. We then take an expenditure weighted median across ELIs for each year. The figure clearly shows that the frequency of price change comoves strongly with inflation. This data therefore strongly favors the menu cost model over the Calvo model.

Figure 15 separates the frequency of price increases and the frequency of price decreases. Here we plot the 12 month average frequency of price change at a quarterly frequency to see a bit more detail. The most striking feature of this figure is that it is the frequency of price increases that varies with the inflation rate, while the frequency of price decreases is unresponsive. Nakamura and Steinsson (2008) show that this asymmetry arises naturally in the menu cost model when prices are drifting upward due to a positive average inflation rate. In this case, prices tend to "bunch" toward the bottom of their inaction region. Because of this bunching, when there is an aggregate shock that changes desired prices, there is a large response of the frequency of price increases (reflecting the relatively large mass at the bottom of the band), but a much smaller response of the frequency of price decreases. This is the same argument as the one described by Foote (1998) for why job

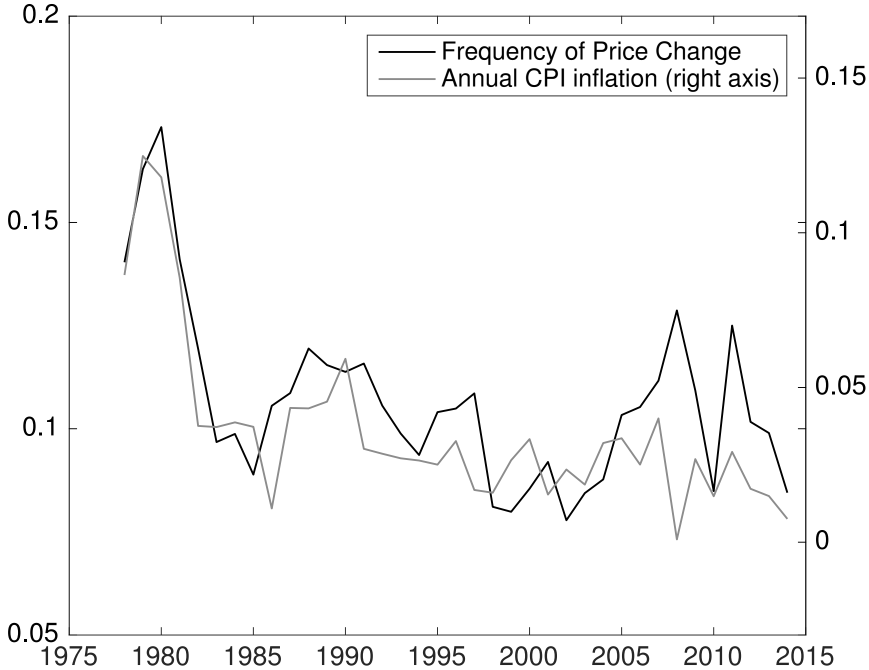

Figure 14: Frequency of Price Changes in U.S. Data

Note: To construct the frequency series plotted in this figure, we first calculate the mean frequency of price changes in each ELI for each year. We then take the weighted median across ELI's.

destruction will be more volatile than job creation in declining industries.[32]

One curious feature of Figure 14 is the spike in the frequency of price changes that occurs in 2008. Looking at Figure 15 and especially the analogous plot for food in Figure A.4 in the appendix, we see however, that inflation was highly volatile in 2008. It first spiked up due to the commodity price boom early in that year, and then fell dramatically with the onset of the recession and the collapse of commodity prices. In light of this unusual volatility of inflation, the spike in the frequency of price changes in 2008 seems less puzzling.

Table 1 summarizes our findings about the frequency and absolute size of price changes during the Great Inflation / Volcker disinflation period and the subsequent low inflation Greenspan-Bernanke period. We see that the frequency of price change has been lower in the latter period and this is driven entirely by a fall in the frequency of price increases. In sharp contrast, the average absolute size of price changes is virtually the same over the period 1978-1987 as it is over the period 1988-2014 despite the fact that inflation was much lower in the latter period.

[32]Figure A.4 presents figures analogous to Figure 15 for two important sectors in our data: food and services. In this figure, the inflation rate that we plot on each panel is the sectoral inflation rate in that sector. In both sectors, the frequency of price increases covaries strongly with inflation, while the frequency of price decreases is largely flat.

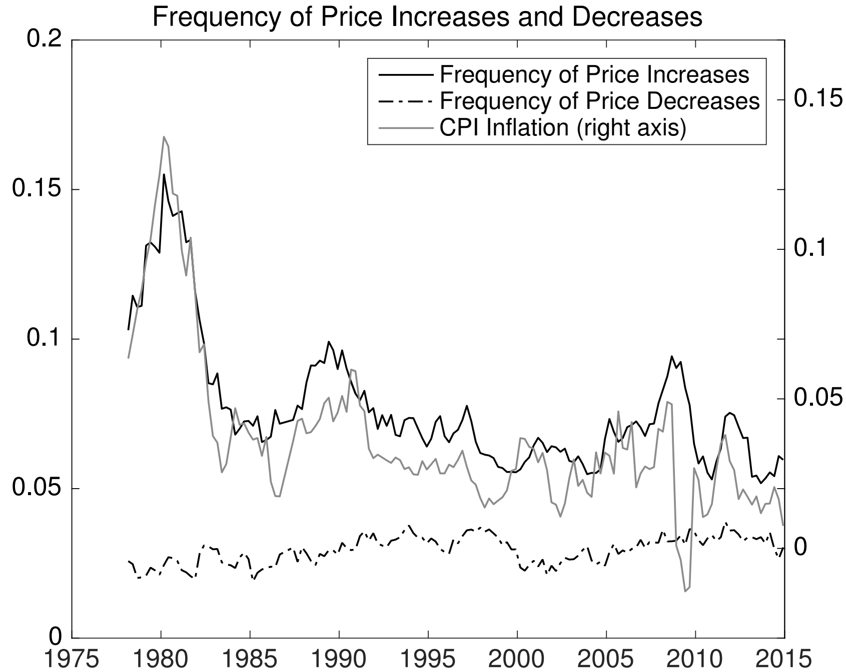

Figure 15: Frequency of Price Increases and Decreases

Note: To construct the frequency series plotted in this figure, we first calculate the mean frequency of price increases and decreases in each ELI for each month. We then take the weighted median across ELI's. Finally, for each quarter we take the average over the last 12 months.

Sample	1978-1987	1988-2014	1979-2014
Frequency of Price Changes	0.124	0.101	0.107
Frequency of Price Increases	0.095	0.069	0.076
Frequency of Price Decreases	0.025	0.031	0.030
Fraction of Price Increases	0.760	0.661	0.688
Absolute Size of Price Changes	0.073	0.075	0.075
Absolute Size of Price Increases	0.073	0.071	0.072
Absolute Size of Price Decreases	0.068	0.082	0.078
Std. Of Price Changes	0.050	0.055	0.054

Table 1: Summary Statistics for Three Sample Periods

6 Have Prices Become More Flexible over Four Decades?

The "menu cost" in the menu cost model is best thought of as a stand-in for a variety of costs associated with price adjustment. Though economists have failed to settle on what exactly this menu cost represents, many theories have been considered, including adverse customer reactions to price changes, limited managerial attention, and the actual costs of changing price tags or reprinting menus. Given all of the technological advancement that has occurred over the past half-century, it seems natural to conjecture that some of the costs of changing prices may have fallen, allowing prices to become more flexible.

Yet, there is no evidence that prices (excluding sales) have become more flexible over time. Figure 14 shows that the frequency of price change (excluding sales) has actually fallen over the past 40 years. Of course, the benefits of changing prices frequently have also fallen over this period since inflation has fallen. For this reason, the evolution of the frequency of price change is not an ideal measure of the evolution of price flexibility.

An alternative (arguably better) measure of price flexibility is the menu cost needed to match the frequency of price change at a particular point in time given the level of inflation at that time. If the menu cost model is able to match the frequency of price change over time with a constant menu cost, this would indicate that prices (excluding sales) have not become more flexible over time.

Figure 16 presents the results of this type of exercise. The broken lines in the figure are the frequency of price increases and decreases in the data. The solid lines are the frequency of price increases and price decreases from a simple menu cost model with a constant menu cost.[33] Evidently, the frequency of price change in the data tracts the model implied frequency of price change quite well over time as inflation rises and falls. If the costs of price adjustment had trended down over the past four decades, one would expect that our model would systematically underpredict the frequency of price change toward the end of the sample period. This is not the case.

Since our simple menu cost model with a fixed cost of price adjustment can explain the overall trend in the frequency of price change over the sample period, we conclude that there is no evidence that prices (excluding sales) have become more flexible over time. One might worry that these facts

[33]For simplicity, in this exercise, we feed the inflation rate into the model directly (as opposed to feeding in a process for nominal aggregate demand and having inflation be an endogenous outcome). The model we use in this exercise is therefore a partial equilibrium model.

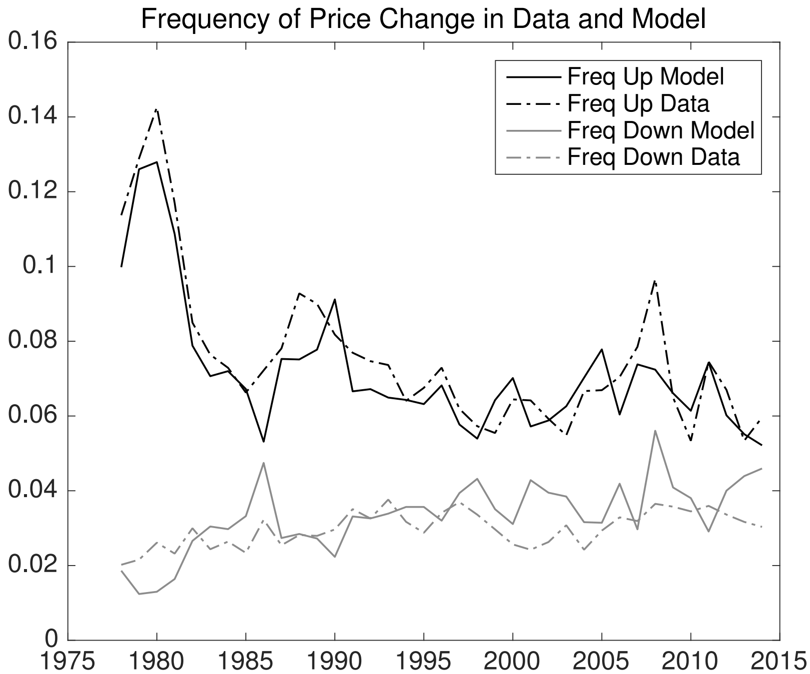

Figure 16: Predicted and Actual Frequency of Price Changes

about price changes excluding temporary sale might be somehow contaminated by the increasing frequency of sales (discussed below); but the same downward trend in the frequency of price change is visible even in sectors with essentially no sales, such as the service sector.

Our result that prices (excluding sales) have not become more flexible over the last 40 years is, in our view, strong evidence against the notion that menu costs should be viewed as technological in nature (e.g., as physical costs of changing price labels). When asked why they did not change their prices more often, by far the most frequent answer given by firm managers is that they fear that this will "antagonize" their customers (Blinder et al., 1998).[34] This suggests that customer-related frictions play in important role in price rigidity. Phelps and Winter (1970) proposed a "customer markets" model to understand price rigidity. According to Okun's (1981) "invisible handshake" version of the customer markets idea, firms have implicit agreements with their customers not to take advantage of tight market conditions by raising their price in exchange for stable prices in weak markets. Nakamura and Steinsson (2011) provide a recent formalization of how customer markets can yield price rigidity.

[34]In Blinder et al. (1998), 64.5% of firms report that they have implicit contracts with their consumers and an overwhelming majority of these firms (79%) indicate that these implicit contracts are an important source of price rigidity. Similar surveys in a host of other countries have since confirmed that the most important reason cited by firm managers for price rigidity is that they are loathe to "damage customer relations" by changing their prices.

One way in which prices *have* become more flexible over time is that the frequency of temporary sales has increased. Temporary sales are distributed very unequally across sectors, occurring frequently in processed and unprocessed food, apparel, household furnishings, and recreation goods, but quite infrequently in other sectors of the economy (see Nakamura and Steinsson, 2008). Figure 17 plots the evolution of the frequency of sales in the sectors in which sales are prevalent. In all five sectors, there has been a dramatic increase in the frequency of sales over our sample. In some categories, the increase seems to continue unabated, while in others (especially apparel and household furnishing) the frequency of sales seems to have plateaued. This trend increase in the prevalence of sales may, in fact, go back considerably before the start of our sample period. Pashigian (1988) documents a trend increase in the frequency of sales going back to the 1960's.

Can the increasing prevalence of sales be reconciled with the customer markets view of price rigidity that we describe above? Nakamura and Steinsson (2011) show that if there is asymmetric information about a firms idiosyncratic shocks, then the firm-optimal pricing policy can look like a price-cap policy, i.e., regular prices with "sales." Since an important limitation of this paper is that it does not provide any satisfying explanation for why the sales occur (they arise simply from "shocks"), we can only speculate on why the frequency of price change might increase in this model. However, the most likely interpretation for sales is probably the importance of dynamic pricing policies on the part of the firm. To the extent that such policies have gotten cheaper to implement (perhaps because of technological innovation in formulating or implementing dynamic pricing policies) this could potentially explain why the frequency of sales has increased so much, and yet be independent of the ultimate reasons for price rigidity in regular prices. These are interesting topics for future research.

7 Conclusion

In this paper, we develop a new comprehensive micro-price dataset going back four decades for U.S. consumer prices to study the costs of inflation. We find little evidence that the Great Inflation of the late 1970's and early 1980's led to a substantial increase in price dispersion—the costs of inflation emphasized in standard New Keynesian models of the economy. We do find that the frequency of price change varies substantially with the inflation rate, in line with the predictions of standard menu cost models. We also find no evidence that regular prices have become more flexible

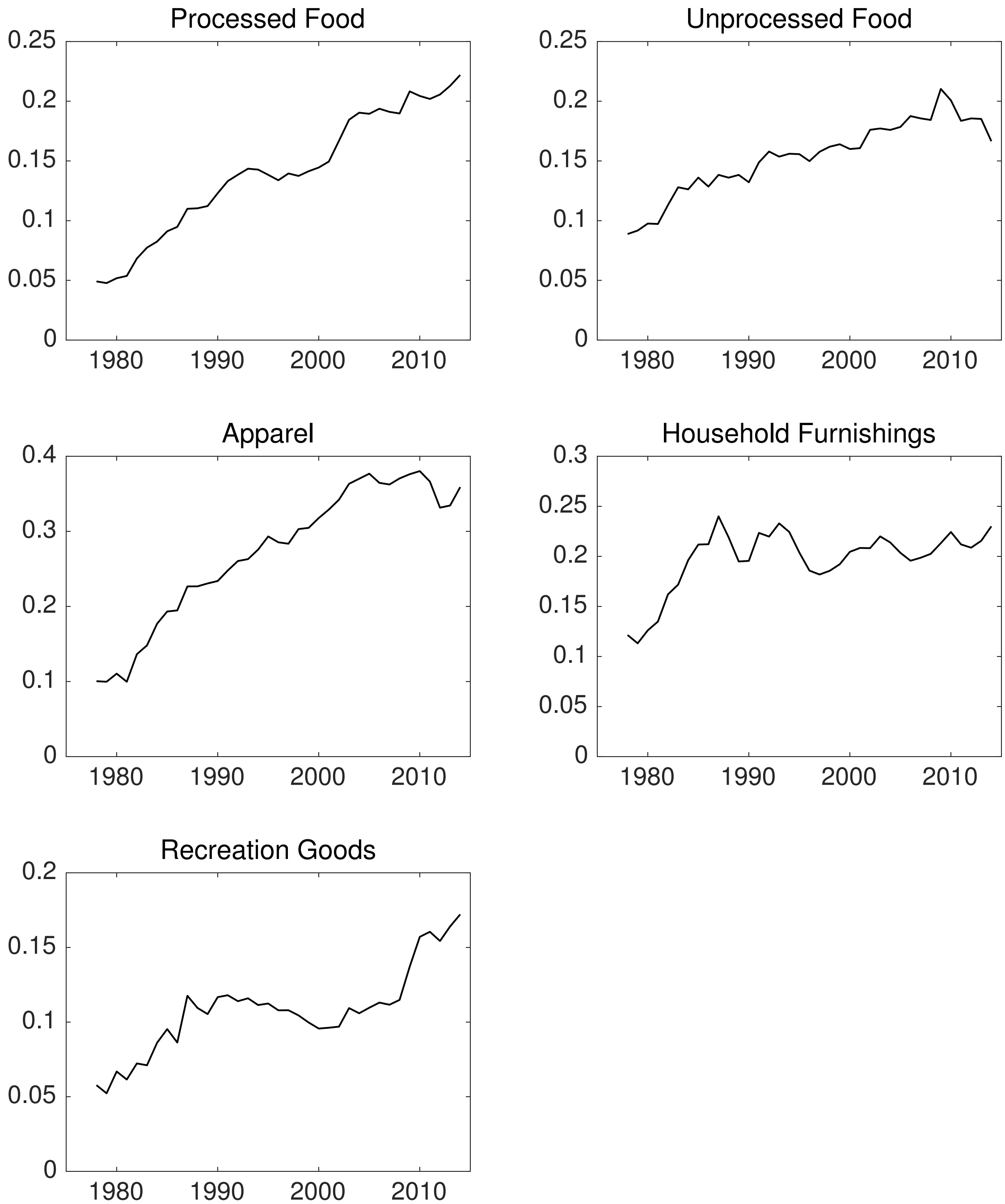

Figure 17: Frequency of Temporary Sales

Note: To construct the series plotted in this figure, we first calculate the mean frequency of temporary sales in each ELI for each year. We then take the weighted mean across ELI's.

over these four decades, despite the many technological improvements that have occurred over this period—suggesting that the barriers to price adjustment are not technological in nature.

A Derivations

A.1 Flexible Price Case

The period t profits of intermediate firm i are given by

$$\Pi_{it} = p_{it} y_{it} - W_t L_{it}. \tag{22}$$

Using the demand curve the firm faces—equation (4)—and the firm's production function—equation (8)—we can rewrite the profit function as

$$\Pi_{it} = p_{it} \left(\frac{p_{it}}{P_t}\right)^{-\theta} C_t - \frac{W_t}{A_{it}} \left(\frac{p_{it}}{P_t}\right)^{-\theta} C_t. \tag{23}$$

Maximization of this expression as a function of p_{it} yields

$$p_{it} = \frac{\theta}{\theta - 1} \frac{W_t}{A_{it}}. \tag{24}$$

Raising the expressions on both sides of this equation to the power $1 - \theta$ and integrating over i yields

$$\int_0^1 p_{it}^{1-\theta} di = \left(\frac{\theta}{\theta - 1} W_t\right)^{1-\theta} \int_0^1 A_{it}^{\theta-1} di. \tag{25}$$

Raising both sides of this expression to the power $1/(1 - \theta)$ yields

$$P_t = \frac{\theta}{\theta - 1} \frac{W_t}{A_f}, \tag{26}$$

where A_f is given by

$$A_f = \left[\int_0^1 A_{it}^{\theta-1} di\right]^{\frac{1}{\theta-1}}. \tag{27}$$

Combining firm i's production function—equation (8)—and the demand curve for firm i's output—equation (4)—yields

$$L_{it} = \left(\frac{p_{it}}{P_t}\right)^{-\theta} A_{it}^{-1} C_t. \tag{28}$$

Integrating over i and using firm i's price setting equation—equation (24)—yields

$$\int_0^1 L_{it}\, di = \left(\frac{\theta}{\theta - 1} \frac{W_t}{P_t}\right)^{-\theta} \int_0^1 A_{it}^{\theta-1} di\, C_t. \tag{29}$$

Using equation (26), this equation can be simplified to yield

$$Y_t = A_f L_t, \tag{30}$$

where Y_t denotes aggregate output and we have $Y_t = C_t$.

A.2 Sticky Price Case

As in the flexible price case, combining firm i's production function—equation (8)—and the demand curve for firm i's output—equation (4)—yields

$$L_{it} = \left(\frac{p_{it}}{P_t}\right)^{-\theta} A_{it}^{-1} C_t. \tag{31}$$

In this case, however, some labor is potentially used to change prices. Let's denote this by L_t^{pc}. Taking this into account and integrating the above expression over i, we get that aggregate labor supply is

$$L_t = \int_0^1 \left(\frac{p_{it}}{P_t}\right)^{-\theta} A_{it}^{-1} di C_t + L_t^{pc} \tag{32}$$

Rearranging this equation and using the fact that $Y_t = C_t$, we get that

$$Y_t = A_t(\bar{\pi})(L_t - L_t^{pc}), \tag{33}$$

where

$$A_t(\bar{\pi}) = \left[\int_0^1 \left(\frac{p_{it}}{P_t}\right)^{-\theta} A_{it}^{-1} di\right]^{-1}. \tag{34}$$

B Data Appendix

The process of scanning the microfilm cartridges left us with about 600 image folders—one corresponding to each cartridge. Each folder contains roughly 2000 images for a total of about 1 million images. The images are called Price Trend Listings and contain a table of data regarding several products (the rows in the table) over a 12 month period (the columns in the table). All data on each image comes from products in a particular product category (ELI). The left most column on each image contains a location (city) identifier, an outlet identifier, a product identifier, and a version identifier. The top row lists the time periods to which the data refers. The right most column contains the data for the month the images was created in. The remaining 11 columns repeat older data on the same products—i.e., show the "price trend" for each product. We refer to the month the image was created in as the "collection period" for this image. Each of the interior cells in the table is divided into three sub-cells. The top sub-cell reports the price. The middle sub-cell reports a number of flags including a sales flag and a flag related to whether the price is imputed. The bottom sub-cell contains the percentage change of the price since the last collection period for that product. Within each collection period, images are sorted by product category (ELI). Within each image, rows are sorted by the values of the identifiers in the left most column. They are first sorted by the outlet identifier, then by the product identifier, and finally by the version identifier.

As we describe in the main text, we used optical character recognition (OCR) software to convert the scanned images to machine readable form. We worked closely with a software company to create custom software that could convert the Price Trend Listings as accurately as possible. While we were able to find ways to eliminate most common systematic errors that we came across (especially in the price variable), it is inevitable given the current state of OCR technology that there are some random errors that remain in the raw data that results from the OCR process. Fortunately, the format of the Price Trend Listings described above implies that there is a large amount of redundancy in the raw dataset. This redundancy can be used to validate the output of the OCR process. Below we describe the procedure we use to validate the output from the OCR procedure.

B.1 Product Categories and Product Identifiers

The first step is to validate and improve on the OCR output for category labels and product identifiers. We first set to missing all ELI values that do not correspond to one of the values on the list of ELI values in the BLS classification. We then use the fact that the images are ordered by ELI within each collection period to fill in missing ELI information in cases where the last observed ELI value and the next observed ELI value are the same. Finally, in cases where there are large blocks of images that still have missing values for the ELI, we manually review the original scanned images to determine which image separates the different ELIs. By these steps we are able to validate the ELI for 99.7% of the images we have.

We use a similar procedure if there is a missing value of a product-identifier. We use the fact that the images are sorted by ELI and the observations within image are sorted first by location, then by outlet, then by product, and finally by version. First, we set identifiers that are out of order to missing. We then fill in identifiers in cases where the identifier before and after a block of observations with missing values for the identifier are the same.

Errors in reading product-identifiers lead to spurious products in our dataset. Whenever such errors occur, an entire row in a single Price Trend Listing image will be associated with this "phantom product" (i.e., this erroneous product code). We will therefore have up to 12 months of price data for these phantom products, which will result in up to 11 months of price change statistics. If the distribution of phantom products is non-uniform across product categories, their presence could bias our results by putting more weight on product categories where there are more phantom products. However, it is unlikely that exactly the same error will occur for multiple images with the same product-month. This implies that product months of phantom products will appear only on a single image (i.e., we won't have more than one replicate for product-months of phantom products). This, in turn, implies that our first algorithm for accepting price observations in to the final dataset (described below) will not accept these observations. We have rerun our results with only data accepted by the first algorithm and they are virtually identical. This makes us confident that the phantom products are not biasing our results.

The presence of the phantom products does artificially inflate the number of observations in the dataset. Whenever the same observation appearing on more than one image is read in different ways from different images, what is suppose to be a single observation, turns into more than one observation. We see signs of this occurring in the early part of our sample and in particular in the latter half of 1979 and the first half of 1980. Over this period, the number of observations per month rises to 170,000 per month. But the number of observations that appear on only a single image also rises very substantially (to over 50,000 per month). We take this as a sign that in this period a substantial number of phantom observations are appearing in the dataset.

B.2 Prices

We use two main procedures to validate the OCR output for prices. First, since each Price Trend Listing contains not only the price for that period but also prices for up to 11 earlier month, each product-month observation may appear multiple times in the raw dataset. For example, suppose we consider a product that the BLS collected a price for from October 1979 to November 1980. The October 1979 price will appeal on an image in October 1979 and will then be repeated on images in each of the subsequent 11 months. The October 1979 price of this product will therefore show up 12 times in the dataset. We refer to these 12 instances as 12 replicates of the same product-month observation.

Most product-month observations will have fewer than 12 replicates. Our data is based on monthly micro-film cartridges from May 1977 to December 1980 and bimonthly micro-film cartridges from January 1981 onward. Product-month observations in the later part of our dataset will therefore appear at most 6 times. Also, certain products in certain cities are sampled only

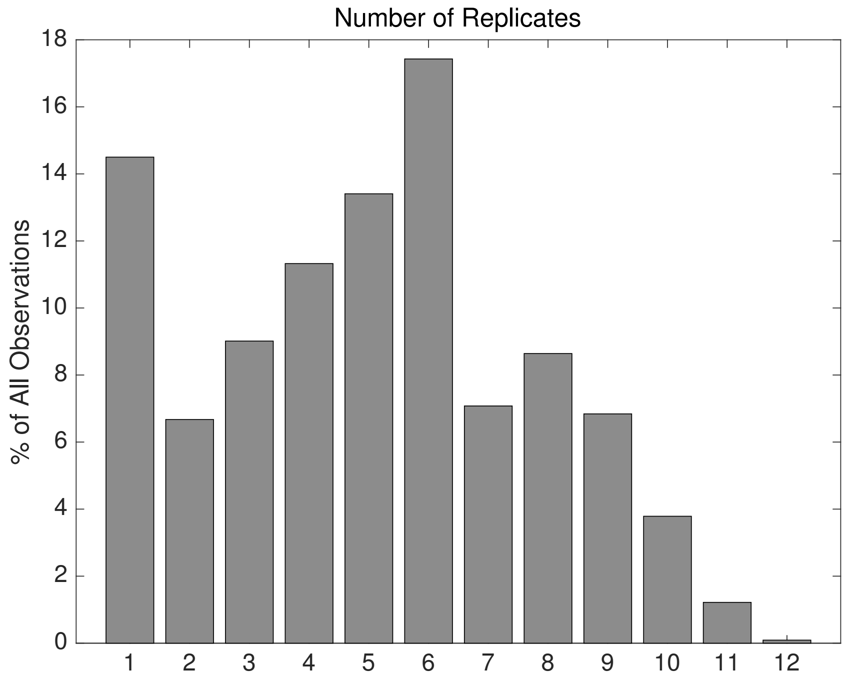

Figure 18: Distribution of Number of Replicates for Each Product-Month Observation

bimonthly. These will also only appear at most 6 times. Finally, product-month observations towards the end of a product's life-time in the BLS sample may appear less often. But even the last observation for a product in many cases appears more than once. Figure 18 plots the distribution of number of replicates in our sample.

We use this redundancy to verify the accuracy of the OCR output for prices. Our rule is to accept the price that we observe most often among the replicates for each product-month as long as we observe this price at least twice. If no price is observed more than once, we don't accept any price using this algorithm (and instead rely on the 2nd algorithm described below). It is very rare that more than one price is observed at least twice. This occurs for only 0.04% of product-months. It is even rarer, that there are more than one prices that are observed at least twice and an equal number of time, i.e., that there is a tie as to which price is observed most often. This occurs for only 0.004% of product-months. In these cases, we accept neither price (and again rely on the 2nd algorithm). Overall, prices are accepted using this algorithm for 86.5% of product-months.

Once we have finish running this first validation algorithm, we take all replicates for product-months for which prices have been accepted and we fill in the accepted price. In other words, we "correct any errors" in all the replicates for the product-months for which the first algorithm accepts observations. We do this in order to improve the chances that the second algorithm is able to validate prices for additional product-months.

The second redundancy we make use of is the percentage change variable. We calculate the percentage change in the price for a particular product-month from the price we observe on the image in that month and the price we observe on the image in the previous month, whenever both are present on the same image. We round this calculated percentage change to the next whole percent. If the value we calculate for the percentage change in this way matches the value reported in the percentage change variable on the image, we accept the price for both the product-month in question and the previous product-month (i.e., both price values used to calculate the percentage change).

The second way in which we use the percentage change variable is that when the following conditions are met:

- The percentage change in the price that we calculate from the price observations does not line up with the percentage change variable read directly from the image in a particular product-month and also does not line up for the same product in the next month.

- The percentage change read from the image for the product-month in question and both the next and last month for that product are all equal to zero

we set the price in the product-month to the value read in the previous month and accept this value into our main dataset. This is meant to catch cases where the OCR software made an error in the price variable, but the percentage change variable gives us a strong indication that the price actually stayed constant.

The procedure we describe above that uses the price change variable on the Price Trend Listing images is repeated for each image that a particular product-month observation occurs on. A price for the same product-month can therefore be accepted more than once (in principle as often as a particular product-month occurs on different images). It is even possible that two or more different prices are accepted for the same product month using this procedure. This only occurs for 0.14% of observations. Whenever this occurs, we drop all accepted observations based on the percentage change procedure. Overall, these procedures for using the percentage change variable raises the overall acceptance rate to 98.4% of the observations in our raw dataset. We drop the remaining observations.

B.3 Price Flags

As we discuss above, the second sub-cell of each cell in the Price Trend Listings images contains a string of characters which code various information regarding the price in question. This string contains at most seven characters. In some cases, some of these characters are left blank. The first three spots are reserved for characters indicating, among other things whether a product is on sale, whether it was unavailable, whether it is a seasonal item, etc. Typically, at most one of these spots will contain a letter and the others will be left blank. The next three spots give information about which pricing cycle the product belongs to (some products are priced monthly and others bimonthly). The last spot may contain the letter "I" indicating that the price was imputed. If the price was not imputed, this spot is left blank. We had the OCR software convert blank spots to # signs to help us tell which spot of the string each character occurred in. However, this conversion was somewhat imperfect.

Our OCR procedure turned out to be less accurate in converting these price flags, but fortunately the price flags are chosen from a restricted set of characters and the errors follow well-defined patterns. Our interest centers on identifying two pieces of information from this string of characters: 1) whether the product was on sale, 2) whether the price was imputed.

The letter "B" is the character that indicates that the product was on sale. We therefore create a sales flag variable and set it to 1 if the letter "B" occurs in the string of characters. Due to worries about accuracy or the OCR procedure for these flags, we manually compared the OCR output with the corresponding images for a subset of the images. This process revealed that the OCR process sometimes converted the letter "B" in the string to "6", "8", "9", "0", "O". We therefore set the sales flag to 1 whenever we observed any of these characters in the string.

As we mention above, the letter "I" in the last spot of the string indicates that the price was imputed. We therefore create an imputation flag variable and set it to 1 if the letter "I" is observed at the end of the string. Our manual comparison of the OCR output and the corresponding images revealed that in some cases the letter "I" was read as "1" by the OCR procedure. The number "1" also appears as a part of the pricing sample part of the string. But our manual inspection indicated that the number "1" appearing at the end of the string and being preceded by another number, gave strong indication that the price was imputed. In these cases, therefore, we set the imputation flag to one.

In addition to this, several of the characters appearing in the first three spots of the string signal that the price was imputed. These include "A" (seasonal item not available), "C" (closeout or clearance sale)[35], "D" (ELI not available), "U" (unable to price), "T" (temporarily unable to price). The first three of these (A, C, D) may also appear in the pricing cycle portion of the string. We therefore set the imputations flag to one whenever we observe these characters in one of the first three spots of the strings. The other three characters should not appear in other parts of the string. We therefore set the imputation flag to one whenever we observe these characters.

As in the case of prices, a price flag should appear in multiple "replicates" due to the structure of the Price Trend Listing, and in principle, these replicates should be the same. In cases where they disagree, we choose the value of the flag corresponding to the majority of replicates. This rule is meant to balance a concern for false positives and false negatives based on our inspection of a subset of cases where is disagreement. The fraction of observations that we drop because of imputation is 9.3%.

[35] BLS documentation we received indicated that "C" referred to "closeout or clearance sales" but out inspection of a subset of images indicated that these observations were imputed (e.g., they tended to include more than two numbers after the decimal place (fractions of a cent).

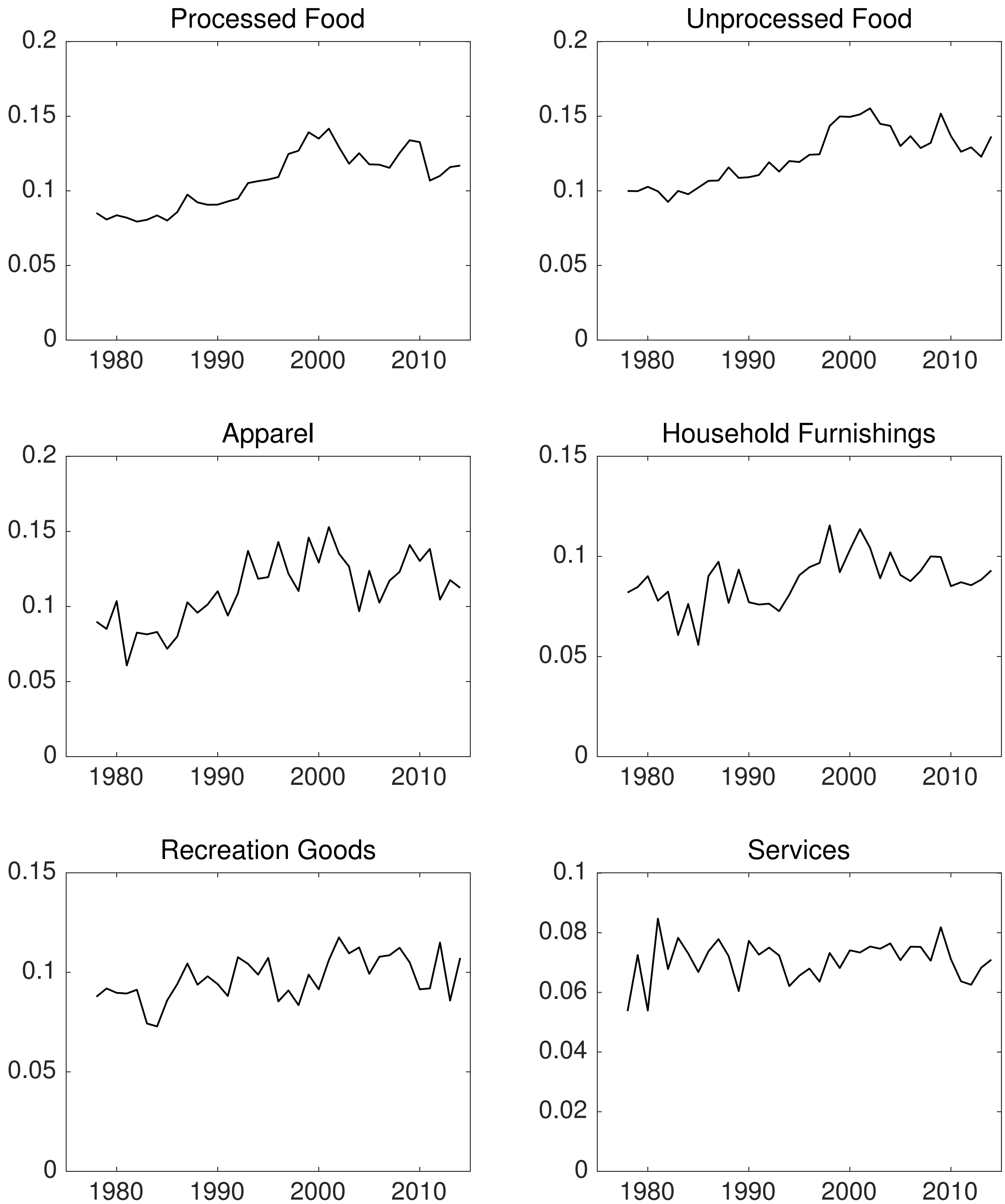

Figure A.1: Mean Absolute Size of Price Changes by Sector

Note: To construct the series plotted in this figure, we first calculate the mean absolute size of price changes in each ELI for each year. We then take the weighted median across ELI's within each sector for each year.

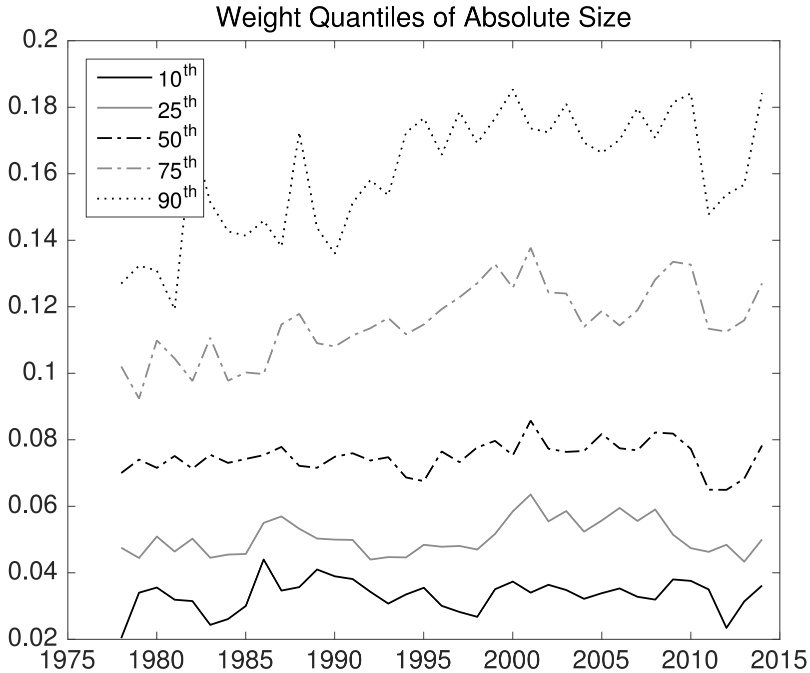

Figure A.2: Quantiles of the Absolute Size of Price Changes

Note: To construct the series plotted in this figure, we first calculate the mean absolute size of price changes in each ELI for each year. We then calculate quantiles of the distribution of the mean absolute size of price changes across ELI's for each year.

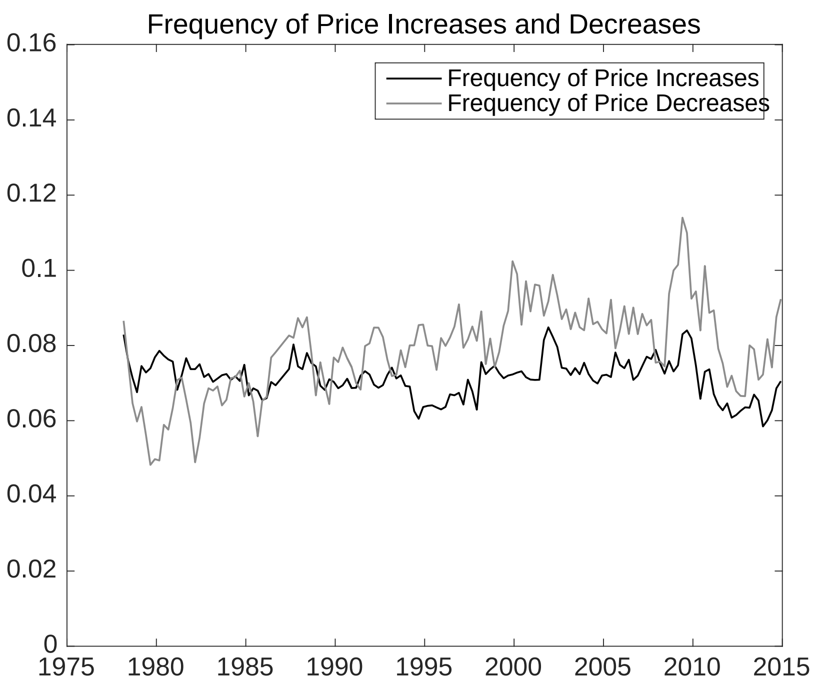

Figure A.3: Absolute Size of Price Increases and Decreases

Note: To construct the series plotted in this figure, we first calculate the mean absolute size of price increases and decreases in each ELI for each month. We then take the weighted median across ELI's. Finally, for each quarter we take the average over the last 12 months.

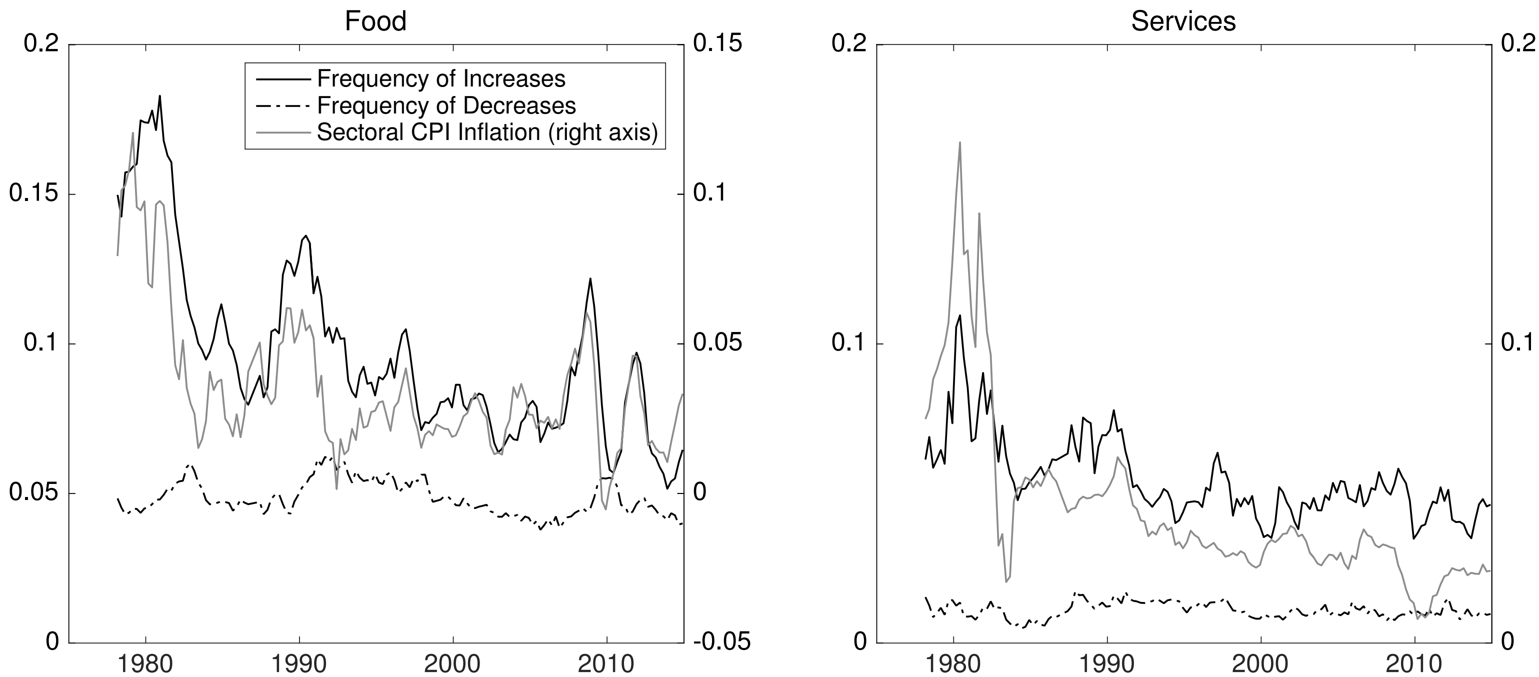

Figure A.4: Frequency of Price Increases and Decreases for Food and Services

Note: To construct the frequency series plotted in this figure, we first calculate the mean frequency of price increases and decreases in each ELI for each month. We then take the weighted median across ELI's for food and services separately and plot these in the two separate panels.

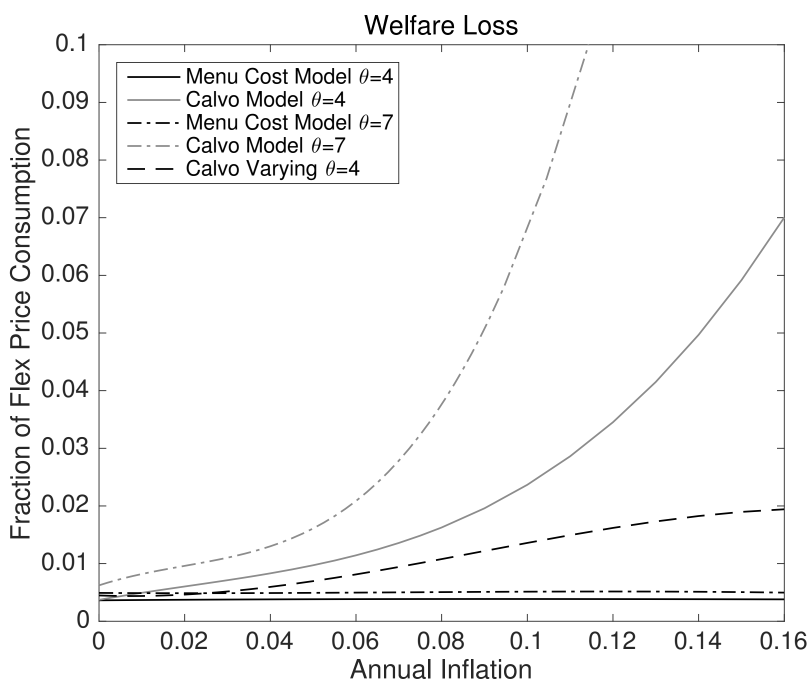

Figure A.5: Welfare Loss

Note: The figure plots the consumption equivalent loss of welfare in each model as a function of the inflation rate relative to welfare when prices are completely flexible. This figure presents the same information than Figure 2 but also adds a line for a version of the Calvo model in which the frequency of price varies with inflation and is chosen to equal the frequency of price change in the menu cost model at each level of inflation

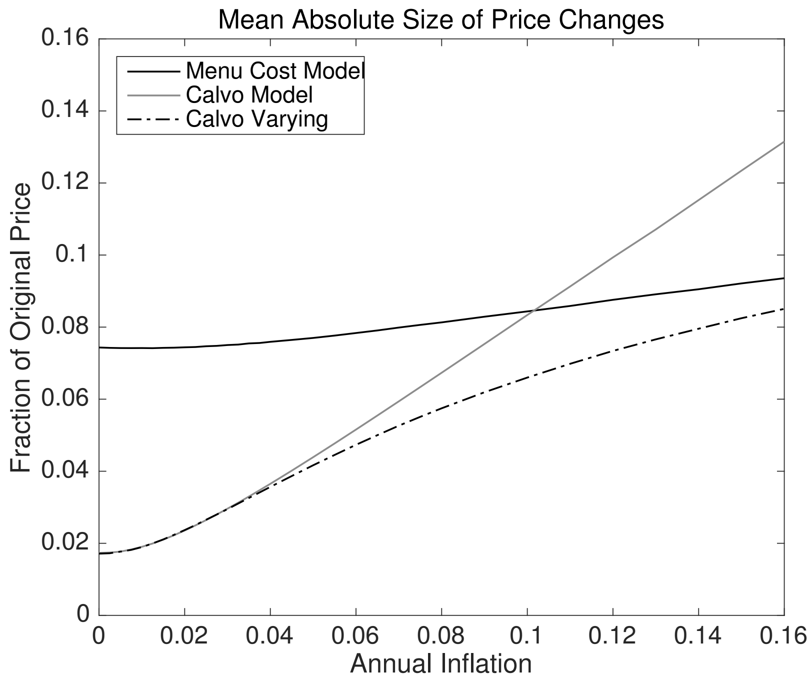

Figure A.6: Absolute Size of Price Changes in Sticky Price Models

Note: The figure plots the mean absolute size of price changes as we vary the steady state level of inflation in the menu cost, the Calvo model with a fixed frequency of price change and the Calvo model with a frequency of price change that varies with inflation and is chosen to equal the frequency of price change in the menu cost model at each level of inflation. It is comparable to Figure 8 in the paper.

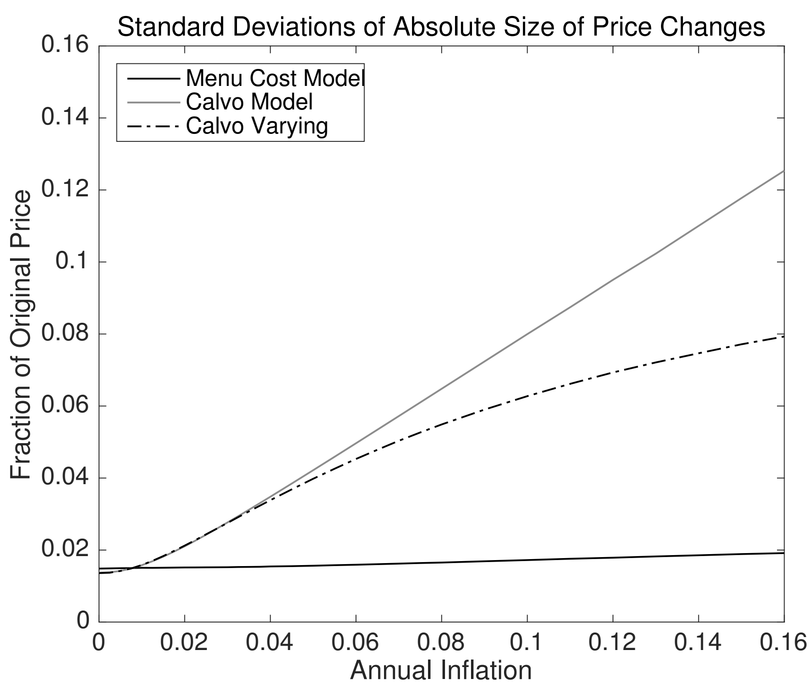

Figure A.7: Standard Deviation of Absolute Size of Price Changes

Note: The figure plots the standard deviation of the absolute size of price changes as we vary the steady state level of inflation in the menu cost, the Calvo model with a fixed frequency of price change and the Calvo model with a frequency of price change that varies with inflation and is chosen to equal the frequency of price change in the menu cost model at each level of inflation. It is comparable to Figure 10 in the paper.

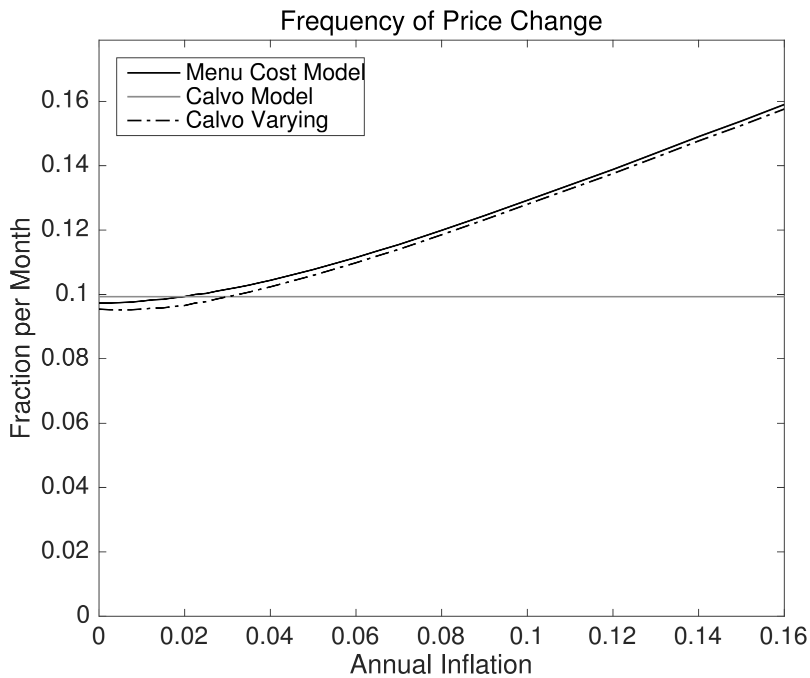

Figure A.8: Frequency of Price Change in Sticky Price Models

Note: The figure plots the frequency of price changes as we vary the steady state level of inflation in the menu cost model, the Calvo model with a fixed frequency of price change and the Calvo model with a frequency of price change that varies with inflation and is chosen to equal the frequency of price change in the menu cost model at each level of inflation. It is comparable to Figure 13 in the paper.

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