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by

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Abstract

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A pivotal question in macroeconomics is how output, employment, and price level react to monetary, fiscal, and productivity shocks, both in business-cycle models and in the data. Sticky prices are often considered as one of the key amplification and propagation mechanisms for such shocks. However, there is still a widespread debate how *sticky* prices are and why they are sticky. This dissertation sheds a new light on this question. Chapter 1 relies on a relatively understudied measure of price stickiness—cross-sectional dispersion of prices—to distinguish between different models of price rigidity, while Chapter 2 measures price stickiness in online markets. With e-commerce becoming a significantly larger sector of the economy, this is one of the first attempts to understand pricing in online markets from data comparable to those used for brick-and-mortar stores. Since different business-cycle models make conflicting predictions about effects of demand shocks, in Chapter 3 I approach this question empirically by estimating the size of fiscal multipliers from military spending data. Such empirical estimates may help researchers and policymakers to distinguish between various models.

In macroeconomic models, the level of price dispersion, which is typically approximated using its relationship with inflation, is a central determinant of welfare, the cost of business cycles, the optimal rate of inflation, and the trade-off between inflation and output stability. While the comovement of price dispersion and inflation implied by standard models is positive, in this dissertation I show that it is actually negative in the data. Chapter 1 shows that sales play a pivotal role: *i)* if sales are removed from the data, the comovement of price dispersion and inflation turns positive; *ii)* models in which price dispersion is due to price rigidity cannot quantitatively match the comovement even for regular prices; *iii)* the Calvo model with sales can quantitatively match both the negative comovement found in the data and the positive comovement for regular prices. Finally, I show that models that fail to match the degree of comovement in the data can significantly mismeasure welfare and its determinants.

Chapter 2 focuses on price-setting practices in online markets examined through the lens of a novel dataset on price listings and the number of clicks from the Google Shopping Platform. This unique dataset contains information on price quotes and the number of clicks at the daily frequency for a broad variety of consumer goods and sellers in the US and UK over the period

of nearly two years. This chapter provides estimates of the frequency of price adjustment, price synchronization across sellers and goods, as well as the distribution of the sizes of price changes. It compares the estimates for the case when information on quantity margin is observed—as in the scanner data from brick-and-mortar stores—with the case when it is not, which is typical in the literature on online prices. It concludes that many internet prices that do not change often obtain very few clicks. The key findings are the following: First, despite the cost of price change being negligible, prices appear relatively sticky. Second, if the quantity margin is accounted for, prices are much more flexible. It remains a question why low-demand sellers do not adjust their prices often, yet maintain costly price listings on the platform. Third, in spite of low costs of monitoring competitors' prices and high benefits from doing so—since search costs for consumers are low too—there is little price synchronization across sellers. Fourth, the distribution of the sizes of price changes is characterized by a non-trivial mass around zero, which is inconsistent with the state-dependent models with fixed menu costs, but favors time-dependent models of price adjustment. Hence, online prices change infrequently, by a large amount, and are not synchronized across sellers.

In Chapter 3, I use a multi-country dataset on disaggregated military spending to document the effect of government expenditure by sector on aggregate output. The data obtained from multiple sources including UN, NATO, and the Stockholm International Peace Research Institute (SIPRI) allow to systematically break down total military expenditure into that on durables versus nondurables and services for 69 countries within 1950-1997 period. I show that the spending multiplier is larger when government spends on durables rather than on nondurables or services, which could be due to differences in price flexibility, intertemporal elasticity of substitution, or some other sectoral factors. Although the estimates suffer from the lack of precision, the finding is robust across data sources and groups of countries. Quantitatively, the durables multiplier could be up to four times as high as that for nondurables and services. I use the dataset to estimate the standard spending multiplier as a litmus test, which results in a conventional fiscal multiplier of the size of about 1 ranging from 0.6 to 1.3 in different samples of countries.

To my parents

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Introduction

This dissertation is motivated by two key, interrelated questions: First, what are the properties of price setting at the firm level and what do they imply for aggregate variables, such as output, unemployment, and inflation? Second, can monetary and fiscal policies be an effective stabilization tool, and if so, to what extent?

Specifically, I compare empirical facts about firm price-setting behavior with predictions of popular macroeconomic models. It is essential to distinguish between models of price setting that make conflicting policy recommendations. In Chapter 1, in particular, I find that properties of the dispersion of prices support time-dependent price adjustment and are inconsistent with fixed menu costs or search costs models. In Chapter 2, I show that time-dependent pricing with significant nominal rigidity is not only a feature of conventional brick-and-mortar stores, but is also present in online markets. These properties of price setting imply that monetary and fiscal policies can be effective stabilization tools. I explore this conjecture in Chapter 3: I use a panel data set for military government spending and estimate that output multipliers for this spending can be large.

Micro Pricing

Macroeconomists have long thought that sticky prices contribute to real effects of monetary shocks and are an important determinant of an effective fiscal policy. However, there is still disagreement how sticky prices actually are and what the nature of price setting is. A rapid growth in availability of micro pricing data allows us to rigorously and quantitatively study these questions.

Economists typically measure price stickiness with the frequency of price changes observed in the data. Firm price-setting behavior, however, also affects properties of the dispersion of prices. Although existence of equilibrium price dispersion is often explained by heterogeneity in terms of sale and store-specific amenities, time-series properties of price dispersion are still not well understood. Existence of price dispersion in markets with low search costs (e.g., online stores) makes this question even more puzzling. By investigating properties of price dispersion one can go a long way in determining the degree of price stickiness. Importantly, price dispersion is an ingredient of welfare calculations and thus is crucial for assessing costs of business cycles and the optimal policy design.

The nature of the rigidity is another ingredient of macroeconomic analyses. If prices appear sticky because firms find it optimal not to adjust them in order to avoid paying costs of nominal price changes, large nominal shocks will not have a strong effect on real variables as inflation will catch up fast. However, if price stickiness is due to time-dependent frictions, i.e. firms do not adjust prices even when a shock is significant, the classical dichotomy is likely to be violated. Hence, understanding the nature of price-adjustment frictions is necessary to better evaluate implications of sticky prices for dynamics of aggregate variables.

The literature provides conflicting evidence whether pricing is time- or state-dependent. Inference about the nature of price adjustment is usually based on the distribution of the sizes of price changes. In time-dependent models price changes of any magnitude are possible, thus the resulting distribution is unimodal with a non-trivial mass around zero. In state-dependent models, on the contrary, the distribution is bimodal, with almost no price changes around zero. In this dissertation I develop an alternative way to differentiate between time- and state-dependent models based on the comovement of price dispersion and inflation. In time-dependent models there is no selection effect on which firms adjust their prices, and hence price dispersion strongly responds to inflation. In state-dependent models, however, only firms at the left tail of price distribution choose to adjust, resulting in a much weaker response.

Although it is generally perceived that prices change often, a lot of those changes are temporary. Whether these temporary changes have macroeconomic implications is at the center of a heated debate. Treatment of temporary price changes determines models' predictions about effectiveness of different macroeconomic policies. Previously, little interaction was found between regular and sales prices. In my research, however, I find that temporary price changes may interact with regular price dispersion by altering incentives to change a regular price.

Price Dispersion and Inflation: New Facts and Theoretical Implications

Price dispersion is pervasive in the data, even for an identical good sold across different stores within a narrowly defined geographical area. Equilibrium price dispersion is often attributed to heterogeneity of terms of sale and store-specific amenities. However, in the data time-series properties of price dispersion are hard to reconcile with variation in store-specific factors over time. Macroeconomic models predict that price dispersion can also arise due to price rigidity, which can explain its comovement with aggregate variables, such as inflation.

In Chapter 1 I differentiate across macroeconomic models by comparing their predictions about the comovement of price dispersion and inflation with that in the data. Workhorse macroeconomic models produce a positive comovement of price dispersion and inflation. Using scanner prices from grocery and drugstores in 50 U.S. metropolitan areas, I document that in the data the comovement is negative. I show that temporary price reductions (sales) can reconcile this finding. A time-dependent model with sales can quantitatively match both the negative comovement for all prices and the positive comovement for regular prices (i.e., sales excluded). Models without sales cannot match the comovement, which may lead to a substantial mismeasurement of welfare.

Chapter 1 contributes to the literature in several ways: First, it shows that time-dependent models perform better in matching empirical properties of price dispersion than state-dependent models do. It is important to differentiate between the two as the former imply real effects of nominal shocks, while the latter are often characterized by monetary neutrality. Second, to the best of my knowledge, this is the first paper showing that sales prices interact with regular prices. The Calvo model without sales cannot match properties of regular prices, while a similar model with sales can. Previously, the literature concluded a) sales are a form of price flexibility, so we live in a world with very flexible prices, or b) sales are essentially irrelevant, so we can safely ignore them. This paper suggests option c) we need to model sales to get the right behavior in regular price setting to match the data, even if sales *per se* are not important for real effects of nominal shocks. Third, models that do not match properties of price dispersion significantly mismeasure welfare and its determinants. Hence, using models with sales for welfare calculations may improve our estimates of the cost of business cycles and the optimal rate of inflation.

Price Setting in Online Markets: Evidence from the Google Shopping Platform

In Chapter 2 Yuriy Gorodnichenko, Oleksandr Talavera, and I focus on price-setting practices in online markets examined through the lens of a novel dataset on price listings and the number of clicks from the Google Shopping Platform. This unique dataset contains information on price quotes and the number of clicks at the daily frequency for a broad variety of consumer goods and sellers in the US and UK over the period of nearly two years. We provide estimates of the frequency of price adjustment, price synchronization across sellers and goods, as well as the distribution of the sizes of price changes. We compare the estimates for the case when information on quantity margin is observed—as in the scanner data from brick-and-mortar stores—with the case when it is not, which is typical in the literature on online prices. We conclude that many internet prices that do not change often obtain very few clicks.

The contribution of Chapter 2 is twofold. First, it is the first research work that sheds light on price rigidity, synchronization, and the distribution of the sizes of price changes in online markets using data similar to those from brick-and-mortar stores in terms of coverage, frequency, and quantity weights availability. As e-commerce has become a sizeable and rapidly growing part of the retail sector, we need to understand if price-setting practices are similar to those in conventional stores. Second, as online markets differ drastically from their offline counterparts in terms of the size of search costs, costs of price adjustment and monitoring competitors' prices, evidence from online markets can be used to better understand the disconnect between existing theories of price adjustment and empirical observations.

Our key findings are the following: First, despite the cost of price change being negligible, prices appear relatively sticky. Second, if the quantity margin is accounted for, prices are much more flexible. It remains a question why low-demand sellers do not adjust their prices often, yet maintain costly price listings on the platform. Third, in spite of low costs of monitoring competitors' prices and high benefits from doing so—since search costs for consumers are low too—we observe little price synchronization across sellers. Fourth, the distribution of the sizes of price changes is characterized by a nontrivial mass around zero, which is inconsistent with the state-dependent models with fixed menu costs, but favors time-dependent models of price adjustment. To summarize, online prices change infrequently, by a large amount, and are not synchronized across sellers.

Evidence on the Size of Fiscal Multipliers from International Military Spending Data

How big is the government spending multiplier? Empirical literature provides contrasting estimates that vary from almost zero to as large as 2.5. The main challenge of empirical research on the size of fiscal multipliers is to identify exogenous shocks, not related to current or anticipated changes in economic activity. Previous research suggests using variation in military spending as plausibly exogenous. However, papers that use data on U.S. military spending still find it difficult to identify the effect of fiscal policy, since the U.S. military expenditure did not vary much since the Vietnam War.

Instead, in Chapter 3 I rely on international military spending data since they are characterized by more time variation. The data set is built using three separate sources: the UN, NATO, and Stockholm International Peace Research Institute (SIPRI). It contains information on disaggregated military expenditure for 69 countries from 1950 to 1997. The spending can be separated into that on durables versus nondurables and services. I further combine the military spending dataset with data on countries' economic performance from the Penn World Tables to estimate the size of the multiplier.

I find that depending on a group of countries considered, the government spending multiplier varies from 0.6 to 1.3, with a pooled estimate of about 1. The multiplier associated with spending on durables is much larger than that for nondurables and services: 2.5 vs. 0.8. I conclude that not only government spending can be used as an effective stabilization policy instrument, but also that its effectiveness crucially depends on what the government spends on.

Chapter 1

Price Dispersion and Inflation: New Facts and Theoretical Implications

> *"Price dispersion is a manifestation—and, indeed, it is the measure—of ignorance in the market. Dispersion is a biased measure of ignorance because there is never absolute homogeneity in the commodity if we include the terms of sale within the concept of the commodity. [...] But it would be metaphysical, and fruitless, to assert that all dispersion is due to heterogeneity."*
>
> — George J. Stigler, 1961, p. 214

1.1 Introduction

Within a single week of June 2011, the price of a Gillette Venus Embrace razor with cartridge varied from $4.99 to $14.79 per unit across stores in the San Francisco Metropolitan Area—with a standard deviation of log prices of 0.32 (0.14 for regular prices, i.e., sales excluded). Economists have long thought that price dispersion exists in equilibrium because, as the quote above suggests, *"there is never absolute homogeneity in the commodity if we include the terms of sale within the concept of the commodity,"* and shopping experience generally differs across stores. However, just a year earlier, in June 2010, weekly prices for the same razor in the same area varied only between $8.99 and $12.59, with a standard deviation of log prices of 0.12 (0.08 for regular prices). It is very unlikely that a difference in shopping experience across the same stores changed so much in a year. Examples like this are pervasive. What determines the level and time variation of price dispersion and what does it mean for aggregate analyses?

From a macroeconomic perspective, price rigidity is often perceived as an important source of price dispersion, with significant implications for the dynamic properties of aggregate variables, welfare calculations, and the design of optimal policy. For instance, in standard New Keynesian models the key cost of business cycles stems from the price dispersion resulting from firms' inability to adjust prices instantaneously. However, different macroeconomic models make conflicting predictions about the level as well as the dynamic properties of price dispersion and the sensitivity of price dispersion to inflation. These contrasting predictions can help us to discriminate across alternative models. To the best of my knowledge, these predictions have not been tested before.

In this paper, I examine the link between price dispersion and inflation and the role sales play in this relationship. The comovement of inflation and price dispersion sheds light on the degree of price rigidity and the type of frictions that prevail in the data. In particular, a higher degree of price rigidity implies a stronger response of price dispersion to inflation. The nature of frictions is important too: models with time-dependent frictions produce stronger responses of price dispersion to inflation than those with state-dependent frictions. Crucially, in models with time-dependent price adjustment (e.g., Calvo 1983) monetary shocks affect real variables, while in state-dependent models with *fixed menu costs* (e.g., Golosov and Lucas 2007) the classical dichotomy holds—nominal variables do not affect real variables. I show that the Calvo model with sales can match the comovement of price dispersion and inflation found in the data, while purely state-dependent models cannot.[1]

To start, I document the degree of cross-store price dispersion and its comovement with disaggregated inflation, using monthly data on prices and total sales in supermarkets and drugstores in 50 U.S. Metropolitan Statistical Areas (MSA). Price dispersion is measured as the standard deviation of prices of a good at the Universal Product Code (UPC) level over stores in a given MSA, aggregated to a market-category of goods level, with annual sales as weights. My major findings are the following: First, price dispersion is pervasive and cannot be fully explained by sales. The average standard deviation of log prices across stores over the period of 2001–2011 is 10.3 log points for all prices and 7.9 log points if sales are excluded. Second, while price dispersion is negatively correlated with inflation at the location-category level, this is driven entirely by the presence of sales: the correlation between inflation and the dispersion in *regular* prices is positive. Third, local labor market characteristics, such as the unemployment rate or total employment, have only small effects on price dispersion and do not change its relationship with inflation. Fourth, I find strong propagation in the response of price dispersion to inflation: For all prices, including sales, a 1 p.p. innovation in annualized monthly inflation decreases price dispersion by 0.032 log points on impact and by 0.016 over the course of 11 months, which remains statistically significant at the 5% level. However, for regular prices, a similar shock to inflation leads to an increase in price dispersion on impact by 0.059 log points, which remains statistically significant for 8 months falling to 0.021 log points.

Next, I investigate whether standard macroeconomic models can account for these facts. I consider several popular models: a workhorse New Keynesian model with time-dependent frictions in price adjustment as in Calvo (1983), a model with state-dependent

[1] I also focus on the degree of price dispersion in the steady-steady as in a wide range of models it affects the per-period utility function, the cost of business cycles, and the optimal policy design. I show that models that fail to match the degree of comovement in the data can significantly mismeasure welfare.

pricing based on the Fixed Menu Cost (FMC) assumption similar to Golosov and Lucas (2007), and a monetary model with search frictions in the product market as in Head, Liu, Menzio, and Wright (2012). The first two models can be cast as a special case of a more general framework referred to as Smoothly State-Dependent Pricing (SSDP) developed in Costain and Nakov (2011a,b), which I test against the data as well. This allows me to nest models and isolate the effects of specific price-adjustment frictions. The setup of the search model differs drastically from that of the others and should be viewed as an alternative explanation of price dispersion and its relationship to inflation. Finally, I examine the Calvo model with sales, based on Guimaraes and Sheedy (2011), to emphasize the role sales play in matching properties of price dispersion in the data.

I find that models that do not allow for sales fail to match empirical findings *even for regular prices*. The Calvo model without sales overstates the comovement of price dispersion with inflation by a factor of 5 to 10, while the FMC model understates it by a factor of 5 to 7. Intuitively, most firms in models with time-dependent frictions cannot adjust their prices in response to an inflationary shock, while those few that can adjust do so by a lot, yielding a very strong response in price dispersion and a very small effect on inflation. In contrast, in state-dependent pricing models, an inflationary shock moves firms outside the (S,s) bounds forcing them to reset their prices, producing a strong impact on inflation and a weak effect on price dispersion. In fact, if menu costs are small, price dispersion may even decrease. Although the SSDP model is naturally closer to the data as it combines time- and state-dependent frictions, the parameterization required to match the comovement of price dispersion and inflation is inconsistent with other evidence on the distribution of the sizes of price changes observed in the data (e.g., Midrigan 2011). In this model, pricing should be more state-dependent than the data on the size of price changes suggest. Finally, while the search model can match the comovement for all prices, it cannot match the comovement of regular price dispersion with inflation nor is it consistent with the persistence in the response of price dispersion to inflationary shocks found in the data. Thus, none of these models is consistent with the stylized facts of regular price dispersion documented in this paper.

I show that the best match with empirical findings, for both all prices and *regular* prices, comes from a Calvo model *with sales* calibrated to match the observed frequency of sales. Intuitively, sales in this model serve as a channel for additional flexibility in pricing that does not interfere with the frequency of regular price changes. Note that for the Calvo model without sales to match the comovement of price dispersion and inflation, the per-period probability of price adjustment should be much higher than suggested by the frequency of regular price changes. In the SSDP model, pricing has to be more state-dependent, meaning less aggregate rigidity. The finding that the Calvo model with sales better matches the properties of regular prices than a similar model without sales implies that sales have an important interaction with regular prices, which is lost when sales are omitted. This implication is at odds with the conclusions drawn by Guimaraes and Sheedy (2011) and Kehoe and Midrigan (2012): they argue that sales have little impact on macroeconomic dynamics and that Calvo models which abstract from sales are sufficient to capture salient features in the data. In contrast, my results suggest that incorporating sales into the model is necessary to capture the comovement of regular price dispersion with inflation.

Because the level and dynamics of price dispersion have direct implications on welfare, the cost of business cycles, and the optimal inflation rate in macroeconomic models, relying on models which are at odds with the empirical properties of price dispersion can lead to non-trivial mismeasurement of optimal policy actions. For example, Coibion, Gorodnichenko, and Wieland (2012) use a version of the Calvo model without sales to quantify the cost of business cycles and to compute the optimal inflation rate. I show that using a measure of price dispersion consistent with the data implies an increase in the welfare loss due to business-cycle fluctuations from 0.005 to 0.007 log points, and a decrease in the optimal inflation rate from 1.3% to 1%.

Related Literature This paper contributes to several strands of literature: First, it introduces new empirical facts about the relationship between price dispersion and inflation. Second, it quantifies the comovement between the two in several prominent general equilibrium models. Third, it highlights the role of price dispersion in welfare calculations. Finally, it provides new evidence about the link between observed micro pricing characteristics and structural parameters in the theory.

The empirical contribution is related to earlier attempts to track the comovement of price dispersion and inflation in the data, such as Van Hoomissen (1988) and Lach and Tsiddon (1992). Similar to this line of work, I look at cross-store price dispersion and sectoral inflation for fast-moving consumer goods across supermarkets. Unlike them, I find a negative correlation between the two. The difference can be explained by several factors: First, I look at grocery stores across the U.S. in the 2000s, while they focus on supermarkets in Israel in the 1970s–1980s. Second, their data contain high-inflation episodes, while inflation is low-to-moderate in my data. I conjecture that sales are more prevalent in my data, driving the difference in results. Finally, the data set used in this paper is much richer and more representative in terms of location and coverage.[2]

This paper also contributes to the literature on the theoretical relationship between inflation and price dispersion. Sheshinski and Weiss (1977) show that correlation between inflation and price dispersion in the presence of costly price adjustment should be positive. Benabou (1988, 1992) combines frictions in price adjustment with search frictions and reaches a similar conclusion. Their models are cast in partial equilibrium and make mostly qualitative statements. In contrast, I consider general-equilibrium models and measure the degree of the comovement quantitatively. I also identify models that can give rise to a negative correlation of inflation and price dispersion, contrary to their result.

Next, this paper provides new evidence on the type and size of frictions in price setting. In particular, to match the stylized facts about price dispersion in models with time-dependent frictions, prices need to be much more flexible than found in the literature

[2]Van Hoomissen's data set contains monthly data for 13 uniquely defined goods during 1971-1984, while Lach and Tsiddon's data contain 26 food products for 1978-84. In comparison, the data set used in this paper covers 31 product categories with dozens of goods across 50 metropolitan areas in the U.S.

(Nakamura and Steinsson 2008). For models that combine time- and state-dependent frictions (e.g., Costain and Nakov 2011a,b), my results imply that price setting should be closer to state-dependent than suggested by the distribution of the sizes of price changes. Finally, the results suggest that sales might affect the way *regular* prices are set. A model with sales is shown to match properties of regular prices that models without sales cannot.

Finally, my results suggest that papers that compute welfare in the Calvo setup (e.g., Coibion, Gorodnichenko, and Wieland 2012) should be careful about the measure of price dispersion they use. Price dispersion observed in the data and its comovement with inflation is inconsistent with the Calvo model. Using the correct measure not only makes a level effect on welfare and the cost of business cycles, but also changes the shape of their relationship with trend inflation. This can result in a non-trivial effect on estimates of the optimal trend inflation.

The paper proceeds as follows. Section 1.2 summarizes testable predictions about price dispersion that standard macroeconomic models make. In particular, price dispersion positively comoves with inflation, while its level and the comovement have a strong effect on welfare. Section 1.3 documents that in the data the degree of price dispersion is large, even if sale prices are excluded, and it is negatively correlated with inflation, contrary to models that emphasize price rigidity. The difference between the data and the models is attributed to the prevalence of sales: excluding sales reverts the correlation to positive. Section 1.4 explores theoretical implications of the relationship between price dispersion and inflation found in the data. First, Section 1.4.1 analyzes implications for the type of price-adjustment frictions. It demonstrates that neither a model with purely time-dependent price setting nor the one with state-dependent setting only can explain the degree of the comovement in the data. A model that combines the two is closer to the data; however, for a given parameterization it can match either the comovement or the distribution of the sizes of price changes, but not both. In Section 1.4.2, I consider implications for modeling sales. I show that including sales into the model not only improves its properties for all prices, but also allows to match the comovement for regular prices. Hence, sales have an important interaction with regular prices, allowing to increase price flexibility without making counterfactual predictions about the frequency of regular price changes. Section 1.4.3 studies welfare implications of price dispersion. It demonstrates that the inability to match empirical properties of price dispersion makes a strong effect on welfare, the cost of business cycles, optimal trend inflation, and the trade-off between output and inflation stability. Finally, Section 1.4.4 emphasizes that models in which price dispersion comes from the search friction in the product market, rather than from price rigidity, can match the comovement of price dispersion and inflation but cannot generate strong propagation observed in the data. I provide a brief discussion and conclude in Section 1.5.

1.2 Summary of Testable Predictions

This section motivates my empirical analysis by summarizing some testable predictions of workhorse macroeconomic models. I concentrate on three results relevant for my work. First, in a wide class of models, price dispersion enters the per-period utility function affecting the cost of business cycles and the trade-off between inflation and output stability. Second, in many models price dispersion comoves with inflation and sometimes (e.g., in the Calvo model) there exists a closed-form relationship between the two, which permits structural estimation. Finally, the steady-state level of inflation can influence the dispersion of prices, and again in some cases (e.g., in the Calvo model) one can derive a simple formula for the link between the steady-state level of price dispersion and steady-state inflation.

The relationship between price dispersion and the per-period utility function can be readily quantified. For example, in the basic New Keynesian setup (Woodford 2003, p. 396), the second-order approximation of the per-period utility function can be written as

$$U_t = -\frac{\bar{Y} u_c}{2} \left\{ (\gamma + \omega) \left(x_t - x^*\right)^2 + \theta (1 + \omega\theta) \sigma_t^2 \right\} + \text{t.i.p.} + \text{h.o.t.} \tag{1.1}$$

where U_t is the per-period utility function, $\bar{Y}$ is the steady-state output, u_c denotes the marginal utility of consumption, γ is the inverse intertemporal elasticity of substitution, ω is the elasticity of marginal cost with respect to output, $x_t - x^*$ is the deviation of the output gap from its efficient level, θ is the elasticity of substitution across goods, $\sigma_t^2 \equiv \mathbb{V}\text{ar}_i \log p_t(i)$ is the variance of prices across firms, t.i.p. stands for terms independent from policy, and h.o.t. denotes higher-order terms. Importantly, this approximation applies quite generally across different models of price setting.

Price dispersion has a negative effect on welfare because in the model it represents the distortion to the optimal allocation that arises from price rigidity. As consumers have a love for variety, price dispersion forces them to consume too much (too little) of goods with prices below (above) the average price. The misallocation is amplified by the elasticity of substitution between goods, θ, and the elasticity of marginal cost with respect to output, ω. The former represents the degree of love for variety and the extent to which consumers respond to price changes. For example, when θ is high, consumers easily reallocate their expenditure toward goods prices for which have not been adjusted to inflationary shocks, amplifying the misallocation effect. The latter, ω, represents the degree of real rigidities, which amplifies misallocation through marginal costs.[3]

If price setting is time-dependent as in Calvo (1983), price dispersion in Equation (1.1) is a function of the current and past inflation, with its persistence and the degree of comovement determined solely by price rigidity (Woodford 2003, p. 399).

$$\sigma_t^2 = \alpha \sigma_{t-1}^2 + \frac{\alpha}{1-\alpha} \pi_t^2 + \text{h.o.t.} \tag{1.2}$$

[3]Ball and Romer (1990) analyze the role of real rigidities and their connection to nominal rigidities.

where α is a fraction of prices that remain unchanged and π_t is inflation. Later, I test this relationship in the data.[4]

It is easy to see why price stickiness implies more persistence in price dispersion. Parameter α in Equation (1.2) controls the share of prices that will not change in the next period. In the limiting case when α goes to one, the whole distribution stays the same, and so does price dispersion. As prices become more flexible, the relationship between the current and the lagged price distribution becomes weaker.

Comovement of price dispersion and inflation is also due to price stickiness. Consider two cases: one with relatively high stickiness parameter, and the other with relatively low. If the economy is hit by a large nominal shock and prices are very sticky, few firms will be able to adjust their price. Those few firms, however, will adjust proportionally to the size of the shock. Since most of the prices remained unchanged, there is little effect on inflation, while price dispersion increases by a lot due to the size of changes made by adjusters. Hence, price dispersion reacts more strongly to shocks than inflation, implying a large slope in the linear relationship. In the second case, when prices are relatively flexible, a lot of firms can adjust, which makes a strong effect on inflation and a weak effect on price dispersion. The slope in the comovement relationship is likely to be small.

Note that the sign of the shock is irrelevant. Deflationary and inflationary shocks affect dispersion in the same way. This intuition applies generically to models with time-dependent pricing: volatile inflation leads to more price dispersion. In contrast, models with state-dependent pricing may have positive or negative relationship to the level and volatility of inflation, and the outcome depends on the specifics of the model, as well as the history and size of shocks hitting the economy.

For the case of positive trend inflation, price dispersion is related to inflation in the steady state as well. With no price indexation, the relationship in the steady state for the Calvo model is

$$\bar{\sigma}^2 = \frac{\alpha}{(1-\alpha)^2}\bar{\pi}^2 + \text{h.o.t.} \tag{1.3}$$

The link between price stickiness and price dispersion is again intuitive. In the Calvo model, firms are symmetric monopolistic competitors, whose optimal markup depends only on the demand elasticity, which is captured by the elasticity of substitution between goods. If prices are flexible and marginal costs are the same across firms, they will charge the same price, implying zero price dispersion in equilibrium. If prices are sticky, however, some firms will not be able to adjust the price, resulting in equilibrium price dispersion. As was the case for dynamics of price dispersion, this result applies to models with time-dependent pricing, but the relationship is ambiguous in models with state-dependent pricing.

[4] Equation (1.2) is derived for the case of zero trend inflation. With positive trend inflation, the right-hand side should also contain the level of inflation.

1.3 Empirical Analysis

Most of the empirical literature on price dispersion studies its micro-level determinants: the value of a good (Pratt, Wise, and Zeckhauser 1979), purchase frequency (Sorensen 2000), number of sellers (Baye, Morgan, and Scholten 2004); or compare price dispersion in online markets with that in brick-and-mortar stores (Brynjolfsson and Smith 2000). Some papers use testable predictions from industrial organization models to distinguish between them.[5] Instead, in this section I focus on the comovement of price dispersion with aggregate variables.

Relatedly, a number of papers focused on the relationship between inflation and the Relative Price Variability (RPV) measured as the cross-sector standard deviation of inflation rates (e.g., Choi 2010, Debelle and Lamont 1997, Grier and Perry 1996, Konieczny and Skrzypacz 2005, Silver and Ioannidis 2001). However, this concept is different from price dispersion as the former measures the variability of responses to inflation across categories, while the latter measures the variability of prices within a category.[6] To study dispersion of prices within categories of goods and narrowly defined geographical locations, one needs scanner price data, which have become available only recently.

In this section I use micro pricing data from grocery and drug stores across the U.S. between 2001 and 2011 to document the degree of price dispersion and its comovement with aggregate variables. As workhorse macroeconomic models suggest that price dispersion comoves with inflation, I compute price dispersion and inflation at the market-category level and examine their comovement in time and cross section. Importantly, this data set allows me to estimate the comovement within a geographical location and a category of goods. In Section 1.3.1 I describe the data set used and how the key measures are computed. Section 1.3.2 then presents empirical facts about the comovement.

[5] Lach (2002) rules for temporal price dispersion against the spatial one. Temporal price dispersion arises in models with randomized strategies such as Varian (1980) or Burdett and Judd (1983). Spatial price dispersion is instead a feature coming from heterogeneity across agents as in Reinganum (1979) or MacMinn (1980).

[6] Most of the papers conclude there is a positive relationship between inflation and relative price variability in accordance with theory; however, some researchers question the result showing a negative, non-linear, or unstable relationship. Debelle and Lamont (1997) find positive correlation between inflation and RPV for a sample of U.S. cities for a period from the mid-1950s to mid-1980s. The usage of between-city variation controls for nationwide shocks. Konieczny and Skrzypacz (2005) second the result for the period of high inflation in Poland in the early 1990s. The effect of expected inflation is found to be stronger than that of the unexpected one. A few papers express their disagreement. Grier and Perry (1996) in a bivariate GARCH-M model show that inflation affects RPV only when inflation uncertainty is not controlled for. Silver and Ioannidis (2001) estimate seemingly unrelated regressions (SUR) for a sample of 9 European countries in the 1980s and find a negative correlation between unexpected inflation and RPV. Finally, Choi (2010) looks at the data for the U.S. and Japan since the 1970s and find regime changes in the relationship. It is found to be positive in a high-inflation environment, while being non-linear (U-shaped around a positive threshold) during the Great Moderation.

TABLE 1.1. DATA SUMMARY

	mean (1)	sd (2)	p10 (3)	p25 (4)	med (5)	p75 (6)	p90 (7)
Number of Goods	215.8	135.6	73	105	176	305	419
Number of Stores	34.1	25.2	11	16	29	43	59
Number of Stores per Good	10.8	6.4	5	6	9	14	18

Notes: The distribution of the average number of goods, stores, and stores per good in a year across markets and categories. Number of market-categories $N = 1,550$. See Section 1.3.1 for details.

1.3.1 Data Description

I use data from Symphony IRI, a market research company.[7] They contain prices and total sales at weekly frequency for consumer goods at the Universal Product Code (UPC) level across grocery and drug stores in 31 categories for 46 U.S. Metropolitan Statistical Areas (MSA) and 4 larger areas that include locations in Mississippi, New England, South Carolina, and West Texas/New Mexico. Most of the locations represent large metropolitan areas, although the data also contain relatively small MSAs, such as Pittsfield, MA or Eau Claire, WI. Goods in the data set are typical for grocery and drugstores: processed and unprocessed food, beverages, alcohol and tobacco, health and beauty products, domestic supplies, etc. Categories are defined for a narrow group of products that are closed substitutes, e.g., hotdogs, coffee, beer, shampoo, detergents, and so on. A complete list of categories and MSAs is provided in Section A.1. The data contain information if the good was on sale in a given period; however, no cost information is provided.

Table 1.1 summarizes the distribution across markets and categories of the *per annum* number of goods, stores, and stores selling an identical good. Since I aggregate the data to the market-category level, these summary statistics represent the sample size of the cross-sectional component. The median market-category (e.g., Blades in San Francisco, CA metropolitan area) contains 176 goods per year and 29 stores that sell them. A typical good is sold by approximately 10 stores. The distribution of the number of goods and stores in the data set over market-categories is heavily skewed to the right as a small number of market-categories contain a disproportionately large number of goods and stores.

Let TR_{mscjt} be the total sales in period t of good j in category c sold by store s located in market m, and Q_{mscjt} be the corresponding quantity sold. The unit price of the good is then computed as

$$P_{mscjt} = \frac{\sum_{\tau \in \mathscr{M}^t} TR_{mscj\tau}}{\sum_{\tau \in \mathscr{M}^t} Q_{mscj\tau}} \tag{1.4}$$

with $\mathscr{M}^t$ being a set of weeks in month t. This measure represents the average effective price consumers paid for a good in a given store within a month.[8] I then compute the

[7]An overview of the data set can be found in Bronnenberg, Kruger, and Mela (2008). See Coibion, Gorodnichenko, and Hong (2012) for application of the data to study cyclical properties of sales, regular price changes, and average prices paid by consumers.

[8]It is fairly common in the literature to aggregate micro pricing data into monthly frequency to remove high-frequency fluctuations due to noise and strictly idiosyncratic patterns. I follow this approach for

store-level inflation rate for a given good as

$$\pi_{mscjt} = \log P_{mscj,t} - \log P_{mscj,t-1} \tag{1.5}$$

Price dispersion is measured by the weighted standard deviation of log prices across stores with sales quantities used as weights.

$$\sigma_{mcjt} = \sqrt{\frac{\sum_s Q_{mscjt} \left(\log P_{mscjt} - \widetilde{\log P_{mcjt}}\right)^2}{\sum_s Q_{mscjt}}} \tag{1.6}$$

where $\widetilde{\log P_{mcjt}} = \left(\sum_s Q_{mscjt} \log P_{mscjt}\right) / \sum_s Q_{mscjt}$ is the average log price weighted by quantities.

This measure represents cross-store price dispersion. I then aggregate inflation and price dispersion at the category level.

$$\pi_{mct} = \sum_{j \in \mathcal{G}^{mct}} \sum_{s \in \mathcal{S}^{mct}} \omega_{mscjt} \pi_{mscjt} \tag{1.7}$$

$$\sigma_{mct} = \sum_{j \in \mathcal{G}^{mct}} \omega_{mcjt} \sigma_{mcjt} \tag{1.8}$$

where

$$\omega_{mscjt} = \frac{\sum_{\tau \in \mathcal{Y}^t} TR_{mscj\tau}}{\sum_{\tau \in \mathcal{Y}^t} \sum_{j \in \mathcal{G}^{mct}} \sum_{s \in \mathcal{S}^{mct}} TR_{mscj\tau}} \tag{1.9}$$

$$\omega_{mcjt} = \frac{\sum_{\tau \in \mathcal{Y}^t} \sum_{s \in \mathcal{S}^{mct}} TR_{mscj\tau}}{\sum_{\tau \in \mathcal{Y}^t} \sum_{j \in \mathcal{G}^{mct}} \sum_{s \in \mathcal{S}^{mct}} TR_{mscj\tau}} \tag{1.10}$$

with $\mathcal{Y}^t$ being a set of months in the same year as month t; $\mathcal{G}^{mct}$, $\mathcal{S}^{mct}$ are a set of goods that belong to category c and a set of stores in market m, respectively. Hence, the weights are fixed within a year.

Descriptive statistics for key variables are provided in Table 1.2. Price dispersion is ubiquitous. The median market-category is characterized by a standard deviation of log prices across stores of 10.4 log points (Panel A). This is smaller than past estimates. For example, Lach and Tsiddon (1992) report price dispersion in a range from 16.4 to 20.3 in Israel for different sample periods during 1970s–1980s, characterized by high inflation. For eighteen months during 1993–1994 in Israel, estimates in Lach (2002) suggest that price dispersion varies a lot across goods, from 11.4 to 19.7 for goods typically sold in grocery stores. He also reports much smaller price dispersion for durables, e.g., 4.9 for refrigerators.

I identify sales by the sales tag provided with the data set. Sales are defined as

consistency and comparability reasons.

TABLE 1.2. DESCRIPTIVE STATISTICS

	mean (1)	sd (2)	p5 (3)	p25 (4)	med (5)	p75 (6)	p95 (7)
				A. ALL PRICES			
Price Dispersion							
All Years	10.3	2.9	5.5	8.3	10.4	12.3	15.4
2002-07	10.3	2.9	5.6	8.4	10.4	12.3	15.3
2008-11	10.5	3.4	5.3	8.2	10.3	12.5	15.9
Inflation							
All Years	0.9	1.3	−1.0	−0.1	0.8	1.8	3.3
2002-07	0.6	1.3	−1.5	−0.3	0.6	1.4	2.7
2008-11	1.5	1.9	−1.0	0.1	1.2	2.5	5.1
				B. REGULAR PRICES			
Price Dispersion							
All Years	7.9	2.5	4.2	6.1	7.8	9.4	12.1
2002-07	7.7	2.5	3.9	5.9	7.6	9.2	11.8
2008-11	8.2	3.0	4.0	6.0	7.8	10.0	13.6
Inflation							
All Years	4.4	1.6	2.0	3.2	4.2	5.5	7.2
2002-07	3.8	1.5	1.5	2.7	3.6	4.8	6.5
2008-11	5.3	2.2	2.3	3.7	5.0	6.6	9.5

Notes: The distribution of the average monthly price dispersion, in log points, and the annualized inflation rate, in percent, across markets and categories. Number of market-categories $N = 1,550$. "All Years" stands for 2002-2011. "Regular Prices" do not include sales. See Section 1.3.1 for details.

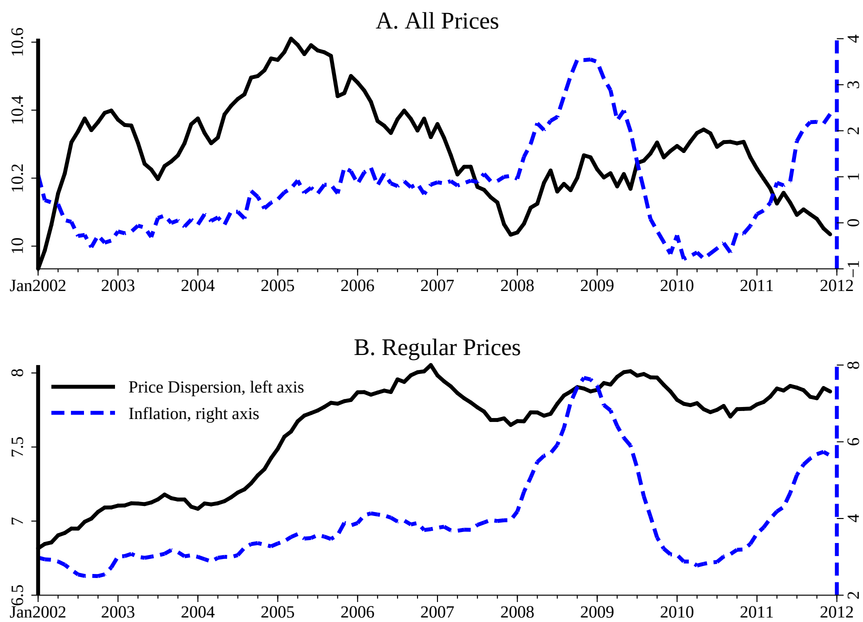
temporary price reduction by more than 5% of the original price. Once sales are removed from the sample (Panel B of Table 1.2), the median market-category price dispersion goes down to 7.8 log point—still substantial.

Since the data set contains a unique episode of the Great Recession, I split my sample around 2008. The split by subsample is also provided in Table 1.2. I find only a small change in the level of price dispersion after 2008 for all prices (Panel A). The mean price dispersion increased by 0.2 log points from 10.3 to 10.5, while the median price dispersion fell from 10.4 to 10.3. What changed substantially, however, is the heterogeneity across categories and markets. The standard deviation of price dispersion increased from 2.9 to 3.4 log points. For regular prices (Panel B), however, there has been a substantial increase in both the level and heterogeneity of price dispersion. The mean price dispersion increased from 7.7 to 8.2 log points (from 7.6 to 7.8 in the median), while the standard deviation grew from 2.5 to 3.0. The increase in heterogeneity could be due to the asymmetric effect of the crisis on metropolitan areas and categories of goods.

It is puzzling, however, why price dispersion changes for regular prices but not for all prices. For instance, it is not obvious if price dispersion was roughly constant before the recession or it exhibited a trend. To clarify this, Figure 1.1 depicts the median price dispersion by month. Before 2006 price dispersion was on an upward trend, both for all and regular prices. Afterward, we observe a substantial fall in price dispersion for all prices, while that for regular prices stays relatively unchanged. The figure also suggests some comovement of price dispersion with inflation. While the comovement is negative for all prices, it is positive for regular prices. My empirical analysis in the next sector confirms that this is also true within markets and categories of goods.

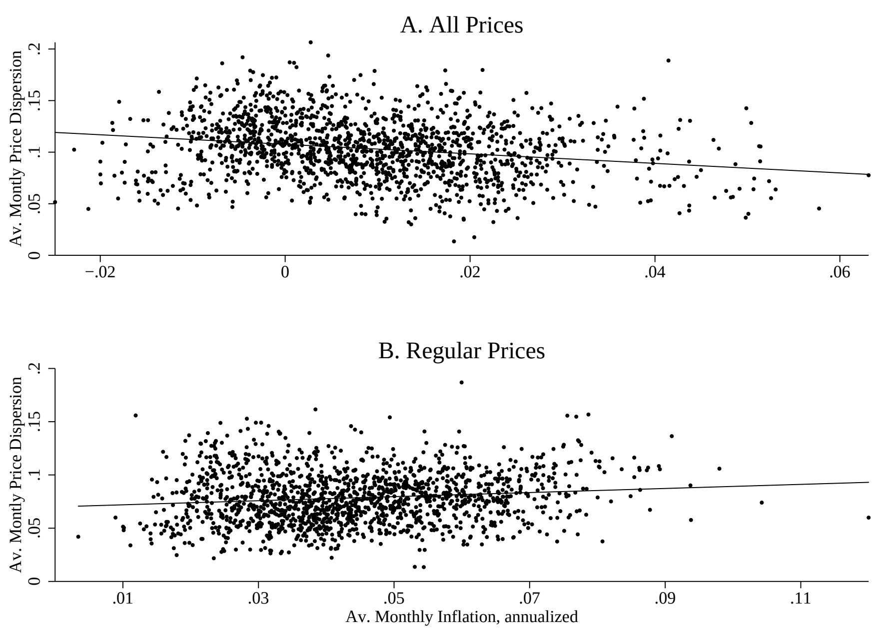
Such comovement can be observed in the cross section too. To illustrate the cross-

FIGURE 1.1. MEDIAN PRICE DISPERSION AND INFLATION OVER TIME



Notes: Black solid line represents the median price dispersion across markets and categories, in log points. Blue dashed line represents the median annualized inflation rate, in percent. "Regular Prices" do not include sales. See Section 1.3.1 for details.

FIGURE 1.2. AVERAGE MONTHLY DATA OVER MARKETS AND CATEGORIES



Notes: Each dot represents a category of goods in a given MSA. The solid line is for the linear fit. "Regular Prices" do not include sales. See Section 1.3.1 for details.

sectional correlation, for each market-category I calculate average price dispersion and average inflation over eleven years. Figure 1.2 presents a scatterplot of these values over markets and categories. The negative comovement in all prices, and the positive one in regular prices still stand. The scatterplot also suggests that the result is not due to outliers.

1.3.2 Comovement of Price Dispersion and Inflation

Structural Estimation In Section 1.2 I discussed specific predictions that the Calvo model makes about the relationship between price dispersion and inflation. I now estimate the structural relationship in the model using the data at hand. Equation (1.2), extended for the case of positive trend inflation, gives rise to the following structural specification.

$$\sigma^2_{mc,t} = \alpha\sigma^2_{mc,t-12} + \beta_1\pi^2_{mc,t} - \beta_2\pi_{mc,t} + \varepsilon_{mc,t} \tag{1.11}$$

where $\sigma^2_{mc,t}$ is the cross-store variance of log prices in a given market-category, $\pi_{mc,t}$ is the corresponding inflation, and $\varepsilon_{mc,t}$ is the error term.

Since the data exhibit seasonal patterns, I apply the twelve-month moving average filter to smooth the series.

$$x^{\mathrm{ma}}_t = \frac{\sum_{i=0}^{11} x_{t-i}}{12} \tag{1.12}$$

where $x_t = \{\sigma_{mct}, \pi_{mct}\}$ and x^{ma}_t are annual averages. This filter implies that $\Delta x^{\mathrm{ma}}_t = (x_t - x_{t-12})/12$, and thus a variation in variables represent a change relative to the same month in the previous year, removing a seasonal component. Since I apply this filter, I use $\sigma^2_{mc,t-12}$ as a lag for $\sigma^2_{mc,t}$ to ensure that persistence is not due to the filter.

The error term in Equation (1.11) is likely to be serially correlated, as well as correlated across groups of goods. To correct for this correlation structure, I report Driscoll and Kraay (1998) standard errors, which tend to be conservative.[9]

In the Calvo model, the coefficient on squared inflation is positive, $\beta_1 > 0$, while that on the level of inflation is negative, $\beta_2 > 0$. Importantly, around the steady state, price dispersion increases with inflation, implying the following condition.

$$2\beta_1\pi - \beta_2 > 0 \tag{1.13}$$

Column (1) of Table 1.3 presents pooled estimates of the relationship for all and regular prices, i.e. excluding sales. For all prices, $\hat{\beta}_1$ is negative and statistically indistinguishable from zero and the condition in Equation (1.13) does not hold. Hence, the data do not support the structural relationship proposed by the Calvo model. For regular prices, although Equation (1.13) is satisfied, two other predictions are violated: $\hat{\beta}_1 < 0$ and $\hat{\beta}_2 < 0$.

[9] Lach and Tsiddon (1992) find serial correlation in the error term of the price dispersion equation. They resort to using the dispersion of price changes instead, making suggestive inference about price levels. Note that the estimation procedure used in this paper was not yet developed at the time of their writing.

TABLE 1.3. EMPIRICAL FINDINGS: PRICE DISPERSION AND INFLATION

	Dep. Var.: σ^2 (Structural Form)			Dep. Var.: σ (Reduced Form)					
						Baseline			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				A. ALL PRICES					
Inflation	-0.002^{**}	-0.002^{**}	-0.003^{***}	-0.095^{***}	-0.025^{***}	-0.029^{***}	-0.029^{***}	-0.030^{***}	-0.032^{***}
	(0.001)	(0.001)	(0.001)	(0.013)	(0.008)	(0.010)	(0.010)	(0.010)	(0.011)
Inflation Squared	-0.013	0.006	0.002						
	(0.012)	(0.008)	(0.006)						
Lag Price Dispersion	0.909^{***}	0.544^{***}	0.545^{***}						
	(0.026)	(0.068)	(0.068)						
Unemployment Rate							-0.010		
							(0.023)		
Log Employment								0.024^{***}	
								(0.006)	
Market-Category FE	N	Y	Y	N	Y	Y	Y	Y	Y
Time FE	N	N	Y	N	N	Y	Y	Y	Y
Lags	N	N	N	N	N	N	N	N	Y
R^2, within	—	0.24	0.24	—	0.00	0.01	0.01	0.01	0.26
N	155,690	155,690	155,690	173,960	173,960	173,960	173,960	173,960	153,942
				B. REGULAR PRICES					
Inflation	0.006^{**}	0.013^{***}	0.010^{***}	0.097^{***}	0.061^{***}	0.034^{***}	0.035^{***}	0.035^{***}	0.059^{***}
	(0.003)	(0.003)	(0.003)	(0.023)	(0.010)	(0.006)	(0.006)	(0.006)	(0.009)
Inflation Squared	-0.041^{**}	-0.056^{***}	-0.049^{**}						
	(0.016)	(0.021)	(0.020)						
Lag Price Dispersion	0.856^{***}	0.537^{***}	0.527^{***}						
	(0.031)	(0.062)	(0.061)						
Unemployment Rate							0.042		
							(0.029)		
Log Employment								-0.004	
								(0.004)	
Market-Category FE	N	Y	Y	N	Y	Y	Y	Y	Y
Time FE	N	N	Y	N	N	Y	Y	Y	Y
Lags	N	N	N	N	N	N	N	N	Y
R^2, within	—	0.08	0.09	—	0.01	0.05	0.05	0.05	0.33
N	155,504	155,504	155,504	173,786	173,786	173,786	173,786	173,786	153,920

Notes: Estimation sample covers 2001-2011. Panel A uses data for all prices, while Panel B uses data for regular prices only, i.e. sales excluded. Columns (1)-(3) report estimates for the structural relationship between price dispersion and inflation as in Equation (1.11) with no fixed effects, with market-category, and market-category+time fixed effects, respectively. The dependent variable is the variance of log prices across stores. Columns (4)-(6) present estimates for the reduced-form specification as in Equation (1.14) for the same selection of fixed effects. The dependent variable is the standard deviation of log prices across stores. Columns (7) and (8), in addition, control for local labor market characteristics. Data on the local unemployment rate and total employment are from the Bureau of Labor Statistics (BLS)–see Footnote 11 for details. Column (9) controls for twelve lags of changes in inflation and price dispersion. The data on inflation and price dispersion is MA(12)-filtered to remove seasonal fluctuations. A change in a variable can be interpreted relative to the same month in a previous year. Driscoll and Kraay (1998) standard errors are in parentheses. Serial correlation of up to 12 lags is allowed. *,**,*** denote 10%, 5%, and 1% significance level, respectively. See Section 1.3.2 for further details.

Column (2) of Table 1.3 presents the estimates when market-category fixed effects are included. In this exercise, I look at the comovement of inflation and price dispersion *within* the same MSA and a category of goods. Although squared inflation turns positive for all prices, it is still statistically insignificant and the condition in Equation (1.13) is still violated. For all prices, previous conclusions remain valid too. In Column (3) I also control for time fixed effects and find similar results.

Finally, pooled specification documents relatively high degree of persistence in price dispersion, consistent with the Calvo model. However, my preferred specifications in Columns (2) and (3), which look at the comovement within markets and categories, report that the estimated persistence is smaller than in the Calvo model consistent with the observed frequency of price adjustment.[10]

Reduced-Form Specification Since the data do not support the relationship between inflation and price dispersion proposed by the Calvo model, in the next sections I am testing whether other popular macroeconomic models are closer to the data. To conduct this test, I need a flexible specification that provides a simple and robust measure of the comovement that can be used for comparison. The structural relationship makes predictions about β_1, β_2, and the relationship between the two, as in Equation (1.13). However, for any plausible value of inflation, the data suggest that price dispersion is essentially driven by the *level* of inflation, and not its squared term, since $\left|\beta_2\right| \gg \left|2\beta_1\pi\right|$. Hence, to compare models with the data, I estimate the following specification.

$$\sigma_{mct} = \beta\pi_{mct} + \gamma_{mc} + \tau_t + \boldsymbol{\delta}'\boldsymbol{X}_{mct} + \varepsilon_{mct} \tag{1.14}$$

where σ_{mct} is the cross-store standard deviation of log prices in a given market-category, π_{mct} is the corresponding inflation, γ_{mc} stands for MSA-category fixed effects, τ_t represents time fixed effects, $\boldsymbol{X}_{mct}$ is the set of control variables, and ε_{mct} is the error term. By focusing on the linear term, I also provide evidence that is not potentially fragile due to sensitivity of nonlinear terms to outliers.

I substitute the variance of log prices with the standard deviation for several reasons. First, plotted data support linear rather than quadratic relationship. As variance is strictly positive, the choice boils down to the shape of the relationship as quadratic transformation preserves the direction of the comovement. Second, other studies that look at the comovement of price dispersion and inflation (Lach and Tsiddon 1992, Van Hoomissen 1988), measure the former with the standard deviation. Hence, my reduced-form results can be compared with previous literature. Third, standard deviation of log prices can be interpreted as the approximate average distance from the mean price, in percent, which facilitates interpretation of the estimates. Finally, the data points to a limited role of the squared term in inflation, and one may be concerned that identification based on nonlinear terms is fragile. Focusing on the linear term in the model and the data is likely to make my conclusions robust in this respect.

[10] The claim that prices in the data look more flexible than in the Calvo model is supported when the model is formally tested against the data in the next sections.

In the baseline specification, I include market-category and time fixed effects. The former are used to study the comovement between inflation and price dispersion *within* a given market-category, while the latter are needed to control for possible time trends. Controlling for time fixed effects does not change the main results of this paper.

Column (4) of Table 1.3 presents pooled estimates of Equation (1.14), when fixed effects are omitted. The comovement is negative for all prices and positive for regular prices. Column (5) shows that the result stands when market-category fixed effects are controlled for.

Estimates of the reduced-form specification in Equation (1.14) with market-category and time fixed effects—which I later use as a benchmark to compare with models—are presented in Column (6) of Table 1.3. A 1 p.p. increase in the annualized inflation rate is associated with a 0.029 log point decrease in monthly price dispersion. Once sales are excluded, price dispersion and inflation exhibit positive comovement, with a 1 p.p. increase in the annualized inflation rate corresponding to 0.034 log point increase in price dispersion.

In contrast to earlier findings of Lach and Tsiddon (1992) and Van Hoomissen (1988), I find a negative relationship between price dispersion and inflation. As they do not distinguish between regular and sales prices, the difference could be reconciled if sales are not important in their data. Other reasons could be attributed to differences in location (they look at grocery stores in Israel) or time sample (they look at 1970s-1980s—a period of high inflation). Hence, to the best of my knowledge, this paper is the first to document a negative relationship between price dispersion and inflation.

Local Labor Markets The state of local labor markets may affect search intensity and the resulting price dispersion through the store-switching process over the business cycle as emphasized in Coibion, Gorodnichenko, and Hong (2012). Since the unemployed incur smaller search costs as they have more time, which is also less valuable, to look for best prices, a distress to local labor markets may lead to a rise in search intensity. To account for this effect, I include two measures of the state of local labor markets as a control variable: the local unemployment rate and log employment. The former accounts for movement from "employed" to "unemployed" status, while the latter also includes flows out of labor force and migration. The data on local labor market characteristics come from the Bureau of Labor Statistics (BLS).[11]

Controlling for the state of local labor markets does not quantitatively change estimates of the comovement of price dispersion and inflation. Column (7) of Table 1.3 shows the estimates for the case when the local unemployment rate is included into the

[11]The data on local unemployment rates come from the Local Area Unemployment Statistics (LAUS). Those on total non-farm employment are taken from the Current Employment Statistics (CES). Each observation is measured at the corresponding MSA level. For the larger areas the following data points are used. For Mississippi and South Carolina the data are taken at the statewide level. For New England they come at the corresponding Census division level (NRD810000 "New England"). For West Texas/New Mexico the data represent the aggregate for New Mexico statewide and the following MSAs in West Texas: Abilene, Amarillo, El Paso, Lubbock, Midland, Odessa, San Angelo.

set of control variables, while Column (8) does so for log employment. I include the two separately as they may be strongly collinear. The local unemployment rate is insignificant in both cases, and log employment is positively associated with price dispersion (all prices). The latter result is consistent with the reasoning that as employment increases, people search less intensely for better prices, which results in higher price dispersion.

Dynamic Properties Expected and unexpected inflation are likely to make different impacts on price dispersion. The search literature emphasizes that even perfectly anticipated inflation should affect price dispersion. However, unanticipated shocks can also contribute through the effect on the frequency and size of price changes.[12] The difference can become even starker if one allows for temporary price reductions, with sales decisions made by firms a period in advance.[13]

Since it is difficult to measure inflationary expectations within an MSA and a category of goods, I only look at the effect of inflationary shocks, as well as their propagation over time. Empirically, propagation could be due to inflation persistence[14] and the contemporaneous effect of inflation on price dispersion, as emphasized in this paper. In theory, Equation (1.2) shows that in the Calvo model price dispersion is itself persistent.

To estimate impulse responses of price dispersion to an inflation shock, I use the direct projections approach (see Jordà 2005, Stock and Watson 2007). This method has a number of advantages over vector autoregression (VAR) in my context: First, it is parsimonious and easy to implement through linear estimation. Second, it can be used for longitudinal data with a large number of panels. Finally, it permits straightforward calculation of standard errors when the error term is correlated across time and goods (e.g., one can use Driscoll and Kraay 1998). I estimate the following specification:

$$\sigma_{mc,t+h} = \beta_h \pi_{mc,t} + \gamma_{mc} + \tau_t + \Psi_{11}^{\sigma}(L)\,\sigma_{mc,t-1} + \Psi_{11}^{\pi}(L)\,\pi_{mc,t-1} + \varepsilon_{mc,t+h} \tag{1.15}$$

where $\Psi_{11}^{x}(L) = \sum_{i=0}^{11} \psi_i^x L^i (1-L)$ is the lag polynomial of order 11 applied to a first-difference of variable x, $x = \{\sigma, \pi\}$. I control for lag-differences instead of lags because, as discussed above, the data are MA(12)-filtered. Differencing helps to control for actual innovation as it represents a change relative to the same month in a previous year, and, hence, it controls for all innovations that happen within a year. Without differencing, lagged values would contain a common component due to annual averaging.

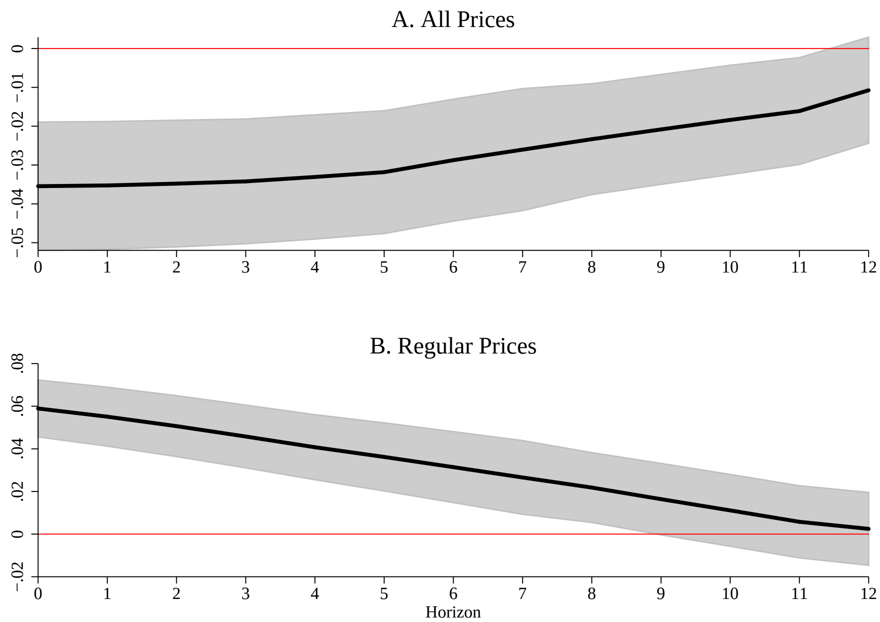
Coefficient β_0 can be interpreted as a contemporaneous response of price dispersion to a 1 p.p. inflation innovation. The estimates are provided in Column (9) of Table 1.3. A 1 p.p. shock to the annualized monthly inflation decreases price dispersion in all prices by

[12]Lach and Tsiddon (1992) test empirically the effect of expected inflation versus that of the unexpected one and find that both effects are positive, with expected inflation having a stronger impact on price dispersion. In contrast, Reinsdorf (1994) finds that only expected inflation has a positive association with price dispersion, while the unexpected one has a negative effect.

[13]Some grocery stores advertise sales on their website and ask loyalty club members to add product items to the membership card to be eligible for a discount. The discounts are valid until the expiration date set by the grocer and announced in advance.

[14]See Fuhrer (2010) for an overview of literature on inflation persistence.

FIGURE 1.3. IMPULSE RESPONSES OF PRICE DISPERSION TO INFLATION INNOVATION



Notes: Each line represents impulse responses of monthly price dispersion to 1 p.p. increase in innovation in the annualized inflation rate over the year based on the direct projections estimation as in Equation (1.15). Shaded area covers two Driscoll and Kraay (1998) standard errors around the estimated response. "Regular Prices" do not include sales. See Section 1.3.2 for details.

0.032 and increases that in regular prices by 0.059. The effect is strong and significant, suggesting that price dispersion responds to inflation innovation.

Impulse response function based on estimates $\hat{\beta}_h$ is plotted in Figure 1.3. The data reveal strong dynamic relationship between price dispersion and inflation. For all prices, the response of price dispersion is significant at 5% level for up to 11 months, falling to −0.016; while for regular prices, it is significant for 8 months, when it falls to 0.021.

Structural Changes As both price dispersion and inflation fluctuate in time series, I examine if the relationship is stable over time by estimating Equation (1.14) separately for each year. The results are plotted in Figure 1.4. The relationship for regular prices is consistently positive, in the range of 0.01–0.04. Note that after the Great Recession started, standard errors decreased substantially. This could be due to increased variability in the explanatory variable as a result of heterogeneity in inflation response.[15]

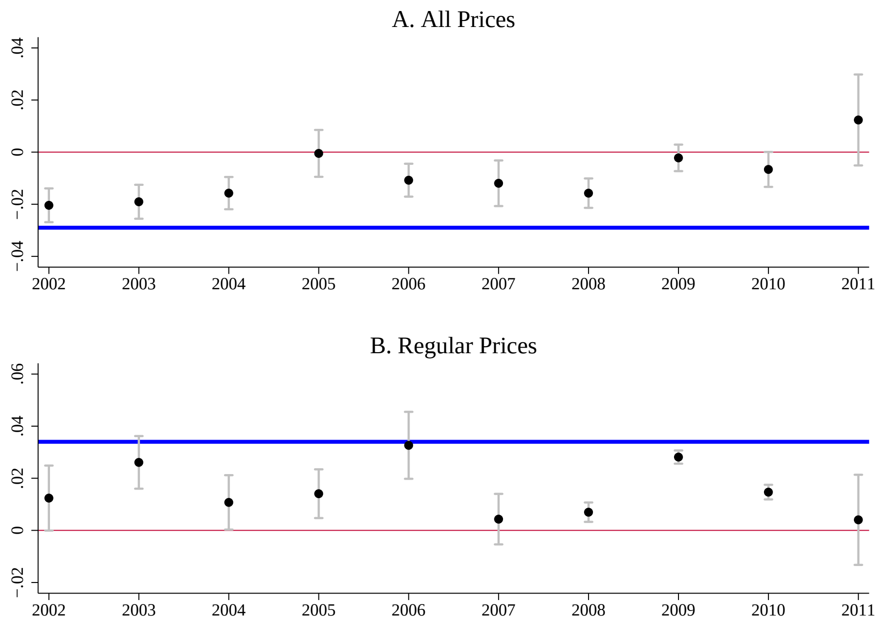
For all prices, the data suggest a structural change around 2008. Until that time, the annual coefficients were within a narrow interval between −0.02 and −0.01;[16] from 2009 on, however, they turned indistinguishable from zero. Note that at this time inflation significantly decreased.

Annual estimates differ from those for the entire sample, potentially, due to several reasons. First, there is usually little variation in inflation within a year. Second, standard

[15]In 2011 the standard error returned to its pre-recession level.

[16]The only exception is 2005, for which the coefficient is close to zero.

FIGURE 1.4. STABILITY CHECK: TIME-SERIES OF THE ESTIMATE



Notes: The graph reproduces the estimate in Column (6) of Table 1.3 for each year separately. Shaded area covers two Driscoll and Kraay (1998) standard errors around the estimate. Thick blue horizontal lines show estimates for the entire sample. See Section 1.3.2 for details.

errors are treated differently. For the entire sample, I allow serial correlation of up to twelve months. Since I only have twelve observations for a given market-category for annual subsamples, I allow serial correlation of up to one month. It is possible that if serial correlation is more severe, confidence intervals of the annual estimates get closer to the estimate for the entire sample. This example highlights that the relationship is difficult to estimate precisely when the time series is short.

1.4 Theoretical Implications

In the previous section I show that price dispersion comoves with inflation in the data. In this section I demonstrate that the comovement have implications for a wide range of macroeconomic models. First, I use the empirical relationship between price dispersion and inflation as a moment not used in calibration to test which type of price rigidity is consistent with the data. Existing literature provides conflicting evidence on whether pricing is time- or state-dependent. I show that the comovement sheds new light on the relative importance of the two frictions. Second, I demonstrate that explicit modeling of sales helps improve models' properties not only for all prices, but for regular prices as well. I argue that as sales provide additional flexibility in pricing, the Calvo model with sales is more promising than the Fixed Menu Cost (FMC) model with sales, and then show that a version of the former can match the data for both all and regular prices. Third, I study implications of price dispersion for welfare calculation. I show that disagreement (between a model and the data) about price dispersion and its comovement with inflation can have a strong effect on measurement of welfare, the cost of business cycles, and design of optimal policy. Finally, I study an alternative class of models that emphasize the role of search frictions in the product market. I show that although a version of such models can match the contemporaneous comovement, it makes counterfactual predictions about its dynamic properties.

1.4.1 Time- vs. State-Dependent Pricing

There is a disagreement in the literature whether pricing is time- or state-dependent. The answer to this question has important implications for the effect of nominal shocks on real variables and the effectiveness of monetary and fiscal policy. Models with time-dependent frictions are characterized by real effects of nominal variables, while many models with state-dependent frictions imply monetary neutrality. Costain and Nakov (2011a,b) attempt to resolve the disagreement by developing a model, in which pricing contains both time- and state-dependent elements, referred to as Smoothly State-Dependent Pricing (SSDP). They show that in this flexible framework, to be consistent with the data on micro pricing, time-dependent frictions should dominate, implying a strong degree of monetary non-neutrality.

In this section I investigate if their model is consistent with the data on the comovement of price dispersion and inflation. Because the model also nests the Calvo model and the Fixed Menu Cost (FMC) model as in Golosov and Lucas (2007), it allows to test which friction is more important to match the data on price dispersion. The SSDP framework is well suited for this question because it allows to fix all other parameters in the model and only vary the relative importance of the menu cost vs. the Calvo friction.

The section proceeds as follows. I first lay out the basics of the model with an emphasis on its pricing mechanism. I then compare two limiting cases of the model—the Calvo vs. the FMC model—for which pricing is either strictly time-dependent or strictly state-dependent. Afterward, I investigate in which direction the relative influence of the two frictions should be altered to match the data, and what it implies for the distribution of price changes.

Baseline Model

The key assumption of the SSDP model is that the probability of price adjustment rises with the gains of doing so. However, there is no menu cost to pay and the probability is determined by an exogenous time-dependent friction. Such a mechanism can be rationalized by Stochastic Menu Costs (SMC) as in Dotsey, King, and Wolman (1999) or bounded rationality as in Akerlof and Yellen (1985). In the former case, the parametric function for the probability of price adjustment comes from the distribution of menu costs, while in the latter it simply represents an error in evaluating the state, reflecting the conjecture that errors are more likely to occur when they are not costly. In the limit, the model nests the Calvo (1983) and the FMC set-up as in Golosov and Lucas (2007).[17]

The baseline model features monopolistically competitive firms with price-adjustment frictions and persistent idiosyncratic productivity. There are two variations on the monetary policy: the Taylor rule setup and the money growth setup. The former is used as a baseline, while the latter allows to compare the FMC results with those in Golosov and Lucas (2007). Overall, there are three types of shocks in the economy: monetary shocks modeled as innovations in the Taylor rule, aggregate productivity shocks (TFP), and idiosyncratic productivity shocks. The latter do not have an effect on aggregate fluctuations due to the law of large numbers. Price dispersion arises from heterogeneity in costs, frictions in price adjustment, and consumers' preference for variety.

Households A representative household maximizes its discounted value of per-period utility stream, $U_t = \sum_{\tau=t}^{\infty} \beta^{\tau-t} u_\tau$, with

$$u_t = \frac{C_t^{1-\gamma}}{1-\gamma} - \chi N_t + \nu \log \frac{M_t}{P_t} \tag{1.16}$$

where γ is the inverse intertemporal elasticity of substitution, and χ and ν are labor supply and real money balances parameters, respectively. The household consumes a variety of goods with the elasticity of substitution ε, aggregated using Dixit-Stiglitz, $C_t = \left(\int_0^1 C_{i,t}^{\frac{\varepsilon-1}{\varepsilon}} di\right)^{\frac{\varepsilon}{\varepsilon-1}}$. The budget constraint is given by

$$\int_0^1 P_{i,t} C_{i,t} di + M_t + \frac{B_t}{1+r_t} = W_t N_t + M_{t-1} + T_t + B_{t-1} \tag{1.17}$$

The nominal bonds, B_t, are in zero supply, and seigniorage, as well as firms' profits, are returned to the household.

Firms Firms are monopolistic competitors whose per period profit function is given by

$$\Pi_{i,t} = P_{i,t} Y_{i,t} - W_t Y_{i,t} \tag{1.18}$$

The firm's production function is linear in labor, $Y_{i,t} = A_{i,t} N_{i,t}$. Idiosyncratic productivity follows AR(1) process in logs.

$$\log A_{i,t} = \rho_A \log A_{i,t-1} + \varepsilon_{i,t}^A \tag{1.19}$$

Demand function is given by $Y_{i,t} = C_t \left(\frac{P_{i,t}}{P_t}\right)^{-\varepsilon}$, where $P_t = \left(\int_0^1 P_{i,t}^{1-\varepsilon} di\right)^{\frac{1}{1-\varepsilon}}$ is a Dixit-Stiglitz price index.

[17]Numerical results for the SSDP model are very close to the SMC model as in Dotsey, King, and Wolman (1999), and together with results for the Woodford (2009) model are available from the author upon request.

Price Adjustment Price adjustment follows Costain and Nakov (2011a), which nests time-dependent and state-dependent models of price adjustment. Specifically, the probability of price adjustment, λ, is a function of the loss from inaction, L.

$$\lambda(L) = \frac{\bar{\lambda}}{\bar{\lambda} + \left(1 - \bar{\lambda}\right)\left(\frac{\alpha}{L}\right)^{\xi}} \tag{1.20}$$

This functional form has two advantages. First, it matches the data on the frequency and distribution of the size of price changes much closer than the Calvo or the FMC model do. Second, it nests the two as a limiting case. When $\xi \to 0$, $\lambda(L) \to \bar{\lambda}$ as in the Calvo (1983) price-adjustment process. When $\xi \to \infty$, $\lambda(L) = \mathbb{1}\{L > \alpha\}$ as in the FMC model. Hence, $\bar{\lambda}$ captures time-dependent frictions, while α represents nominal frictions in price adjustment, e.g., menu cost. Parameter ξ captures relative importance of the two. The loss function from not adjusting the price given the overall state is $L\left(P_{i,t}\right) = \max_P V(P) - V\left(P_{i,t}\right)$.

Shocks The idiosyncratic productivity follows an AR(1) process as in Equation (1.19). Following Costain and Nakov's (2011a) approach, I consider two versions of the model. The baseline version is based on the Taylor rule in the form

$$\check{R}_t = \varphi_R \check{R}_{t-1} + \left(1 - \varphi_R\right)\left(\varphi_\pi \check{\pi}_t + \varphi_C \check{C}_t\right) - z_t \tag{1.21}$$

where $\check{X} = \log X - \log \bar{X}$ is a log-deviation from the steady-state value.

In the alternative version, referred to as Money Growth hereafter, the growth rate of money supply is a constant perturbed by an AR(1) shock.

$$\frac{M_t}{M_{t-1}} = \mu \exp z_t \tag{1.22}$$

$$z_t = \varphi_M z_{t-1} + \varepsilon_t^M \tag{1.23}$$

This alternative is only used for comparison purposes to be consistent with Golosov and Lucas (2007).

Equilibrium Dynamics

The household first-order condition gives the Euler equation

$$\mathbb{E}_t\left[\frac{P_{t+1}C_{t+1}^{\gamma}}{P_t C_t^{\gamma}}\right] = \beta\left(1 + r_t\right) \tag{1.24}$$

together with two intratemporal conditions

$$\chi C_t^{\gamma} = \frac{W_t}{P_t} \tag{1.25}$$

$$\frac{r_t}{1+r_t}\nu^{-1}\frac{M_t}{P_t} = \frac{W_t}{P_t} \tag{1.26}$$

The firm's Bellman equation can be written as

$$V(P,A,\Omega) = \Pi(P,A,\Omega) + \mathbb{E}\left[\frac{1}{1+r_t}\left\{V\left(P,A',\Omega'\right) + \underbrace{\lambda\left(L\left(P,A',\Omega'\right)\right)L\left(P,A',\Omega'\right)W\left(\Omega'\right)}_{\text{adjustment gain}}\right\}\right] \tag{1.27}$$

where $\Omega \equiv \left(z_t, r_{t-1}, \Psi_{t-1}\right)$ is the aggregate state with the last variable being the lagged distribution of firms over prices and productivity levels.

Finally, the labor market clearing condition implies $N_t = \Delta_t^w C_t$, where

$$\Delta_t^w = \int_0^1 A_{i,t}^{-1}\left(\frac{P_{i,t}}{P_t}\right)^{-\varepsilon} di \tag{1.28}$$

is the Dixit-Stiglitz measure of price dispersion weighted by productivity.

Simulations and Results

I first describe calibration of the model and simulation of the series. Then I compare the comovement of price dispersion found in the data for regular prices with that in the baseline SSDP model, as well as in its limiting cases: the Calvo and the FMC models. Since the Calvo model produces structural relationship between price dispersion and inflation, I first estimate the structural relationship for the data simulated in the Calvo model. The results confirm that the Calvo model is not a good representation of the data in terms of matching the comovement. Hence, I then move to estimate the flexible reduced-form specification proposed in the empirical analysis. I compare the results for the reduced-form Calvo specification with estimates for the FMC and the baseline SSDP model and show that none of them can get sufficiently close to the data. Finally, I investigate how the relative importance of time- and state-dependent frictions can explain the mismatch. The key finding is that the SSDP model can be calibrated to match either the distribution of the size of price changes or the comovement of price dispersion and inflation, but not both. To match the comovement, price adjustment should be more state-dependent than in the baseline specification.

Calibration and Simulations The model is calibrated based on parameters used in the literature for related models. In particular, utility function parameters (β, γ, ε, χ, ν) are taken from Golosov and Lucas (2007). Parameters of the price-adjustment function (α,

TABLE 1.4. BASELINE MODEL CALIBRATION

	Notation (1)	Value (2)
Preferences		
Discount factor	β	$1.04^{-\frac{1}{12}}$
Intertemporal ES	γ	2
ES across goods	ε	7
Disutility of labor	χ	6
Money demand	ν	1
Policy		
Annualized trend inflation	$\bar{\pi}$	4.4%
Interest rate smoothing	φ_R	0.9
Response to inflation	φ_π	4
Response to output gap	φ_C	0.5
Shocks Persistence		
Monetary	φ_M	0
TFP	φ_A	0.95
SSDP Adjustment		
Menu cost	α	0.037
Calvo-type friction	$\bar{\lambda}$	0.110
Smoothness	ξ	0.23
Price Adjustment in the Limit		
Freq. of P changes (Calvo)	$\bar{\lambda}$	0.1
Menu cost (FMC)	α	0.065

Notes: See Section 1.4.1 for details.

$\bar{\lambda}$, and ξ) are chosen to minimize the distance between the model and the data for the frequency and distribution of price changes and are based on calculations in Costain and Nakov (2011a,b). Parameters that govern monetary policy rule (φ_R, φ_π, φ_C) and shocks properties (φ_M, φ_A) are taken from Costain and Nakov (2011a). Finally, I set the value for the trend inflation ($\bar{\pi}$) based on the observed trend inflation for regular prices in my data. The baseline parameterization choice is summarized in Table 1.4.

I then generate a history of shocks for 2,200 periods, burning the first 200 observations, and compute price dispersion and inflation in the model. I consider three cases for different sources of variation: monetary shocks only, TFP shocks only, and both shocks.

I compare the Calvo, FMC, and SSDP models by estimating the comovement of price dispersion and inflation for the simulated data based on the reduced-form relationship. As discussed earlier, the reduced-form specification is suggested by the data and is less fragile since it does not include higher-order terms. In addition, the structural relationship is only valid for the Calvo model; the analog is not known for the FMC or SSDP model. As a counterpart of Equation (1.14), I estimate the following regression.

$$\sigma_t = \beta\pi_t + \gamma + \varepsilon_t \tag{1.29}$$

where σ_t is the standard deviation of log prices simulated in the model and π_t is the simulated inflation. I run the MA(12) filter on both series to make sure that my results are not driven by an effect the filter might have on persistence of the series or their

TABLE 1.5. CALVO MODEL VS. DATA: STRUCTURAL ESTIMATION

	Model			Data	
	Monetary (1)	TFP (2)	Both Shocks (3)	All Prices (4)	Regular Prices (5)
Lag Price Dispersion	0.908	0.905	0.906	0.545	0.527
Inflation Squared	$8.3\cdot10^{-5}$	$-6.0\cdot10^{-5}$	$-1.5\cdot10^{-5}$	0.002	−0.049
Inflation	0.066	0.070	0.068	−0.003	0.010

Notes: The table compares estimates from the specification suggested by the Calvo model for the simulated and actual data. The dependent variable is the variance of log prices, σ^2, simulated in the Calvo model. Columns (1)-(3) use the data simulated for the monetary shock, the TFP shock, and both of them, respectively. See Sections 1.3.2 and 1.4.1 for details.

comovement. I do robustness checks in Section A.1 by considering the same regressions without the filter and obtain similar results.

Since the Calvo model produces the exact structural relationship between price dispersion and inflation, before comparing the models based on the reduced-form estimation, I verify that the structural relationship in the Calvo model is inconsistent with the data. For this I estimate the analogue of specification in Equation (1.11) for the simulated data.

$$\sigma_t^2 = \alpha\sigma_{t-12}^2 + \beta_1\pi_t^2 - \beta_2\pi_t + \gamma + \varepsilon_{mc,t} \tag{1.30}$$

where σ_t^2 is the variance of log prices simulated in the model and π_t is the simulated inflation. In the vicinity of MA(12) filter and to be consistent with the empirical analysis, I use σ_{t-12}^2 as a lag of price dispersion. Below I discuss the results for the structural estimation, followed by the reduced-form estimates.

Calvo Model (Structural Estimation) The model and the data disagree along several dimensions (Table 1.5). First, price dispersion in the model is too persistent. This implies that to match the data, the Calvo model needs more flexibility in pricing. Second, the comovement is mostly driven by the linear term, motivating the reduced-form estimation. Finally, the model predicts positive comovement, while in the data it is only positive for regular prices. Even for regular prices, the degree of the comovement in the Calvo model is much stronger than in the data.

Calvo Model (Reduced Form) The reduced-form measure of the degree of the comovement confirms that the Calvo model cannot match the data. First, for the baseline calibration, the degree of the comovement β is more than 10 times bigger in the model than in the data for regular prices, and the negative comovement for all prices cannot be obtained (Table 1.6). Second, varying persistence of shocks or central bank's response to inflation does not improve the match. Third, even without trend inflation, the Calvo model overestimates the comovement by more than 5 times.

To match the data, prices should be extremely flexible. For the Calvo model to perform well, the monthly frequency of price adjustment should be 0.5. However, such frequency is at odds with the observed duration of price spells in the data.

The result is quite intuitive. In the Calvo model, a large nominal shock does not affect

Table 1.6. Price Dispersion and Inflation in the Calvo Model

	Model			Data	
	Monetary (1)	TFP (2)	Both Shocks (3)	All Prices (4)	Regular Prices (5)
Baseline	0.388	0.547	0.505	−0.029	0.034
Alternatives					
Response to Inflation $\varphi_\pi = 10$ (4)	0.380	0.545	0.462		
Persistence of TFP Shock $\varphi_A = 0.4$ (0.95)	0.388	0.292	0.388		
Persistence of M Shock $\varphi_M = 0.8$ (0)	0.420	0.547	0.427		
Trend Inflation $\bar{\pi} = 0$ (4.4%)	0.181	0.229	0.209		
Probability of Price Change $\bar{\lambda} = 0.5$ (0.1)	0.041	0.038	0.041		

Notes: The table reports estimated slope coefficients for regression of price dispersion on inflation for the data simulated in the Calvo model. In the first column variation comes from monetary shocks only, in the second column–from the productivity shocks only, and in the last column from both shocks. Alternative parameterization considers one parameter change at a time. Baseline values are in parentheses. See Section 1.4.1 for details.

the number of firms that adjust their price. If the frequency of price adjustment is small, very few firms change their prices making only a small effect on the aggregate price level. At the same time, those firms that are able to reset prices will do so by a lot, thereby increasing price dispersion. Hence, nominal shocks have a small effect on inflation and rather strong effect on price dispersion. In terms of the estimated comovement, small changes in inflation are associated with large changes in price dispersion making the coefficient relatively large. To match the data, more firms should be able to adjust their price amplifying the response of inflation and dumping the response of price dispersion.

One way to achieve additional flexibility, which will be shown to work very well, is to introduce sales in the Calvo model. A possibility of sale gives firms an opportunity to change their actual price when their regular price is rigid. Adding sales can also help differentiate between the comovement in regular and all prices, which are different in the data.

Alternatively, as we need stronger response of inflation to large shocks, state-dependent pricing models may be more successful, since in these models price rigidity arises only when shocks are small enough.[18] Hence, I proceed to study the FMC model, followed by the SSDP model.

Fixed Menu Cost The estimates of Equation (1.29) are presented in Table 1.7. As before, I examine the comovement due to each shock separately (monetary vs. TFP) and together. In the baseline specification, the comovement is very small: 5-7 times smaller than in the data. Changing persistence of shocks or removing trend inflation do not make the estimates close to the data. Changes in the size of the menu cost do not affect the

[18] The idea that inflation drives price dispersion when pricing is state-dependent goes back to Sheshinski and Weiss (1977). In the presence of costly price adjustment, the optimal pricing is the (S,s) strategy. An increase in the inflation rate leads to an increase in the size of price changes making price dispersion bigger. The model, however, abstracts away from the consumer side, as without search frictions one can hardly justify non-zero demand at any price above the minimum. It assumes that the inflation rate is exogenous and deterministic contrary to stochastic aggregate models. In subsequent work, Sheshinski and Weiss (1983) consider stochastic inflation and prove the certainty equivalence result.

TABLE 1.7. PRICE DISPERSION AND INFLATION IN THE FIXED MENU COST MODEL

	Model			Data	
	Monetary (1)	TFP (2)	Both Shocks (3)	All Prices (4)	Regular Prices (5)
Baseline	0.007	0.004	0.005	−0.029	0.034
Alternatives					
Persistence of TFP Shock $\varphi_A = 0.4$ (0.95)	0.007	0.001	0.007		
Persistence of M Shock $\varphi_M = 0.8$ (0)	0.007	0.004	0.007		
Trend Inflation $\bar{\pi} = 0$ (4.4%)	0.011	0.009	0.010		
Menu Cost $\alpha = 0.005$ (0.065)	−0.000	−0.001	−0.002		
Menu Cost $\alpha = 0.15$ (0.065)	0.007	0.004	0.006		

Notes: The table reports estimated slope coefficients for regression of price dispersion on inflation for the data simulated in the Fixed Menu Cost model. In the first column variation comes from monetary shocks only, in the second column–from the productivity shocks only, and in the last column from both shocks. Alternative parameterization considers one parameter change at a time. Baseline values are in parentheses. Simulated series are MA(12)-filtered similar to the data. See Section 1.4.1 for details.

TABLE 1.8. PRICE DISPERSION AND INFLATION IN THE SMOOTHLY STATE-DEPENDENT PRICING MODEL

	Model			Data	
	Monetary (1)	TFP (2)	Both Shocks (3)	All Prices (4)	Regular Prices (5)
Taylor Rule Setup	0.153	0.162	0.157	−0.029	0.034
Money Growth Setup	0.157	0.150	0.154		
Alternatives (Taylor Rule)					
Response to Inflation $\varphi_\pi = 10$ (4)	0.151	0.156	0.153		
Persistence of TFP Shock $\varphi_A = 0.4$ (0.95)	0.153	0.135	0.152		
Persistence of M Shock $\varphi_M = 0.8$ (0)	0.156	0.162	0.156		
Trend Inflation $\bar{\pi} = 0$ (4.4%)	0.112	0.116	0.114		

Notes: The table reports estimated slope coefficients for regression of price dispersion on inflation for the data simulated in the Smoothly State-Dependent Pricing (SSDP) model. In the first column variation comes from monetary shocks only, in the second column–from the productivity shocks only, and in the last column from both shocks. The first two lines are for the "Taylor Rule" and "Money Growth" setups, respectively. Alternative parameterization considers one parameter change at a time relative to the "Taylor Rule" baseline. Baseline values are in parentheses. See Section 1.4.1 for details.

result much. Note that when the menu cost is very small, the relationship may even become negative.

The intuition for this is the following. Firms set their prices guided by an (S,s)-rule. A nominal shock forces "marginal" firms to adjust, thus having a strong effect on inflation, but it has only a very limited effect on price dispersion in relative prices. Consequently, the change in price dispersion relative to the change in inflation is small. If the menu cost is very small, most firms will adjust their price to the same value, which may lower price dispersion.

Baseline SSDP Model The results on the comovement of inflation and price dispersion in the SSDP model and the data are in Table 1.8. For the baseline calibration, the SSDP model predicts the comovement 4-5 times bigger than in the data. This is better than the Calvo model or the FMC model do, but still substantially off. Both versions of the model (money growth and the Taylor rule) produce similar estimates.

Parameters of the model—such as persistence of shocks, Central Bank's response to inflation, or zero trend inflation—cannot improve the match. The qualitative similarity between the SSDP and the Calvo model is due to the choice of the smoothness parameter ($\xi = 0.23$), which puts a higher weight on time-dependent frictions.[19]

The fact that the estimates lie between the Calvo model and the FMC model is quite intuitive: In the Calvo model, in the wake of an inflationary shock every firm has an equal chance to reset the price. Hence, a situation when a firm that lags behind the price level is able to adjust is equally likely as the situation when a firm with the highest price makes its good even dearer. In the FMC model, however, there is a strong selection effect: only firms that are far enough from the optimal price will adjust, partially offsetting the effect of inflation on price dispersion. As the SSDP model nests either model as a special case, its behavior strongly depends on estimated parameters. Since Costain and Nakov's (2011a) estimates imply the price adjustment is closer to Calvo, it is no surprise that the relationship between inflation and price dispersion is so too. However, the data suggest that the estimated SSDP is too close to Calvo and overestimates the role of time-dependent frictions. Although, price dispersion responds much stronger to inflation in the data than Golosov and Lucas (2007) would suggest, clearly implying monetary non-neutrality, the degree of non-neutrality produced by the SSDP model may be overstated.

SSDP Model with Alternative Smoothness A strong side of the SSDP model is that by varying the smoothness parameter ξ, one can achieve any intermediate case between the strictly Calvo and the FMC pricing. As the former overestimates the degree of the comovement and the latter underestimates it, there exists a value of ξ that matches it.

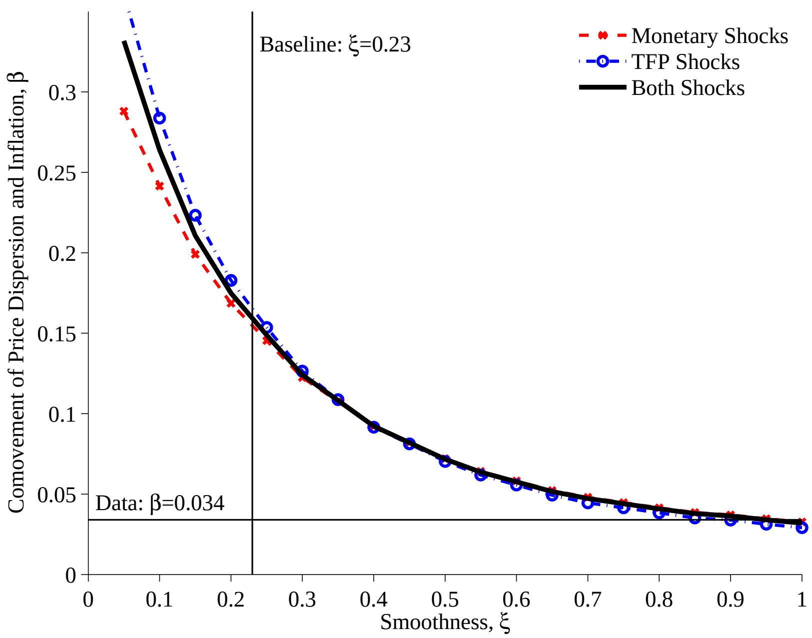
Since the smoothness parameter is calibrated to match the distribution of the size of price changes in the data, matching price dispersion leads to a mismatch in the former. This result is shown in Figure 1.5. Panel A shows the comovement of price dispersion and inflation for the three data-generating processes and different values of ξ. To match the comovement, ξ should be set to approximately 0.95, far above its baseline value of 0.23. Hence, this implies that price setting should be more state-dependent than suggested by the distribution of the size of price changes. Panel B confirms this intuition: for the new value of ξ, the histogram of price changes looks much closer to bimodal distribution, with almost no price changes around zero—in contrast to the data (Midrigan 2011).

Summary Empirical evidence on the relationship between price dispersion and inflation supports neither purely time-dependent nor purely state-dependent price setting. A model that contains both frictions has a potential to match the data. However, it requires pricing to be more state-dependent than suggested by the distribution of price changes. Hence, such models can match either the distribution of price changes or the comovement of price dispersion and inflation, but not both.

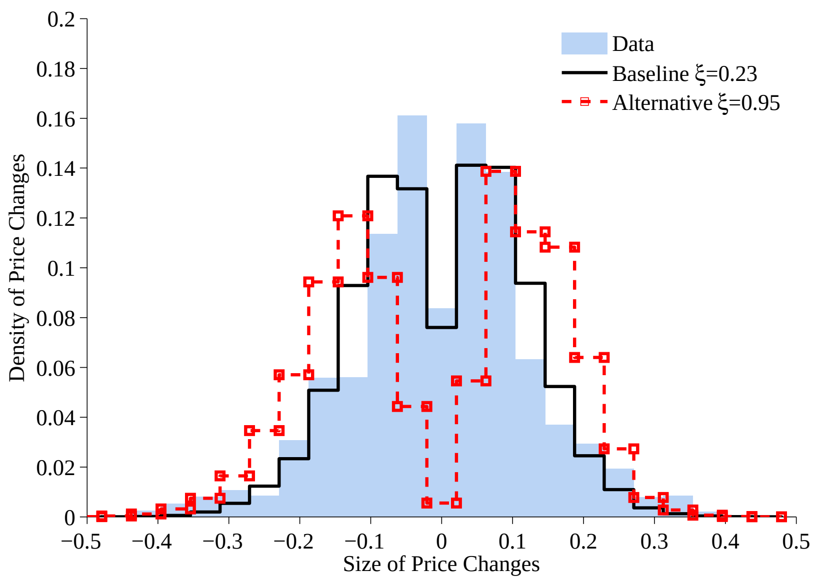
[19] See Costain and Nakov (2011a,b) for more details.

FIGURE 1.5. SMOOTHNESS PARAMETER IN THE SSDP MODEL

A. COMOVEMENT OF PRICE DISPERSION AND INFLATION



B. DISTRIBUTION OF PRICE CHANGES



Notes: Panel A depicts estimated slope coefficients for regression of price dispersion on inflation for the data simulated in the Smoothly State-Dependent Pricing (SSDP) model for monetary, TFP, and both shocks. Panel B demonstrates the distribution of the size of price changes in the data, the baseline value of the smoothness parameter $\xi = 0.23$, and the value that matches the comovement of price dispersion and inflation in Panel A, $\xi = 0.95$. See Section 1.4.1 for details.

1.4.2 Sales and Regular Prices

The empirical analysis shows that sales have a strong effect on properties of the data. Models without sales considered in the previous section cannot match even the direction of the relationship between price dispersion and inflation for all prices. To match the data with sales, one arguably needs a model with sales. On top of this, as sales interact with regular prices, a model with sales has a potential to also improve on matching properties of regular prices, relative to a similar model without sales.

Based on the analysis in the previous section, the Smoothly State-Dependent Pricing (SSDP) model would be a good candidate to introduce sales to. However, as the model is relatively complex, adding sales would make it intractable. In light of this complexity, I consider a time-dependent model with sales. I do so for the following reasons. First, a calibrated version of the SSDP model suggests that pricing is much closer to time-dependent than to state-dependent. Second, the Calvo model with sales would move closer to the data, while the Fixed Menu Cost (FMC) model with sales would move further away. This is due to the finding in the previous section that to match the data on price dispersion and inflation, the Calvo model needs more price flexibility, while the FMC model needs less of it. As sales clearly add flexibility to pricing, I argue that to match the data on the comovement, sales should be introduced into the Calvo model. Finally, this guess is verified below by the finding that the Calvo model with sales can get very close to matching the comovement for both all and regular prices.

In this section I consider the Calvo model with sales to answer mainly two questions. First, can a model with sales explain the negative comovement for all prices found in the data? Second, can sales improve properties of the model for regular prices? The answer for both questions is affirmative.

Framework Sales are introduced through the difference between the elasticity of substitution between goods and brands as in Guimaraes and Sheedy (2011), hereafter referred to as GS. Brands, which are close substitutes, have "loyal" customers, who see their favorite brand as superior to other brands, and "bargain-hunters"—price-sensitive consumers who are indifferent between the brands. This leads to equilibrium in mixed strategies, in which firms alter the regular price between the high—to extract surplus from "loyals"—and the low (sales)— to attract "bargain-hunters." As mentioned in the literature review section, existence of "loyal" customers has long been considered an important source of price dispersion in the industrial organization literature.[20]

The key feature of sales in this model is strategic substitutability. Firms want to put their goods on sale only when other firms do not do so. In the Calvo framework, when

[20] Alternatively, one could consider a model with sales of Kehoe and Midrigan (2012). In the Calvo version of their model, they introduce additional probability of being able to reset the price temporarily. Since they consider sales as an exogenous process, while Guimaraes and Sheedy (2011) model sales explicitly, I make a choice in favor of the latter. It would be interesting to see, however, if the result still holds in *the Calvo version* of Kehoe and Midrigan (2012). I expect that *the menu-cost version* of their model has less potential to match the data due to inability of FMC models to produce significant price dispersion.

a firm does not have a chance to change their regular price, it can still set a temporary sales price. In essence, sales relax the degree of price rigidity, which is exactly what is needed since the Calvo model overshoots the response.

Specifically, let $\mathcal{G}$ be the set of goods of measure one, and $\mathcal{B}$ be the set of brands for each good. For a given household, there is a set of goods $\Lambda \subset T$ for which the household is "loyal" to a particular brand. Denote the brand the household is "loyal" to as $\mathcal{B}(i)$, $i \in \Lambda$. For other goods the household is a "bargain-hunter," meaning it gets utility from consuming any brand. The Dixit-Stiglitz consumption aggregator can be written as

$$C = \left(\int_{\Lambda} C_{i,\mathcal{B}(i)}^{\frac{\varepsilon-1}{\varepsilon}} di + \int_{G \backslash \Lambda} \left(\int_{\mathcal{B}} C_{i,b}^{\frac{\eta-1}{\eta}} db \right)^{\frac{\eta}{\varepsilon}} di \right)^{\frac{\varepsilon}{\varepsilon-1}} \tag{1.31}$$

where ε is the elasticity of substitution across products and $\eta > \varepsilon$ is the elasticity of substitution across brands within a good.

The preferences described above are further embedded into Erceg, Henderson, and Levin (2000). Hours are modeled as the composite labor input

$$H = \left(\int H(i)^{\frac{\varsigma-1}{\varsigma}} di \right)^{\frac{\varsigma}{\varsigma-1}} \tag{1.32}$$

where $\varsigma > 1$ is the elasticity of substitution across labor types. The growth rate of money supply is given by

$$\log \mu_t = \rho_M \log \mu_{t-1} + \varepsilon_t^{\mu}, \ \varepsilon_t^{\mu} \overset{iid}{\sim} N\left(0, \left(1 - \rho_M\right) \sigma_M\right) \tag{1.33}$$

There are Calvo-type frictions in price- and wage-setting with corresponding parameters ϕ_p and ϕ_W.

Simulations and Results The model is calibrated according to GS with one exception. I set the elasticity of substitution between brands to a lower value than in GS (16.45 vs. 19.8), while the elasticity of substitution across goods is increased (3.15 vs. 3.01). Note that the former parameter has no counterpart in the data and is not directly observable. Both this paper and GS calibrate these parameters to match the frequency of sales. However, the target frequency in their paper (7.4%) based on Nakamura and Steinsson (2008) is much smaller than the frequency of sales observed in the data used in this paper (depending on the measure, from 19.5% to 23.7%—see Coibion, Gorodnichenko, and Hong 2012 for details). The baseline parameters chosen here allow the model to match the comovement of price dispersion in regular and all prices only negligibly overstating the frequency of sales (24.8%). The effect of the elasticities on the frequency of sales are shown in Figure 1.6. I then compare the results for my baseline calibration with the case of GS parameterization. Baseline parameter values are summarized in Table 1.9.

I simulate 2,000 prices for 2,200 periods—burning the first 200 observations—and

TABLE 1.9. SALES MODEL CALIBRATION

	Notation (1)	Value (2)
Preferences		
Discount factor	β	$1.03^{-\frac{1}{12}}$
Intertemporal ES	θ_c	0.333
ES across goods	ε	3.15
ES across brands	η	16.45
Frisch LS elasticity	θ_h	0.7
Technology		
L Elasticity of *Y*	α	0.667
ES across labor	ς	20
Frictions		
Price stickiness	ϕ_p	0.889
Wage stickiness	ϕ_W	0.889
Shocks		
Persistence	ρ_M	0.536
Volatility	σ_M	0.02
Heterogeneity		
Fraction of loyals	λ	0.735
Size of sales sector	σ	0.255

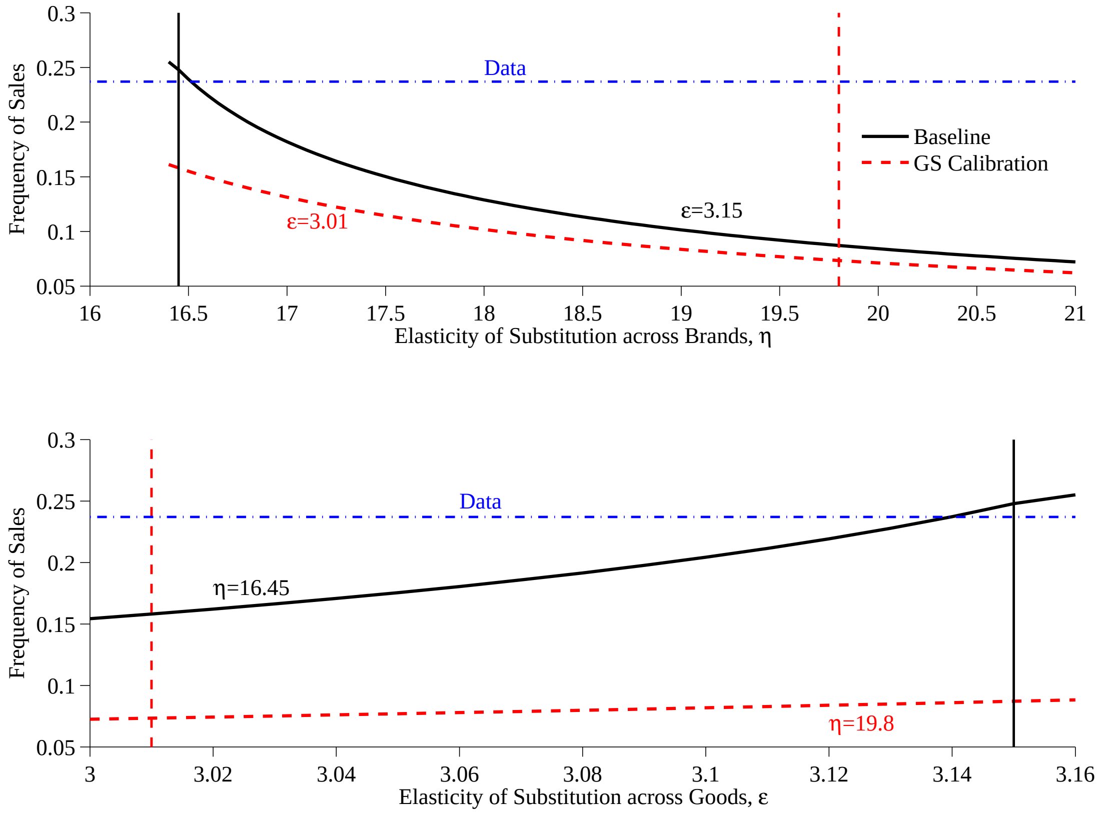
Notes: See Section 1.4.2 for details.

TABLE 1.10. PRICE DISPERSION AND INFLATION IN THE MODEL WITH SALES

	Model		Data	
	All Prices (1)	Regular Prices (2)	All Prices (3)	Regular Prices (4)
Baseline	−0.033	0.033	−0.029	0.034
GS, 2 sectors	−0.135	−0.000		
GS, 1 sector	−0.095	−0.003		
Volatility of M Shock $\sigma_M = 0.2$ (0.02)	−0.022	0.047		
Alternatives (Relative to Baseline)				
Volatility of M Shock $\sigma_M = 0.2$ (0.02)	0.056	0.182		
Persistence of M Shock $\rho_M = 0$ (0.536)	−0.035	0.033		
Price Stickiness $\phi_p = 0.65$ (0.889)	−0.008	0.001		
Wage Stickiness $\phi_W = 0.65$ (0.889)	−0.037	0.029		
ES across Brands $\eta = 19.8$ (16.45)	−0.138	0.002		
ES across Goods $\epsilon = 3.01$ (3.15)	−0.127	0.012		
Fraction of Loyal Customers $\lambda = 0.95$ (0.735)	−0.110	0.014		
Share of Sales Sector $\sigma = 1$ (0.255)	−0.019	0.027		

Notes: The table reports estimated slope coefficients for regression of price dispersion on inflation for the data simulated in the Calvo model with sales. GS refers to calibration in Guimaraes and Sheedy (2011). Alternative parameterization considers one parameter change at a time relative to the baseline. Baseline values are in parentheses. See Section 1.4.2 for details.

FIGURE 1.6. MATCHING THE FREQUENCY OF SALES IN THE CALVO MODEL



Notes: The top panel shows how the frequency of sales varies with the elasticity of substitution across brands, η. The bottom panel shows the same for the elasticity of substitution across good, ε. Black solid lines represent my baseline values that *i)* match the comovement of inflation and price dispersion; *ii)* nearly match the frequency of sales in the data. Red dashed lines represent the alternative calibration based on Guimaraes and Sheedy (2011). Blue dash-dot line is for the frequency of sales in the data. See Section 1.4.2 for details.

compute inflation and price dispersion for all and regular prices. I then estimate the reduced-form comovement as specified in Equation (1.29).

In short, the model with sales outperforms any other model considered in terms of matching the comovement for both regular and all prices (Table 1.10). The degree of the comovement is -0.033 (-0.029 in the data) for all prices and 0.033 (0.034 in the data) for regular prices. The model with GS calibration can get close to the data only if shocks are too volatile.

Volatility of shocks, price stickiness, and the fraction of loyal customers all have a strong effect on the comovement, while wage stickiness and persistence of shocks do not. The share of sales sector has a much stronger effect on the frequency of sales than on the comovement.

The result that the Calvo model with sales can go a long way in matching the data not only for all prices, but for regular prices as well suggests that sales have an important interaction with regular prices. They provide an additional source of flexibility missing in a model that ignores sales without affecting the frequency of regular price changes.

1.4.3 Welfare Implications

Section 1.2 highlights that in models with price rigidity, price dispersion is an important ingredient of welfare calculation, while Section 1.4.1 demonstrates that without sales such models cannot match empirical facts about price dispersion. That is why this section focuses on implications of the mismatch for welfare calculation. As the closed-form relationship between welfare, price dispersion, and inflation is only known for the Calvo model, I use a version of it to study this question. I consider a model of Coibion, Gorodnichenko, and Wieland (2012), which explicitly models the effects of positive optimal trend inflation. Hence, it allows to study the effect of the mismatch not only on the measurement of welfare and the cost of business cycles, but also on design of optimal policy.

Coibion, Gorodnichenko, and Wieland (2012) extend the standard Calvo model for the case with positive trend inflation. In this model, the second-order approximation of the utility function is given by

$$U_t = \Theta_0 + \Theta_1 \mathbb{V}\mathrm{ar}\left(\hat{y}_t\right) + \Theta_2 \mathbb{V}\mathrm{ar}\left(\hat{\pi}_t\right) + \text{h.o.t.} \tag{1.34}$$

where y is the output gap, c is consumption, $\Theta_i,\ i = 0, \ldots, 2$ are functions of parameters of the model, and h.o.t. stands for higher-order terms. Notation $\hat{x}$ represents log-deviation of variable x from the steady state. Price dispersion affects the welfare through a steady-state effect, Θ_0, and the variability of inflation, Θ_2. In this model, steady-state price dispersion is approximated by steady-state inflation as in Equation (1.3).

This framework gives rise to the positive trend inflation as the outcome of welfare maximization. On one hand, steady-state inflation leads to higher steady-state price dispersion and lower utility. On the other hand, positive trend inflation reduces the probability that the economy hits the liquidity trap, improving the welfare. If the degree of price dispersion in the steady state is underestimated, the estimate of the optimal inflation will be biased upward.

I first look at the level of price dispersion in the model and the data. I take the level of trend inflation that equals to 4.4%—average inflation for regular prices in the data. Column (2) of Table 1.11 reports the level of steady-state price dispersion computed using Equation (1.3), measured with the standard deviation rather than the variance to ensure consistency with the baseline empirical results. In Column (3) I report the corresponding slope as the increase in the standard deviation of prices due to an increase in inflation. In the baseline model (price stickiness $\alpha = 0.55$), the level of price dispersion is close to that in the data (0.073 in the model vs. 0.079 in the data), but the slope is way off (1.65 in the model vs. 0.03 in the data). To match the slope, prices need to be nearly flexible ($\alpha = 0.001$), which counterfactually would result in almost no price dispersion in equilibrium. Hence, by varying the price-adjustment parameter it is possible to match

TABLE 1.11. STEADY-STATE PRICE DISPERSION AND STICKINESS

Stickiness (1)	Level (2)	Slope (3)
0.55	0.073	1.648
0.001	0.001	0.032
Data:	0.079	0.034

Notes: Stickiness is measured by the Calvo probability that prices remain the same. Column (2) shows the resulting level of steady-state standard deviation of prices. Column (3) shows the slope in the relationship between the steady-state price dispersion and inflation, measured as a change in the steady-state standard deviation of prices over a change in trend inflation. Data entry is for regular prices. See Section 1.4.3 for details.

TABLE 1.12. PRICE DISPERSION AND WELFARE

	Actual (1)	Proxy (2)
Total Loss	−0.245	−0.014
due to:		
Steady State	−0.238	−0.009
Output Gap	−0.000	−0.000
Inflation	−0.007	−0.005

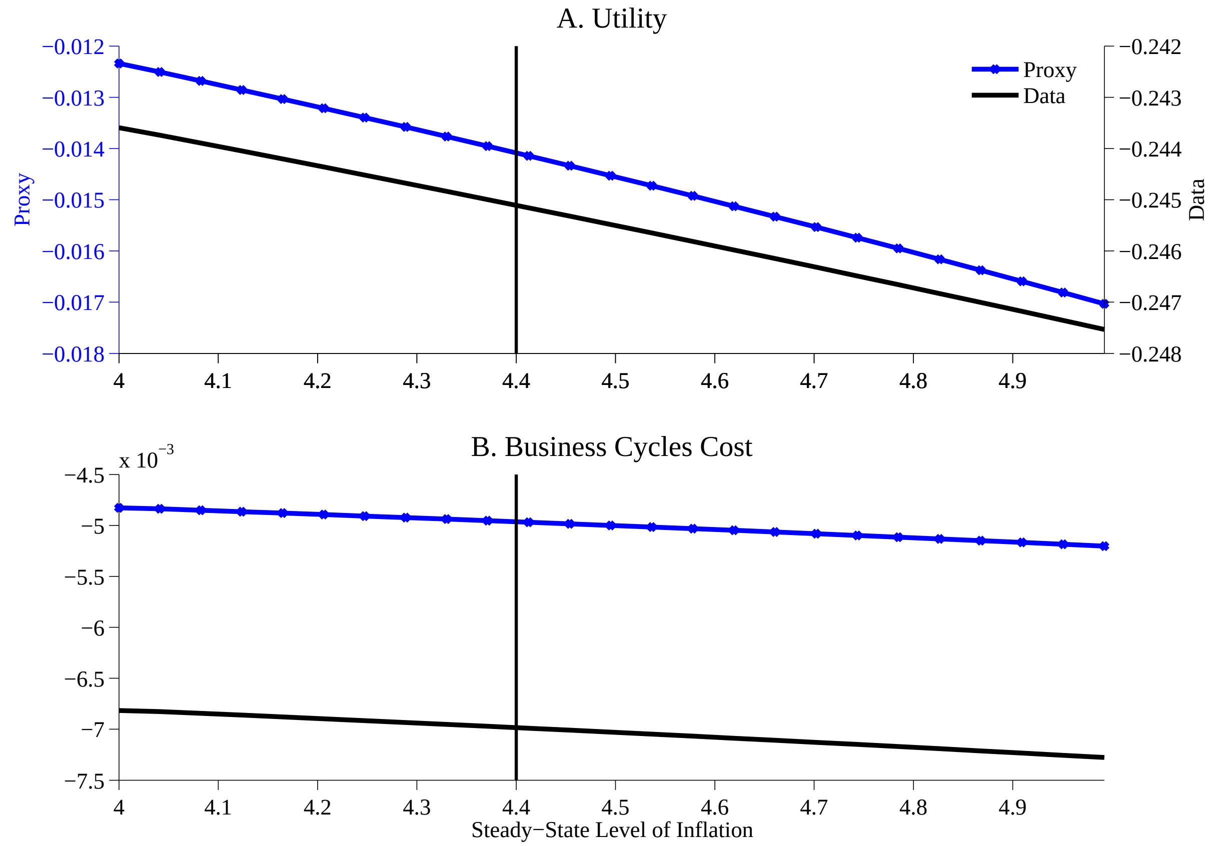
Notes: The table reports the welfare loss when price dispersion observed in the data is used—Column (1)—and when it is approximated by inflation as in Equation (1.3)—Column (2). The break-down into steady-state vs. output-gap, inflation, and consumption variability is computed using Equation (1.34). See Sections 1.2 and 1.4.3 for details.

either the degree of price dispersion in the steady state or its response to trend inflation, but not both.

This discrepancy between the steady-state levels of price dispersion in the model and in the data affects measurement of per-period utility, the business-cycle cost, and the trade-off between output and inflation stability. To measure these effects, I compute the welfare based on the degree of price dispersion observed in the data. Table 1.12 reports the results. The difference between utility based on price dispersion in the data and that in the model is almost 25 log points. Although most of the difference is due to steady-state effect, the total contribution of variability in output and inflation is bigger by 0.2 log points, which is slightly below 50% of the cost of business cycles in the model. Finally, this difference comes exclusively from the loss due to inflation variability, which affects the optimal trade-off between inflation and output stabilization. These estimates are likely to represent the upper bound of the mismatch since at least some dispersion comes from heterogeneity in shopping experience and differences in amenities. However, the fact that price dispersion comoves with aggregate variables to a degree unlikely to be explained by time variation in shopping experience suggests that mismeasurement of price dispersion and its relationship with inflation can have a strong effect on welfare calculation.

Beyond the level effect of price dispersion, mismatch in its reaction to inflation leads to a change in the shape of the utility function. Figure 1.7 shows the difference in slopes around 4.4% trend inflation. Panel A suggests that around this point the slope of the

FIGURE 1.7. WELFARE AND BUSINESS CYCLES COST OF PRICE DISPERSION



Notes: The figure reports the welfare (Panel A) and the business-cycle cost (Panel B) computed with price dispersion in the Calvo model approximated with inflation (blue line with a marker) and that observed in the data (black solid line). The functions linearized around the level of trend inflation observed in the data (vertical line). The slope in the model is derived from Equation (1.3) and that in the data–from Equation (1.14). See Sections 1.2, 1.3.2 and 1.4.3 for details.

utility function may be smaller than suggested by the Calvo model. Using this relationship to recompute the optimal inflation rate leads to a decrease in the optimal trend inflation from 1.3% in the baseline model to 1% when the level of price dispersion and its response to inflation are taken from the data.

Hence, the effect of the mismatch on welfare and optimal trend inflation can be substantial. Admittedly, it is hard to consistently estimate the difference between price dispersion in the model and the data far away from the observed point of 4.4% trend inflation. Nonetheless, I provide evidence that abstracting away from the fact that workhorse macroeconomic models cannot match price dispersion and its comovement with inflation could have policy implications that are too big to ignore.

1.4.4 Search Frictions in the Product Market

Up to this section, I have only considered implications of price dispersion for models with frictions in price setting. In these models, price dispersion has an important allocation effect. Alternatively, price dispersion can be explained by search frictions in the product market. Importantly, in the search models price dispersion also comoves with inflation in equilibrium. Some of the early search models still require price-adjustment frictions to generate price dispersion.[21] Indeed, without search costs, all firms would have to price the good competitively to have customers; and without price-adjustment frictions, all firms would always charge the monopoly price, thereby eliminating price dispersion in the absence of idiosyncratic shocks.[22] In the money search literature, however, nominal frictions are not essential, implying that price dispersion does not have any misallocation effect and is not particularly important for macroeconomic analysis.[23]

In this section I consider a popular example in this literature (Head, Liu, Menzio, and Wright 2012), and investigate if their model can match empirical facts about the comovement of price dispersion and inflation. In this model there are two markets that convene sequentially: the search market of the Burdett and Judd (1983) type and the conventional Arrow-Debreu market. Inflation expectations determine the money balances that consumers carry over from the conventional market into the next period's search market, which together with the actual inflation will determine price dispersion.

In this model the comovement of price dispersion and inflation is negative. Higher inflation leads to an increase in inflation expectations, which decreases the amount of money carried over into the search market and, therefore, results in smaller equilibrium price dispersion.

The Head et al. (2012) model introduces price-adjustment frictions rather mechanically because these frictions are not essential for the main mechanism in the model. There exists equilibrium price distribution, and firms are free to move along it. The stickiness is introduced by exogenously limiting a share of firms that can adjust the price; however, such form of stickiness does not imply misallocation. Further details are relegated to Section A.2.

The comovement of price dispersion and inflation is reported in Table 1.13. The model matches the instantaneous comovement closely. Volatility of shocks and the size of search frictions have a strong effect on the results. In particular, when search cost is very low (probability of obtaining a price quote is very high), the degree of price

[21] An example is Benabou (1988), who merges (S,s) price adjustment with sequential search literature. In his model, higher inflation stimulates search, which lowers the boundaries of inaction and makes the distance between them wider, implying higher price dispersion. The model is generalized in Benabou (1992) allowing for heterogeneity in search costs and endogenous exit of high-price sellers. Benabou (1993) and Tommasi (1994) focus on the repeat-purchase case. Diamond (1993) considers a model with "sticker" costs—only prices of newly produced goods can be adjusted—rather than menu costs of price adjustment. All models make the same conclusion about positive relationship between inflation and price dispersion in the partial equilibrium framework.

[22] This case is studied in Diamond (1971) and is known as the Diamond paradox.

[23] One of the early examples is Head and Kumar (2005).

dispersion and its reaction to inflation is very small.

However, there are a few moments in the data that are not captured well. First, in the data I document a response of price dispersion to inflation innovation that lasts for a considerable amount of time. In the model, however, a one-time unexpected shock to inflation has only a contemporaneous effect with no propagation. Hence, future research on money search models should address this issue in order to be consistent with the data.

Second, the model predicts that adjustment in price dispersion due to an inflation shock happens exclusively in the left tail of the distribution. To illustrate this, Figure 1.8 plots the equilibrium distribution of prices and its response to a change in inflation. Panel A considers an unexpected change to inflation, Panel B looks at an expected change, and Panel C singles out the expectation effect (by considering a news shock to inflation, which does not realize in the next period).[24] In all three cases, the upper bound real price does not change with inflation: the adjustment is due to the lower bound and the minimum price for which demand is unconstrained. The distribution of real prices changes only between the lower bound and the constraint threshold, staying essentially the same above the threshold. In the data, however, even if the left tail of price distribution is removed (e.g., sales), there is still a strong comovement of price dispersion and inflation.

1.5 Discussion and Concluding Remarks

This section provides a brief discussion of the results, their scope, plausibility of the underlying assumptions, as well as implications for the literature. First, the comovement between price dispersion and inflation is due to underlying shocks, implying that estimates could be sample-specific. Second, this paper focuses on prices of fast-moving consumer goods, and so the results are confined to this particular sector. Third, I look at the sales in the Calvo environment with one type of shocks, and test model's predictions against the data on price dispersion and the frequency of sales. It is yet to be seen if this model fails to match other features of the data or if introducing sales into the SSDP model can give more robust results. Fourth, there are channels through which price dispersion may affect welfare not accounted for in the Calvo model. A broader framework to study this relationship may be needed.

The comovement between price dispersion and inflation in the data is likely to depend on the nature of the shocks. Models considered in this paper allowed only for monetary and productivity shocks. The variation in the data could be coming from other sources too, especially during the Great Recession. It is thus interesting to see what models with financial frictions predict about the relationship. Besides, there are other types of shocks unaccounted by the model, such as energy price shocks. I leave the study of how other shocks influence price dispersion for future research.

Results shown in this paper are valid for a particular sector: fast-moving consumer goods. This, by itself, is an important sector that represents about 10-15% of the econ-

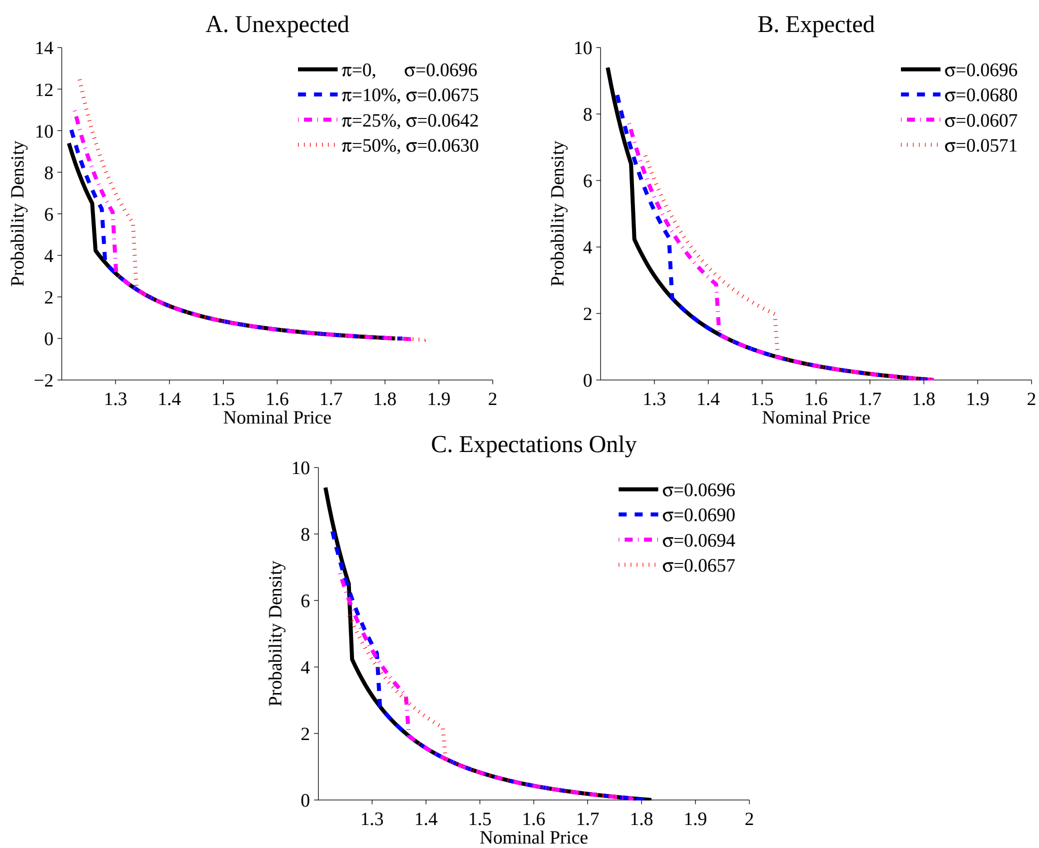
[24] The original model does not distinguish between expected and unexpected inflation. I present this extension in Section A.2.

TABLE 1.13. PRICE DISPERSION AND INFLATION IN THE MODEL WITH SEARCH

	Model	Data	
		All Prices	Regular Prices
	(1)	(2)	(3)
Baseline	−0.029	−0.029	0.034
Alternatives			
Volatility of M Shock $\sigma_M = 0.2$ (0.02)	0.057		
Persistence of M Shock $\varphi_M = 0.8$ (0)	−0.031		
Probability of Soliciting P $\lambda = 0.01$ (0.4)	−0.024		
Probability of Soliciting P $\lambda = 0.95$ (0.4)	−0.000		

Notes: The table reports estimated slope coefficients for regression of price dispersion on inflation for the data simulated in the monetary search model. Alternative parameterization considers one parameter change at a time relative to the baseline. Baseline values are in parentheses. See Section 1.4.4 for details.

FIGURE 1.8. PRICE DISTRIBUTION IN THE HLMW MODEL



Notes: The figure shows the distribution of nominal prices in the search market. Panel A shows the effect of unexpected change in inflation on price distribution. Panel B considers the case when inflation is perfectly anticipated. Panel C shows the effect of expectations only, i.e. changes in price distribution due to unfulfilled inflationary expectations. In each legend, π stands for the inflation rate and σ is the resulting price dispersion. The kink in the density function is due to constraint demand: if the price drawn is below a certain threshold, $p < \hat{p}$, consumers spend all the cash available in the search market. If price is higher than the threshold, they will follow the unconstrained demand function. See Section 1.4.4 and Section A.2 for details.

omy. However, it is not clear if the relationship still holds for aggregate inflation and price dispersion. In particular, prices of durables or intermediate goods need not have the same properties as prices for nondurables; as well as wholesale prices may have different properties than retail prices. Sales are rare and prices are more flexible in those sectors. The relationship between price dispersion and inflation may be closer to that for regular prices in my data. I hope that future research will explore properties of price dispersion in other industries.

The theoretical analysis in this paper considers sales only within the Calvo model. However, the SSDP model outperforms Calvo in matching properties of regular prices. Hence, one may expect that the SSDP model with sales could outperform the Calvo model with sales. Developing a model that combines time-dependent and state-dependent pricing with sales in a tractable way is an interesting direction for future research. It would be also interesting to see how sales can interact with search frictions. Sales are likely to be more prevalent when search costs are low. Although the effect of this interaction is an interesting exercise, the key inconsistency that search models should overcome is their inability to generate dynamic response, which cannot be remedied by introduction of sales.

Price dispersion may have an effect on welfare not captured in standard models. In the Calvo model, for example, price dispersion has a negative effect on welfare due to the misallocation effect, as sticky prices interfere with consumption smoothing across varieties. However, price dispersion may also have a positive effect on welfare as it provides an opportunity for consumers with low search costs—and typically low consumption and high marginal utility—to reallocate their consumption toward cheaper goods, which should raise aggregate welfare.

Regardless of the direction of the effect of price dispersion on welfare, a key message from this paper is that welfare measurement should be anchored to price dispersion observed in the data. As data sets on disaggregated prices become widely available, and computational costs of processing those data fall, there is no reason why researchers could not or should not use price dispersion measured in the data.

Next, models that intend to match micro pricing data should not treat sales as noise to be filtered out. In this paper, I show that not only properties of sale prices differ from those for regular prices, but also that sales can interact with regular prices. A model with sales is more successful in matching properties of regular prices than a similar model without sales. Moreover, I show that the frequency of sales in the data is a key moment to parameterize the model in order to match properties of regular prices.

Finally, macroeconomic models with price stickiness should aim at matching price dispersion in the data, in addition to usually targeted frequency of price changes, the size of price changes, and its distribution. As shown in the example of the SSDP model, these measures are interrelated and all have implications for the overall degree of stickiness and non-neutrality of monetary shocks.

Chapter 2

Price Setting in Online Markets: Evidence from the Google Shopping Platform

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2.1 Introduction

This paper focuses on price setting practices in online markets examined through the lens of a novel dataset on price listings and the number of clicks from the Google Shopping Platform. This unique dataset contains information on price quotes and the number of clicks at the *daily* frequency for broad variety of consumer goods and sellers in the US and UK over the period of nearly two years. We provide estimates of the frequency of price adjustment, price synchronization across sellers for a given good and across goods for a given seller, as well as the distribution of the sizes of price changes. We compare these estimates for the case when information on quantity margin is unobserved, similarly to the previous literature on online prices, with the case when it is available, as in the data from brick-and-mortar stores.

The contribution is twofold. First, it is the first paper that sheds light on price rigidity, synchronization, and the size of price changes in online markets using data similar in terms of coverage, frequency, and *quantity weights* availability to those from brick-and-mortar stores, which is important as e-commerce has become a sizeable and rapidly growing part of the retail sector. Second, as online markets differ drastically from their offline counterparts in terms of the size of search costs for consumers, costs of price adjustment for retailers, and easiness to monitor competitors' prices, evidence from online markets represents another dimension for understanding connection/disconnect between existing theories of price adjustment and empirical estimates at hand.

Our key findings are the following. First, despite small physical costs of price changes, the frequency of price adjustment is not too high, though higher than in brick-and-mortar stores, implying the duration of a spell of 7-12 weeks, depending on treatment of sales. Second, if the quantity margin is accounted for, prices appear to be much more flexible with the median duration of spell falling to 4-7 weeks. It remains a question why low-demand sellers do not adjust their prices as often, yet maintain costly price listings on the platform. Third, in spite of low costs of monitoring competitors' prices and high benefits from doing so since search costs for consumers are low, we observe little price synchronization across sellers. A median good has no synchronization within a week. Even within three-month period since a trigger price change less than 40 percent of sellers, on average, change their prices. The pattern, however, looks a bit different for high-demand sellers, 15 percent of whom adjust their prices within a week for a medium good, which goes up to 60 percent over the course of three months. Fourth, the distribution of the size of price changes has nontrivial mass around zero, which is inconsistent with significant menu costs but favors Calvo (1983) price adjustment mechanism. When online sellers change their prices, they do it, on average, by 22 percent, which goes down to 17 percent when clicks are accounted for. Hence, online prices change infrequently, by a large amount, and are not synchronized across sellers. Despite the drastic difference in search, menu, and monitoring costs, price adjustment in online markets does not look very different from that in brick-and-mortar stores suggesting there is more to add to the story of why prices do not perfectly respond to shocks.

We then proceed to examine the timing of price adjustment during high-demand episodes. Warner and Barsky (1995) emphasize that firms use such episodes to *permanently* reset prices. We first identify when consumer activity in online markets peaks and then check if online retailers are more likely to change prices during such periods and, if so, whether the adjustments are of permanent or temporary nature.

Time dependence in price setting can make an immense impact on the timing of monetary policy.[1] In models with nominal frictions in price adjustment, monetary policy shocks have real effects only to the extent those shocks are not fully and immediately absorbed by the change in the price level. If firms indeed are more likely to review prices when demand is expected to peak, monetary policy implemented during such episodes will be less effective.

Our findings are somewhat mixed. First, consumers tend to shop online at the beginning of the working week (Monday, Tuesday) rather than during a weekend. Second, there is a significant spike in clicks at the beginning of a month, when most consumers receive their paycheck, and a small one in the middle of a month, possibly due to consumers paid biweekly. The end of a month features a drastic drop in consumer activity reflecting a period of tightening belts. Third, remarkably, there is little evidence that sellers adjust their prices in response to such volatility in demand, which would be the case if prices were perfectly flexible. Fourth, there are significant and synchronized price

[1] Olivei and Tenreyro (2007) show that monetary policy is more effective if implemented during the first two quarters of the year due to uneven staggering of wage contracts across quarters. Uneven staggering of price adjustment should have analogous implication for the timing of monetary policy shocks.

changes prior and post conventional shopping seasons, such as Thanksgiving and Christmas, with prices rarely coming back to their original level. It remains unclear why sellers react to low-frequency seasonal changes in demand but do not respond to *predictable* high-frequency changes within a week or month. Hence, we find only a partial confirmation to Warner and Barsky's hypothesis.

Finally, we document ubiquitous price dispersion in online markets and explore its relation to the market size. Our finding is that bigger markets are associated with a high degree of price dispersion. This is consistent with the theory of market segmentation into "shoppers"—customers looking for the best price—and "loyals"—price insensitive customers for whom seller's brand, awareness, and trust matter the most (Baye and Morgan 2009, Brynjolfsson and Smith 2000, Morgan, Orzen, and Sefton 2006). At the same time, we find that big markets tend to have a small frequency of price adjustment. This could be due to two effects at work. On the one hand, having more customers in the market increases firm's cost of being inattentive. On the other hand, it allows for higher degree of price discrimination and more room for high-price sellers, who are shown not to adjust prices as often as low-price ones. Empirically, the latter effect appears to dominate. In addition, we demonstrate that sellers with market power exhibit higher degree of variability in prices over time. This could be so since larger market share increases firm's return on precision of demand elasticity estimates and gives more incentives for price experimentation (Baye et al. 2007).

Internet commerce is a sizeable and growing segment of the retail sector. According to the Census Bureau of the Department of Commerce, U.S. retail e-commerce sales in the third quarter of 2012 amounted to $57 billion, which is about 5% of total retail sales.[2] This is a rapid change from 1.5% in 2003. Retail e-commerce sales increased by 17% relative to the same quarter in 2011. To compare, total retail sales grew by 5% during the same period. Between 2003 and 2008, the growth rate of online sales in clothes, sporting goods, food, beer and wine, and appliances exceeded 200% each.[3] Throughout the last decade, the share of retail e-commerce has been on a nearly linear upward trend. Recent developments in e-commerce sector, including Google pushing its price comparison platform and Amazon diversifying into the tablet market to promote internet sales, suggest that the upward trend is likely to be sustained in the future.

The rise in e-commerce penetration is a global phenomenon. According to Cisco's calculations, the size of global e-commerce was slightly over $600 billion in 2009 and is expected to reach $1.4 trillion by 2015.[4] Between 2006 and 2011, the average annual growth rate of global online retail sales was at the breathtaking mark of 13 percent.[5] The four biggest markets are the US, Japan, the UK, and Germany. Comparing price setting practices in the US and UK (in this draft, and Germany in the following draft), therefore,

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[2] http://www.census.gov/retail/mrts/www/data/pdf/ec_current.pdf

[3] http://www.census.gov/compendia/statab/2011/tables/11s1055.pdf

[4] http://www.cisco.com/web/about/ac79/docs/retail/Global-Multichannel_ppt.pdf

[5] A.T. Kearney's estimates: http://www.atkearney.com/paper/-/asset_publisher/dVxv4Hz2h8bS/content/e-commerce-is-the-next-frontier-in-global-expansion/10192

helps us identify similarities and differences between the top markets.

Using the UK data along the US ones is further motivated by the fact that the Britons are the leading nation in terms of online spending per person. In 2011, the value per head of business-to-consumer (B2C) e-commerce was GBP 1,083, up 14% from GBP 950 in 2010.[6] High penetration of online trade in the two countries is largely due to availability of credit cards, a history of mail order and catalogue shopping, as well as an early arrival of e-retailers like Amazon and eBay. Yet, there are striking differences between the two markets. The UK is eight times denser than the US. This means that it is easier to organize fast and frequent deliveries, but it is not as safe to leave a package at the door due to thefts and rainy weather. At the same time, American homes are, on average, 2.8 times larger than those in the UK. Smaller British homes imply smaller fridges, which together with longer commute time lead to a higher demand for frequent and timely groceries. For instance, in 2010 3-4% of all spending on groceries in the UK were made online.[7] E-retailers have to adjust to consumers' needs by providing delivery within the same day and offering short delivery windows or pick-up facilities. We find that despite the differences between the markets, price setting behavior is largely the same in the two countries.

Although e-commerce has been growing rapidly, there are only a few studies that focus on price adjustment in the sector. The data available before typically cover a limited number of consumer goods in categories that feature early adoption of e-trade, such as books and CDs (Brynjolfsson and Smith 2000), or span a short period of time, usually not exceeding a year (Lünnemann and Wintr 2011). In spite of increasing efforts to scrape more and more prices online to enrich data coverage (Cavallo 2012, Cavallo, Neiman, and Rigobon 2012, Cavallo and Rigobon 2011), we are aware of just one dataset that contains information on the quantity margin.[8] The Google Shopping Platform data used in this paper, instead, combine broad coverage of consumer goods with information on the number of clicks each price quote received at the daily frequency for almost two years, something that has not been within the reach of researchers in the past.

High-quality online price data are not only useful to estimate price rigidity and other properties of price adjustment in online commerce, but they also allow comparing those with estimates available from brick-and-mortar stores. Empirical studies on price stickiness usually document substantial price rigidity in brick-and-mortar retail stores (Klenow and Kryvtsov 2008, Klenow and Malin 2010, Nakamura and Steinsson 2008). Theoretical models explain it either with exogenous frictions (Calvo 1983), according to which each period only an exogenously given fraction of firms is allowed to reset prices, or with existence of menu costs (Mankiw 1985)—a cost firms are required to pay to change prices.

[6] Ofcom report: `http://stakeholders.ofcom.org.uk/binaries/research/cmr/cmr12/icmr/ICMR-2012.pdf`

[7] Cisco's estimates. See the reference above.

[8] Baye et al. (2009) use data from the Yahoo! Kelkoo price comparison site to estimate price elasticity of clicks. They demonstrate significant discontinuities in clicks elasticity at the minimum price in the PDAs market. The data cover 18 models sold by 19 different retailers between September 2003 and January 2004.

Other possible explanations of price stickiness are based on search costs for consumers (Benabou 1988, 1992), costs of updating information set (Mankiw and Reis 2002), or sticker costs (Diamond 1993)—inability to change price for inventories. However, all these explanations do not look very plausible in online markets where costs of monitoring competitors' prices, search for a better price, or adjusting a price quote on a platform are negligible. Yet, we observe a fair amount of price stickiness in online markets, which suggests there is something more to add to the story.

Reasons for why prices are sticky have important implication for real effects of nominal shocks. For example, in the standard New Keynesian model with staggered price adjustment, nominal shocks change relative prices and, hence, affect real variables. In contrast to this result, Head et al. (2012) construct a model with price stickiness coming from search costs that delivers monetary neutrality. In rational inattention framework, firms can be attentive to some types of shocks and inattentive to other types, with drastic consequences for effectiveness of monetary policy. The fact that none of the simple explanations of imperfect price adjustment in traditional markets seems to fit well into the e-commerce story, yet prices are found to be sticky and disperse, suggests that more research is likely to emerge on price rigidity and its implication for real effects of nominal demand shocks.

Our paper proceeds with the data description in the next section. Section 2.3 overviews methodology and provides estimates of the frequency of price adjustment, synchronization, and the size of price changes. Section 2.4 examines variation of prices in cross section, as well as quantifies the degree of price dispersion, its determinants, and nature. Section 2.5 looks at variation of prices over time, including around conventional sales seasons, and then focuses on time dependence of price changes. It concludes with documenting the reaction of price rigidity to unforecasted changes in aggregate variables. Discussion and concluding remarks are left for Section 2.6.

2.2 Data

The data set is a stratified random sample of price quotes and clicks for goods with at least one click on a given day on Google Shopping price comparison site in the US and UK. It includes a seller unique identifier and a narrowly defined category of goods. The sample contains 52,788 goods in the US and 52,804 goods in the UK for the period from May, 2010 till February, 2012. The number of sellers in the sample is 27,315 and 8,757 in the US and UK, respectively. To enhance comparison of prices, we drop prices denominated in a foreign currency. This filter eliminates a negligible number of observations[9]. We also have a handful of duplicated observations in the data. When observations are the same in terms of country, good, seller, date, and price, we aggregate them by taking the

[9]We only keep prices denominated in the US dollar in the US and the British pound in the UK. A negligible number of observations from the US site were denominated in the Australian dollar, while on the UK site a similarly small number of quotes came from euro-denominated goods.

sum over clicks[10]. When observations are the same in terms of country, good, seller, and date only (but differ in price), we take the mode price and aggregate clicks the same way as before. If more than one mode occurs, we take the one with the smallest price[11]. Finally, we treat any price above 500,000 as a missing value since most of them look like 999,999 or 9,999,999. This leaves us with 52,776 and 52,767 goods and 27,308 and 8,757 sellers in the US and UK, respectively. Hence, the damage from dropping foreign-currency denominated and missing prices constitutes only twelve goods and seven sellers in the US and 37 goods and no sellers in the UK.

Since we do not observe a price quote for every good available through the Google Shopping site, but only for those that obtained at least a click, we aggregate the data to weekly frequency, which makes our results comparable with previous studies. We do this by keeping the *mode* price within a country-good-seller cluster for a given week. As with aggregating duplicated observations, we take mode rather than mean or median to avoid generating artificial price quotes, which would be the case for median when the number of observations on a given week is even. If there are more than one mode price per week, we keep the one with the earliest first occurrence. Such procedure disregards high frequency fluctuations but should not have an effect on macroeconomic implications of our results. Later, we examine the amount of variation lost from weekly aggregation.

2.2.1 Google Shopping Platform

Google Shopping Platform is a sizeable and growing price comparison platform based on fully commercialized Product Listing Ads system, which operates in a number of countries, among which are the United States, United Kingdom, Australia, Germany, France, Japan, China, Italy, the Netherlands, Spain, Switzerland, the Czech Rep., and Brazil. By fall 2012, Google Shopping has fully replaced the outdated Google Product Search system, which combined commercial Product Listing Ads created through AdWords—Google's online advertisement platform—with information freely available online.

The information available to consumers on the platform includes product's name and image, brief description, number of reviews, availability, and the minimum price online. They can also choose to browse other items in the same category. The information on online sellers of the good—name, rating with the number of reviews, base price, total price with taxes and shipping fee, and a link to the seller's website—is located below. The order in which sellers appear is based on their *quality rank* (reviews, click-through rate, etc.) and a bid price a seller chooses to pay per click. A consumer can easily re-sort the sellers by average review score, base, or total price. On the same page, Google

[10] We do not know why some observations appear to have separate entries on the same date but variation in clicks suggests that each represents a consumer activity for a given good.

[11] We take mode rather than mean or median to avoid generating observations with a price quote that did not exist. For example, if we have only two observations with price equal to, say, \$1 and \$2, taking mean or median creates a price quote of \$1.5, but, in fact, the good has never been offered at this price. We take the minimum price because our subsequent results show that consumers tend to click more on smaller prices. The number of duplicated observations is so small that this procedure does not affect our results in any way.

Shopping also provides information on nearby brick-and-mortar stores where this good is available, with no information on price though.

When a seller sets up a Product Listing Ads account, it can choose devices on which the ad will appear, geographical location of viewers, a language they speak, as well as a bid for *cost-per-click* and the daily budget. The cost-per-click bid price together with seller's quality rank will determine its position in the search result. Note that an observation can temporarily leave the dataset (or the number of clicks can be capped) if the seller's daily budget is depleted or it does not pay its monthly bill. Also note that there is no explicit cost of displaying an ad or changing a price quote. A seller pays only when a shopper *clicks* on the listing ad, although there is an implicit cost of maintaining a listing with no clicks as the click-through rate falls with every *impression* (a display of the listing), which makes it more expensive to bid for the same position in search in the future. To change a price, a seller simply logs in to their account and adjusts the corresponding information.

The information on an ad campaign available to sellers consists of the number of clicks for a given periods, the number of impressions, the *click-through rate* (clicks divided by impressions), average cost-per-click, number of *conversions* (specific actions, such as a purchase, on the seller's website), cost per conversion, and total cost of the ad. Google recommends sellers to get rid of ads with less than one percent click-through rate as those are likely to damage their quality rank.

2.2.2 Notation

Throughout the text we use p_{ist} and q_{ist} to denote the price and the number of clicks, respectively, of good i offered by seller s at time t. Time is discrete and measured in either days or weeks, which will be clarified on occasion, and ends at T–the last day (week) observed. Good i uniquely belongs to category j. We denote the sets of all goods, all categories, all sellers, and all time periods as $\mathscr{G}$, $\mathscr{M}$, $\mathscr{S}$, and $\mathscr{T}$: $\mathscr{G} = \{1,\ldots,N\}$, $\mathscr{M} = \{1,\ldots,M\}$, $\mathscr{S} = \{1,\ldots,S\}$, and $\mathscr{T} = \{1,\ldots,T\}$, with N being the number of goods in the dataset, M–the number of categories, and S–the number of sellers. We use $\times$ to denote the Cartesian product of sets, and # to denote set cardinality. Hence, $(\mathscr{G} \times \mathscr{S})$ represents the set of all pairwise combinations of goods and sellers and $\#(\mathscr{G} \times \mathscr{S}) = N \cdot S$ stands for the number of all such combinations. Let also $\mathscr{L} \subseteq (\mathscr{G} \times \mathscr{S})$ be the set of actual *quote lines*, i.e. items of a particular good sold by a particular seller in the dataset and $L = \#\mathscr{L}$ be the number of such quote lines. Finally, think of $\mathscr{O} \subseteq (\mathscr{G} \times \mathscr{S} \times \mathscr{T})$ as of the set of all individual observations (*price quotes*) in the dataset and of O as of the number of them. We use three classifications of goods. Categories in each of them are referred to as "top-level", "broad", and "narrow" ones. We will provide an explanation and examples for the three later on. Subscripts i and s indicate that a set or a number is taken with respect to a given good or seller. Superscript j indicates aggregation by industry. For instance, $N_s \leq N$ is the number of goods sold by seller s, $\mathscr{G}_s \subseteq \mathscr{G}$ is the set of all goods sold by seller s, $\mathscr{S}_i \subseteq \mathscr{S}$ is the set of all sellers that offer good i, $S_i \leq S$ is the number of sellers that offer good i, $\mathscr{M}_s \subseteq \mathscr{M}$ is the set of industries in which seller s offers at least one good, $M_s \leq M$ is the number of such industries, $\mathscr{G}^j \subseteq \mathscr{G}$ is a set of goods that belong to category j with $N^j \leq N$ being the number of such goods, and $\mathscr{S}^j \subseteq \mathscr{S}$ is a set of sellers that sell at least one good of category j, with $S^j \leq S$ being the number of such sellers. We denote averages with bars and sums with capital letters (for example, $\overline{p}_{is} = \frac{1}{T}\sum_t p_{ist}$ and $Q_{it} = \sum_{s\in\mathscr{S}} q_{ist}$). We will further define more complex variables as they appear in the text.

2.2.3 Aggregation and Selection

We aggregate the data from daily into weekly frequency for two reasons. First, most of the previous results on price stickiness were obtained from weekly data. Hence, aggregation helps enhance comparison with the literature. Second, because we observe only prices that get at least one click on a day, the dataset features multiple missing values. We do not know which of those are due to no click and which are due to stockout.

To check that we do not lose much variation in prices due to the aggregation procedure, we compute the share of intraweek variation in total daily variation for each quote-line and then aggregate it into a good level. The former is calculated as

$$\omega_{is} = \frac{\widehat{\mathbb{V}}_t[\log p_{ist} - \log p_{ist}^{\text{weekly}}\ ]}{\widehat{\mathbb{V}}_t[\log p_{ist}\ ]} \cdot 100 \tag{2.1}$$

where p_{ist} is the price at the daily frequency, p_{ist}^{weekly} is the mode price for a given week (see detailed explanation above), and $\widehat{\mathbb{V}}$ is the sample variance. The aggregation over sellers is performed separately without weights, $\overline{\omega}_i = \frac{1}{S_i}\sum_{s\in\mathscr{S}_i} \omega_{is}$, and with clicks used as within-good weights, $\overline{\omega}_i^w = \sum_{s\in\mathscr{S}_i} \frac{Q_{is}}{Q_i}\omega_{is}$. We also report the weighted distribution of $\overline{\omega}_i^w$ with between-good weights $W_i = \frac{Q_i}{Q}$.

The share of intraweek variation in prices for a median good is zero. This is so for almost each top-level category.[12] When we assign more weight to goods with more clicks (and, consequently, fewer missing values at the daily frequency), the share of intraweek variation remains small (below 13% in median). Hence, the amount of information lost from weekly aggregation is negligible.

Since many goods are not *actively* traded online even if they are advertised on the Google Shopping Platform, the data features numerous missing price quotes even at the weekly frequency. Moreover, missing values for price quotes imply even more missing values for price *changes* as consecutive price quotes are used to define the latter.

A median good in the US sample has only seven weekly price quotes for the time span between the first and the last observations of 43 weeks. The price quotes are typically spread in time leading to only one price change observed in median. However, the distribution of the number of price quotes observed has a heavy right tail so that in the mean

[12] Categories "Furniture" and "Mature" are the exceptions in the US data. In the UK the only such exception is "Baby and Toddler". In all the three cases, however, the share of within-week variation of prices is less than 1.5%.

we observe seventeen price quotes with nine price changes.

We also compute similar statistics for goods with at least one *non-zero* price change, which is required to estimate the size of price changes and synchronization. Only one good in three has such an observation. These goods span over 69 weeks in median, with 36 weekly price quotes and sixteen weekly price changes (either zero or not) available. Unlike in the previous case, the mean and the median are remarkably close.

In addition, we test if there is a smaller chance to observe a price change when sellers keep their price above average. For this purpose, we regress a dummy variable for an observed non-zero price change, $\mathbb{I}\{\max_t \Delta \log p_{ist} > 0\}$, on the deviation of price from the mean across sellers, $\overline{\log p}_{is} - \frac{1}{S_i}\sum_{s \in \mathcal{S}_i} \overline{\log p}_{is}$. The results suggest that a seller that typically keeps the price one percent above the average is 4.5 p.p. less likely to have a price change.

2.2.4 Descriptive Statistics

Goods and Sellers The sample of goods in the data represents 22 categories of consumer products, such as "Apparel and Accessories", "Cameras and Optics", or "Electronics". Those top-level categories are split into subcategories. For instance, "Apparel and Accessories" is split into "Clothing", "Watches", "Jewellery", etc., and "Electronics" is split into "Computers", "Audio", "Video", "Networking", "Communications", and others. The broad subcategories are further divided into narrow ones. Thus, "Clothing" is narrowed down to "Costumes", "Vests", "Dresses", etc., and "Computers" are further split into "Hard Drives", "Video Cards", "Motherboards", "Processors", and others. Table 2.1 provides further examples. The elasticity of substitution tends to get smaller with the level of aggregation. Hence, in a narrow subcategory the goods are much more substitutable than on the top level.

To see how the categories differ from each other, in Table 2.2 we report the moments of the distribution of goods and sellers across them. A median top-level category includes about 1,000 goods, which is only 36 and 5 for broad and narrow subcategories, respectively. The numbers are very similar in the US and UK. However, in the US there are more sellers in a typical industry. The countries compare as 1,805 vs. 738 sellers at the top level and 33 vs. 10 sellers at the narrow level.

The number of goods and sellers differ a lot between categories, even at the top level. For example, in the US 5^{th} smallest industry (approximately, 25^{th} percentile) is represented by 334 goods and about 1,000 sellers, while the 5^{th} largest has 7,606 goods and 6,182 sellers.

On average, sellers offer seventeen goods in the US and 23 goods in the UK (see Table 2.3). However, the distribution is skewed to the right, with majority being small sellers. A median seller offers two goods in the US and three goods in the UK. Seventy-five percent of sellers sell six (nine) goods and fewer in the US (UK). But the number of goods sold can go as high as 30,000 in the US or 7,000 in the UK. Hence, even though British sellers offer more goods on average, the US market features bigger sellers in the right tail. Sellers in "Media" (books, DVDs) and "Electronics" offer more goods in both

TABLE 2.1. EXAMPLES OF CATEGORIES OF GOODS, BY AGGREGATION LEVEL

Category Level	Categories, M (1)	Examples (2)
Top	22	Apparel and Accessories Cameras and Optics Electronics Food, Beverages and Tobacco Hardware Software
Broad	216	Clothing, Watches, Jewelry Cameras, Optics, Camera and Optic Accessories Computers, Audio, Video, Networking, Communications Beverages, Food Items, Tobacco Tools, Electrical Supplies Computer Software, Video Game Software
Narrow	2,055	Costumes, Vests, Dresses, Socks, T-Shirts Digital Cameras, Video Cameras, Surveillance Cameras, Webcams Hard Drives, Video Cards, Motherboards, Processors Liquor and Spirits, Coffee, Beer Flashlights, Handheld Power Drills, Compressors, Wrenches, Screwdrivers Operating Systems; Office, Tax and Accounting; Antivirus and Security

Notes: Column (1) shows the number of categories in a given aggregation level. Column (2) provides some examples of categories. Examples are chosen to represent categories with more observations. Each line in the "Top" section represents a top level category. Each line in the "Broad" section represents subcategories separated by commas for a top-level category above. Each line in the "Narrow" section represents subcategories separated by commas (or semi-colons) that correspond to the first category in the corresponding line of the "Broad" section. For instance, "Apparel and Accessories" is a top-level category. It includes among others "Clothing", "Watches", and "Jewelry" as three broad subcategories. "Apparel and Accessories / Clothing" contains among others five narrow subcategories: "Costumes", "Vests", "Dresses", "Socks", "T-Shirts". The list of subcategories is not exhaustive and is meant to provide an example only.

countries (about 30 goods in the former category and fifteen in the latter). Sellers in "Food, Beverages, and Tobacco", on average, sell fewer than two goods online.

We find it useful for further analysis to differentiate between retailers that sell a big variety of goods and those that specialize on just a handful of products. For this purpose, we split sellers into five groups based on the number of top-level categories, in which they offer products. Those groups include sellers that operate within one, two, three to five, six to ten, and more than ten top-level categories. About two thirds of all sellers operate within a single category of goods. Only six percent of sellers operate in more than five categories (Table 2.4). The numbers are similar in the two countries.

Online retailers in categories that cover lots of products tend to specialize. For instance, "Media" and "Electronics", for which the number of goods offered by an average seller is the highest, have the biggest share of the single-category firms.[13] In the US, firms that sell luggage, bags, and office supplies tend to diversify.

The more categories a seller covers, the more goods it offers on average. In the US single-category sellers offer about three goods on average, those that cover two categories offer ten goods, sellers in three to five categories offer 25 goods. The number of goods grows dramatically in further categories: sellers in six to ten categories offer 65 goods on average, while gigantic sellers that operate in more than ten industries sell 550 goods. The relationship is observed at every percentile of the distribution.

[13]In the US, 80 percent of sellers in "Media" are single-category sellers, as are 55 percent of those in "Electronics". The numbers are 68 and 46 percent, respectively, in the UK.

TABLE 2.2. NUMBER OF GOODS AND SELLERS, BY CATEGORY LEVEL

Category Level	Mean (1)	St.Dev. (2)	p5 (3)	p25 (4)	Median (5)	p75 (6)	p95 (7)	Max (8)	M (9)
Panel A: USA									
Number of Goods, N^j									
Top	2,398.9	3,302.1	43	334	1,092	2,831	7,606	14,370	22
Broad	253.7	1,066.8	1	6	36	139	1,185	14,157	208
Narrow	26.1	321.1	1	2	5	16	71	14,157	2,023
Number of Sellers, S^j									
Top	2,360.3	2,076.4	174	1,041	1,805	3,350	6,182	8,888	22
Broad	391.1	669.1	3	36	136	390	1,983	3,464	208
Narrow	79.2	158.9	1	7	33	92	298	3,464	2,023
Number of Quote-Lines, L^j									
Top	20,809.3	27,356.6	314	4,380	12,524	23,099	85,738	105,525	22
Broad	2,201.0	7,245.6	4	50	290	1,313	11,972	85,214	208
Narrow	226.3	1,984.0	1	9	43	144	754	85,214	2,023
Panel B: UK									
Number of Goods, N^j									
Top	2,398.5	3,296.4	48	338	1,091	2,945	7,693	14,197	22
Broad	252.5	1,048.3	1	7	37	139	1,071	13,898	209
Narrow	26.0	313.3	1	2	5	16	74	13,898	2,028
Number of Sellers, S^j									
Top	807.5	675.9	97	301	738	1,042	1,931	2,967	22
Broad	139.4	242.8	1	13	43	141	696	1,264	209
Narrow	32.2	63.5	1	3	10	33	132	1,057	2,028
Number of Quote-Lines, L^j									
Top	9,005.8	13,790.3	154	1,355	3,324	9,581	41,426	55,091	22
Broad	948.0	3,511.6	1	17	79	405	4,030	40,712	209
Narrow	97.7	935.9	1	3	13	54	348	40,712	2,028

Notes: Columns (1)-(8) show moments of the distribution across categories, $j \in \mathscr{M}$, of the number of goods, N^j, sellers, S^j, and quote-lines, L^j, within a category. Column (9) shows the total number of categories, M, in a given classification. Rows represent three different aggregation levels for categories.

Clicks and Prices Since each price and quantity in our dataset varies across two cross-sectional dimensions—goods and sellers—it is essential to compare the distribution along both of them. For this purpose, we consider a number of indexes that vary over one dimension but average observations over the other. In this section we disregard time variation, which will be examined in detail later. To take the time variation out of the way, we consider total clicks for a quote line, i.e. the sum of all clicks it gets[14]. Hence, we eliminate time dimension by considering $Q_{is} = \sum_t q_{ist}$. To eliminate one of the cross-sectional dimensions, we simply average it out. Thus, $\overline{Q}_i = \frac{1}{S_i} \sum_{s \in \mathscr{S}_i} Q_{is}$ is the number of total clicks received by an average seller of good i and $\overline{Q}_s = \frac{1}{N_s} \sum_{i \in \mathscr{G}_s} Q_{is}$ is the number of total clicks received by an average good offered by seller s.

Table 2.5 reports the distribution of the average number of total clicks across goods by category. In terms of average clicks, in the US goods in categories “Furniture”, “Baby and Toddler”, and “Camera and Optics” get the most. However, in terms of the overall number of clicks, “Electronics” is by far a leading category, having obtained every third click from

[14]Alternatively, we can aggregate clicks by year, but since the dataset does not even span over two full years, it seems reasonable to simply sum up the clicks.

Table 2.3. Number of Goods Offered by a Seller, by category of goods

Category, j	Mean (1)	St.Dev. (2)	Median (3)	p75 (4)	p95 (5)	Max (6)	S^j (7)
Panel A: USA							
Apparel and Accessories	10.3	41.5	2	6	41	1,365	2,061
Arts and Entertainment	7.6	45.0	2	4	24	1,865	2,779
Baby and Toddler	2.8	5.9	1	2	10	83	654
Business and Industrial	1.4	2.1	1	1	3	35	324
Cameras and Optics	4.9	20.0	1	3	17	609	2,492
Electronics	11.9	69.6	2	5	32	3,328	8,888
Food, Beverages and Tobacco	1.8	2.7	1	2	5	31	174
Furniture	3.6	10.6	1	2	11	227	1,253
Hardware	7.2	38.7	1	4	22	1,588	3,200
Health and Beauty	10.9	57.9	2	5	43	2,683	3,676
Home and Garden	7.5	53.7	2	4	24	3,256	6,182
Luggage and Bags	4.3	16.4	1	3	14	433	1,549
Mature	2.8	3.6	1	3	10	34	385
Media	25.5	249.0	1	4	45	8,870	3,365
Office Supplies	6.2	22.5	1	3	25	570	1,408
Pet Supplies	11.5	41.8	2	5	51	853	1,241
Services	1.9	2.0	1	2	5	14	119
Software	4.2	10.7	1	3	17	181	1,041
Sporting Goods	6.3	23.3	2	4	23	738	2,781
Toys and Games	6.9	38.6	1	4	23	1,799	3,350
Vehicles and Parts	4.1	11.3	1	3	15	317	1,539
Not Classified	3.7	24.0	1	3	10	1,260	3,465
All Categories	***16.8***	***231.0***	***2***	***6***	***48***	***30,119***	***27,308***
Panel B: UK							
Apparel and Accessories	11.2	33.0	2	7	56	500	797
Arts and Entertainment	7.9	25.8	2	4	30	372	963
Baby and Toddler	4.5	7.5	1	4	22	60	301
Business and Industrial	1.3	1.1	1	1	2	12	116
Cameras and Optics	6.5	15.0	2	5	30	171	842
Electronics	18.6	71.1	2	8	71	1,457	2,967
Food, Beverages and Tobacco	1.9	1.6	1	2	6	8	97
Furniture	2.4	6.0	1	2	6	65	408
Hardware	9.8	32.1	2	5	40	563	1,042
Health and Beauty	13.4	37.9	2	7	67	434	1,362
Home and Garden	7.8	45.9	2	4	26	1,579	1,931
Luggage and Bags	4.3	11.8	2	3	15	196	679
Mature	2.1	2.4	1	2	8	10	20
Media	36.5	229.5	2	7	107	5,371	1,136
Office Supplies	3.8	10.5	1	3	11	179	651
Pet Supplies	8.5	36.3	2	4	23	467	295
Services	2.1	2.5	1	2	6	18	112
Software	5.5	11.4	2	5	22	171	593
Sporting Goods	8.2	30.0	2	4	31	510	950
Toys and Games	8.9	35.0	2	5	32	821	1,073
Vehicles and Parts	3.6	7.2	1	3	13	78	390
Not Classified	3.3	9.1	1	2	11	183	1,039
All Categories	***22.6***	***156.7***	***3***	***9***	***78***	***7,125***	***8,757***

Notes: Columns (1)-(6) show moments of the distribution over sellers of the number of goods in category j sold by seller s, N_s^j, by industry. Column (7) shows the number of sellers in an industry, S^j.

TABLE 2.4. DISTRIBUTION OF NUMBER OF CATEGORIES REPRESENTED ACROSS SELLERS, %, BY CATEGORY

Categories, M_s	1	2	3–5	6–10	>10	S^j
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: USA						
Apparel and Accessories	42.1	16.5	18.8	13.1	9.5	2,061
Arts and Entertainment	25.9	20.0	28.0	16.2	9.8	2,779
Baby and Toddler	9.3	11.0	30.4	24.9	24.3	654
Business and Industrial	6.8	9.0	16.4	26.9	41.0	324
Cameras and Optics	22.4	19.3	26.0	20.5	11.9	2,492
Electronics	55.4	17.1	15.0	8.7	3.8	8,888
Food, Beverages and Tobacco	14.4	14.4	25.9	26.4	19.0	174
Furniture	20.3	14.4	27.6	20.4	17.4	1,253
Hardware	20.6	16.8	29.6	22.9	10.1	3,200
Health and Beauty	48.6	14.3	15.5	13.1	8.5	3,676
Home and Garden	33.4	18.1	26.4	16.4	5.7	6,182
Luggage and Bags	10.3	15.4	28.6	28.6	17.1	1,549
Mature	11.2	7.5	30.4	31.7	19.2	385
Media	80.4	6.2	6.5	4.0	2.9	3,365
Office Supplies	10.9	13.7	28.3	27.5	19.7	1,408
Pet Supplies	34.0	13.6	20.4	16.7	15.3	1,241
Services	2.5	5.0	14.3	26.9	51.3	119
Software	20.3	17.7	26.0	19.7	16.3	1,041
Sporting Goods	26.2	14.6	25.2	22.7	11.3	2,781
Toys and Games	34.8	19.2	24.4	13.0	8.5	3,350
Vehicles and Parts	22.1	15.1	22.5	24.2	16.2	1,539
Not Classified	14.1	21.0	34.7	20.8	9.4	3,465
All Sellers	***67.2***	***15.4***	***11.8***	***4.3***	***1.3***	***27,308***
Panel B: UK						
Apparel and Accessories	44.5	14.3	16.7	14.3	10.2	797
Arts and Entertainment	25.3	20.7	25.8	17.1	11.1	963
Baby and Toddler	14.6	14.3	20.6	25.9	24.6	301
Business and Industrial	5.2	11.2	26.7	25.0	31.9	116
Cameras and Optics	14.6	17.0	35.4	21.4	11.6	842
Electronics	46.2	18.8	20.8	10.2	3.9	2,967
Food, Beverages and Tobacco	24.7	13.4	26.8	16.5	18.6	97
Furniture	8.8	13.5	28.9	28.4	20.3	408
Hardware	22.1	15.6	32.1	20.3	9.9	1,042
Health and Beauty	55.7	11.0	14.6	10.9	7.7	1,362
Home and Garden	27.7	18.2	30.7	16.9	6.5	1,931
Luggage and Bags	9.3	13.0	35.1	29.0	13.7	679
Mature	5.0	5.0	25.0	15.0	50.0	20
Media	68.0	10.7	10.6	5.1	5.6	1,136
Office Supplies	8.1	15.1	33.2	27.5	16.1	651
Pet Supplies	39.3	16.3	12.5	12.5	19.3	295
Services	0.0	7.1	32.1	42.9	17.9	112
Software	10.1	17.7	36.3	23.4	12.5	593
Sporting Goods	30.1	15.4	25.6	18.2	10.7	950
Toys and Games	33.2	17.2	23.6	16.0	10.0	1,073
Vehicles and Parts	13.1	13.3	25.1	28.5	20.0	390
Not Classified	7.3	16.6	37.5	26.6	12.0	1,039
All Sellers	***63.5***	***16.1***	***14.1***	***4.8***	***1.5***	***8,757***

Notes: Columns (1)-(5) show the distribution of sellers by the number of categories entered in percent. Column (6) shows the total number of sellers in an industry, S^j.

online shoppers. “Home and Garden”, “Health and Beauty”, “Media”, “Cameras and Optics”, as well as “Toys and Games” are also sizeable.

The more categories a median seller penetrates, the more clicks it receives. At the same time, there are a handful of single-category sellers that obtain disproportionately big number of clicks. The number of categories covered matters less for the number of clicks per good received by an average seller of a given size.

We then move to the distribution of prices. Table 2.6 shows the percentiles of the pooled distribution of prices in levels, p_{ist}, together with the mean and standard deviation of log prices, $\log p_{ist}$.[15] A median good in the sample costs around \$40 in the US. The most expensive products are in “Services”, “Cameras and Optics”, “Business and Industrial”, “Apparel and Accessories”, “Software”, and “Furniture”. “Food, Beverages, and Tobacco” are the cheapest.

To see if the comovement between prices and clicks mostly comes from the demand or supply side, we plot the relationship between the mean deviation of log price from its average across sellers against that for clicks. To be more specific, we first compute the deviations for each observation

$$\widetilde{\log q}_{ist} = \log q_{ist} - \frac{1}{S_{it}} \sum_{s \in \mathcal{S}_{it}} \log q_{ist}$$
$$\widetilde{\log p}_{ist} = \log p_{ist} - \frac{1}{S_{it}} \sum_{s \in \mathcal{S}_{it}} \log p_{ist}$$

and then we average them across goods and time to compute $\overline{\log q}_s = \frac{1}{\sum_t \sum_{i \in \mathcal{G}_t} \mathbb{I}\{q_{ist}>0\}} \sum_{it} \widetilde{\log q}_{ist}$ and $\overline{\log p}_s = \frac{1}{\sum_t \sum_{i \in \mathcal{G}_t} \mathbb{I}\{q_{ist}>0\}} \sum_{it} \widetilde{\log p}_{ist}$. The relationship between the two is shown in Figure 2.1. We can see that for periods when a seller reduces the price relative to the average one for a given good, the number of clicks relative to the competitors weakly goes up. The reasons for the weak goodness of fit may be aplenty. For example, a seller with little awareness among consumers might not get many clicks regardless of price or that the change in price matters only if the price is close to the minimum over sellers. Also, if an industry is dominated by supply shocks, a change in relative prices might be less noticeable to a consumer when most sellers jack up the prices simultaneously. To consider heterogeneity across goods, we compute good-level correlations between the deviations:

$$r_i = corr_{st}\left(\widetilde{\log p}_{ist}, \widetilde{\log q}_{ist}\right)$$

We report the distribution by category in Table 2.7. For a median good the correlation is negative—a pattern that persists for each category separately suggesting that the relationship in Figure 2.1 is not produced by disproportionate influence of small number of categories.

[15] As the distribution of prices has a fat right tail, we prefer to report mean and standard deviation of logs to assign smaller weight to extreme values.

TABLE 2.5. AVERAGE (OVER SELLERS) NUMBER OF TOTAL (OVER TIME) CLICKS FOR A GOOD, BY CATEGORY

Category, j	Mean (1)	St.Dev. (2)	Median (3)	p75 (4)	p95 (5)	Max (6)	N^j (7)	Q^j (8)
Panel A: USA								
Apparel and Accessories	8.7	18.4	4	9	27	424	2,645	273,758
Arts and Entertainment	6.5	11.7	3	6	23	170	2,873	235,265
Baby and Toddler	12.3	27.5	5	11	52	273	160	37,274
Business and Industrial	6.6	19.2	2	4	13	146	67	7,058
Cameras and Optics	11.7	21.6	6	12	40	334	978	364,239
Electronics	9.6	30.1	4	8	32	1,282	7,606	1,897,729
Food, Beverages and Tobacco	8.7	17.7	4	7	31	124	67	3,170
Furniture	13.7	30.8	5	14	49	431	334	82,747
Hardware	6.1	11.4	3	6	21	180	2,831	234,928
Health and Beauty	8.1	24.8	4	8	25	1,132	4,425	529,164
Home and Garden	9.4	19.0	4	9	34	430	5,150	800,007
Luggage and Bags	9.1	25.8	4	8	29	590	1,077	100,763
Mature	6.9	7.7	5	9	14	46	43	8,330
Media	2.5	12.0	2	2	7	1,384	14,370	412,348
Office Supplies	5.6	12.3	3	5	17	186	849	70,215
Pet Supplies	7.3	15.1	3	7	25	329	1,106	144,109
Services	2.2	2.2	1	2	6	11	26	1,312
Software	6.3	14.2	2	6	24	245	506	121,931
Sporting Goods	8.4	23.4	4	8	28	776	2,335	248,745
Toys and Games	7.9	18.1	4	8	25	364	2,777	323,619
Vehicles and Parts	6.5	12.6	3	7	22	193	575	64,880
Not Classified	6.7	16.1	3	7	22	474	1,976	156,326
All Goods	***6.7***	***19.7***	***3***	***6***	***23***	***1,384***	***52,776***	***6,117,917***
Panel B: UK								
Apparel and Accessories	5.0	11.0	2	4	17	224	2,761	71,383
Arts and Entertainment	4.7	12.8	2	4	16	390	2,945	68,026
Baby and Toddler	9.9	23.7	4	11	34	285	169	20,861
Business and Industrial	4.2	6.7	2	4	21	36	48	1,447
Cameras and Optics	7.5	16.9	3	7	28	321	978	79,391
Electronics	6.3	20.4	2	5	22	936	7,693	701,729
Food, Beverages and Tobacco	7.0	11.8	3	8	26	71	69	2,092
Furniture	7.0	13.2	3	7	26	144	338	13,939
Hardware	4.8	14.2	2	4	15	462	2,770	76,110
Health and Beauty	6.5	36.0	2	5	20	2,005	4,425	256,249
Home and Garden	5.4	23.4	2	4	18	1,440	5,311	218,948
Luggage and Bags	5.1	9.3	2	5	18	193	1,037	20,685
Mature	2.4	3.5	1	2	10	18	30	111
Media	1.7	13.5	1	2	4	1,578	14,197	138,208
Office Supplies	3.9	12.9	2	4	10	300	792	16,421
Pet Supplies	4.5	14.3	2	4	14	338	1,145	13,148
Services	1.9	1.9	1	2	6	11	50	887
Software	5.1	17.0	2	4	16	314	545	94,643
Sporting Goods	8.2	22.4	3	7	27	449	2,392	98,673
Toys and Games	5.2	12.9	2	5	17	365	3,179	89,905
Vehicles and Parts	3.3	5.8	2	3	10	91	620	6,878
Not Classified	3.6	7.1	2	3	13	101	1,273	26,878
All Goods	***4.6***	***18.9***	***2***	***4***	***15***	***2,005***	***52,767***	***2,016,612***

Notes: Columns (1)-(6) show the moments of the distribution over goods of the number of total clicks obtained by an average seller for each good, $\overline{Q}_i = \frac{1}{S_i}\sum_{s\in\mathscr{S}_i}\sum_t q_{ist}$. Column (7) shows the total number of goods in a category, N^j. Column (8) shows the total number of clicks in a category, $Q^j = \sum_{i\in\mathscr{G}^j}\sum_{s\in\mathscr{S}_i}\sum_t q_{ist}$.

TABLE 2.6. DISTRIBUTION OF PRICES, LOCAL CURRENCY, BY CATEGORY

	$\log p_{ist}$		p_{ist}					
Category, j	Mean (1)	St.Dev. (2)	p5 (3)	p25 (4)	Median (5)	p75 (6)	p95 (7)	O^j (8)
Panel A: USA								
Apparel and Accessories	5.41	1.81	19	75	150	499	7,380	115,038
Arts and Entertainment	3.97	1.85	3	14	40	249	1,150	118,857
Baby and Toddler	3.99	1.22	7	25	60	115	500	12,061
Business and Industrial	4.44	1.49	5	29	173	250	380	2,036
Cameras and Optics	5.26	1.48	14	60	230	598	1,399	78,516
Electronics	4.47	1.53	8	31	90	236	898	545,909
Food, Beverages and Tobacco	2.07	1.11	1	3	10	17	35	1,528
Furniture	4.70	0.80	27	72	120	180	345	32,548
Hardware	3.54	1.50	3	12	31	100	465	122,824
Health and Beauty	3.07	1.06	4	11	22	41	132	227,841
Home and Garden	3.66	1.28	5	17	35	85	384	293,269
Luggage and Bags	3.69	0.97	8	22	40	75	190	32,840
Mature	3.55	0.96	9	20	29	53	233	5,180
Media	2.90	1.10	3	10	16	38	104	277,823
Office Supplies	2.84	1.36	2	8	15	35	184	38,660
Pet Supplies	3.05	1.18	3	9	20	48	158	76,560
Services	6.95	1.04	111	674	1,205	1,400	2,630	920
Software	5.06	1.55	12	65	137	487	2,400	24,028
Sporting Goods	4.10	1.21	9	27	55	130	488	98,986
Toys and Games	3.23	1.14	5	13	23	50	190	124,153
Vehicles and Parts	4.14	1.34	6	22	70	190	475	32,553
Not Classified	3.14	1.16	4	12	20	40	150	64,371
All Price Quotes	***3.84***	***1.56***	***5***	***16***	***40***	***124***	***695***	***2,326,501***
Panel B: UK								
Apparel and Accessories	4.81	1.58	12	53	98	209	2,982	38,762
Arts and Entertainment	4.17	1.9	3	14	70	281	1,395	36,850
Baby and Toddler	3.70	1.2	4	20	40	100	260	8,162
Business and Industrial	3.18	1.25	3	9	36	48	216	675
Cameras and Optics	4.80	1.42	12	40	134	379	990	28,354
Electronics	4.17	1.47	6	25	68	167	605	246,408
Food, Beverages and Tobacco	2.06	0.86	2	5	7	18	24	999
Furniture	4.17	1.21	9	27	76	180	300	4,968
Hardware	3.30	1.41	3	10	26	67	335	41,357
Health and Beauty	2.88	1.01	3	9	20	35	79	88,893
Home and Garden	3.39	1.34	4	12	28	70	300	73,042
Luggage and Bags	3.39	1.01	6	15	30	55	136	11,316
Mature	3.84	1.12	10	24	47	98	426	89
Media	2.35	0.96	3	6	10	18	46	85,143
Office Supplies	2.85	1.25	3	9	15	28	170	8,643
Pet Supplies	2.54	1.18	2	5	11	27	100	8,234
Services	6.26	1.56	88	159	288	1,629	6,296	744
Software	4.62	1.59	8	30	80	387	1,157	16,508
Sporting Goods	4.05	1.39	8	22	50	136	749	39,833
Toys and Games	2.78	1.09	3	8	14	30	123	39,187
Vehicles and Parts	3.50	1.33	4	12	40	80	271	4,524
Not Classified	2.96	1.23	3	9	19	42	152	11,703
All Price Quotes	***3.63***	***1.55***	***4***	***13***	***33***	***103***	***541***	***794,394***

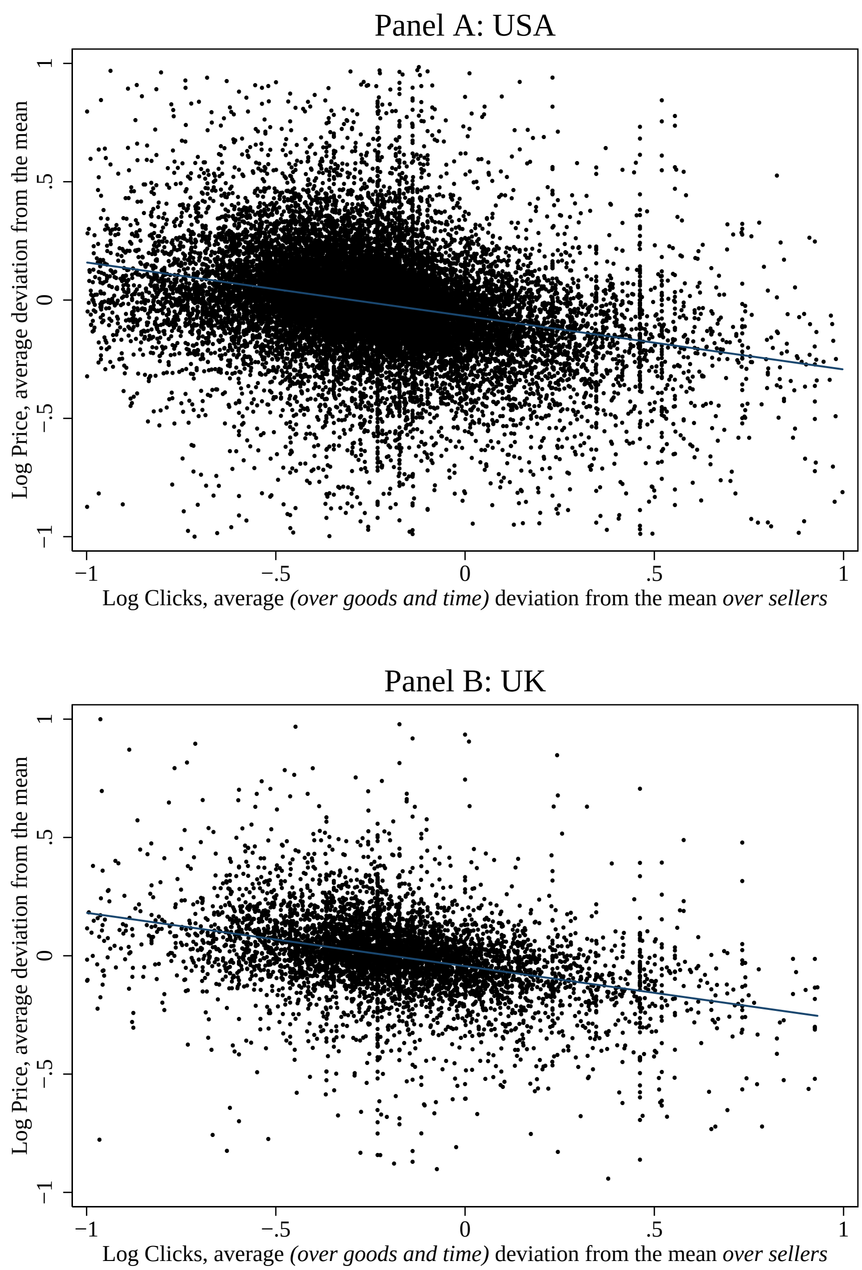
Notes: Columns (1)-(2) show the moments of the distribution of log prices in a given category, $\log p_{ist}$. Columns (3)-(7) show the moments of the distribution of prices (in levels) in a given category, p_{ist}. Column (8) shows the total number of price quotes in a category, O^j.

TABLE 2.7. DISTRIBUTION OF POOLED CORRELATIONS OF THE DEVIATION OF LOG-PRICE FROM ITS AVERAGE ACROSS SELLERS AND THAT FOR THE LOG-NUMBER OF CLICKS, BY CATEGORY

Category, j	Mean (1)	St.Dev. (2)	p5 (3)	p25 (4)	Median (5)	p75 (6)	p95 (7)	N^j (8)
Panel A: USA								
Apparel and Accessories	−0.21	0.36	−0.77	−0.41	−0.24	−0.03	0.43	1,226
Arts and Entertainment	−0.17	0.34	−0.74	−0.35	−0.15	0.00	0.42	1,114
Baby and Toddler	−0.26	0.34	−1.00	−0.42	−0.25	−0.04	0.29	71
Business and Industrial	−0.25	0.40	−0.89	−0.51	−0.26	0.00	0.59	20
Cameras and Optics	−0.16	0.35	−0.72	−0.35	−0.18	0.00	0.53	470
Electronics	−0.16	0.35	−0.73	−0.35	−0.18	0.00	0.46	3,459
Food, Beverages and Tobacco	−0.02	0.47	−0.79	−0.37	−0.07	0.41	0.74	30
Furniture	−0.20	0.28	−0.57	−0.37	−0.21	−0.04	0.28	185
Hardware	−0.14	0.33	−0.62	−0.32	−0.17	0.00	0.49	1,026
Health and Beauty	−0.22	0.35	−0.79	−0.42	−0.22	−0.01	0.38	2,077
Home and Garden	−0.17	0.35	−0.73	−0.36	−0.18	−0.00	0.46	2,250
Luggage and Bags	−0.20	0.39	−0.89	−0.43	−0.22	−0.00	0.59	381
Mature	−0.06	0.24	−0.51	−0.19	−0.10	0.09	0.28	33
Media	−0.07	0.40	−0.77	−0.29	−0.07	0.13	0.71	2,894
Office Supplies	−0.12	0.35	−0.75	−0.29	−0.12	0.05	0.42	348
Pet Supplies	−0.14	0.30	−0.61	−0.31	−0.14	0.02	0.38	605
Services	−0.28	0.50	−1.00	−0.58	−0.13	0.02	0.16	4
Software	−0.20	0.40	−0.89	−0.44	−0.19	0.02	0.50	180
Sporting Goods	−0.21	0.36	−0.72	−0.42	−0.23	−0.04	0.47	771
Toys and Games	−0.18	0.38	−0.76	−0.41	−0.21	0.02	0.51	1,237
Vehicles and Parts	−0.15	0.32	−0.63	−0.31	−0.18	−0.00	0.41	256
Not Classified	−0.16	0.39	−0.85	−0.37	−0.18	0.02	0.56	681
All Goods	**−0.16**	***0.36***	**−0.75**	**−0.36**	**−0.17**	***0.01***	***0.50***	***19,318***
Panel B: UK								
Apparel and Accessories	−0.30	0.44	−0.99	−0.59	−0.35	−0.10	0.68	575
Arts and Entertainment	−0.25	0.47	−1.00	−0.54	−0.27	−0.04	0.71	434
Baby and Toddler	−0.24	0.38	−0.77	−0.44	−0.32	−0.16	0.71	72
Business and Industrial	−0.42	0.53	−1.00	−0.91	−0.47	−0.03	0.40	6
Cameras and Optics	−0.28	0.38	−0.82	−0.52	−0.33	−0.07	0.36	275
Electronics	−0.24	0.40	−0.96	−0.49	−0.25	−0.02	0.49	2,072
Food, Beverages and Tobacco	−0.29	0.47	−1.00	−0.55	−0.40	−0.08	1.00	17
Furniture	−0.33	0.47	−1.00	−0.65	−0.43	−0.05	0.71	50
Hardware	−0.22	0.44	−1.00	−0.50	−0.25	0.03	0.55	465
Health and Beauty	−0.28	0.43	−1.00	−0.55	−0.33	−0.04	0.58	1,202
Home and Garden	−0.27	0.45	−1.00	−0.56	−0.33	−0.05	0.67	734
Luggage and Bags	−0.27	0.53	−1.00	−0.66	−0.36	0.03	0.79	197
Mature	−0.63	.	−0.63	−0.63	−0.63	−0.63	−0.63	1
Media	−0.15	0.50	−1.00	−0.47	−0.18	0.10	0.95	1,246
Office Supplies	−0.30	0.40	−0.98	−0.57	−0.32	−0.04	0.43	98
Pet Supplies	−0.32	0.52	−1.00	−0.72	−0.38	−0.02	0.73	127
Services	0.07	0.47	−0.59	−0.14	−0.04	0.25	1.00	8
Software	−0.19	0.42	−0.83	−0.41	−0.22	0.00	0.86	116
Sporting Goods	−0.32	0.47	−1.00	−0.66	−0.41	−0.08	0.62	644
Toys and Games	−0.22	0.50	−1.00	−0.56	−0.27	0.04	0.93	608
Vehicles and Parts	−0.25	0.52	−1.00	−0.60	−0.28	−0.07	1.00	55
Not Classified	−0.29	0.44	−1.00	−0.58	−0.32	−0.03	0.45	162
All Goods	**−0.25**	***0.45***	**−1.00**	**−0.54**	**−0.29**	**−0.01**	***0.68***	***9,164***

Notes: Columns (1)-(7) show moments of the distribution across goods of pooled correlations of the deviation of log price from its average across sellers and that for the log number of clicks, $r_i = corr_{st}\left(\widetilde{\log p}_{ist}, \widetilde{\log q}_{ist}\right)$, where $\widetilde{\log p}_{ist} = \log p_{ist} - \frac{1}{S_{it}} \sum_{s \in \mathscr{S}_{it}} \log p_{ist}$ and $\widetilde{\log q}_{ist} = \log q_{ist} - \frac{1}{S_{it}} \sum_{s \in \mathscr{S}_{it}} \log q_{ist}$. Column (8) shows the number of goods in a category, N^j.

FIGURE 2.1. LOG CLICKS VS LOG PRICE, AVERAGE DEVIATION FROM THE MEAN



Notes: Each dot represents averaged over goods and time deviations of log price and log clicks from their means over sellers, $\overline{\log p}_s = \frac{1}{\sum_t \sum_{i \in \mathscr{G}_t} \mathbb{I}\{q_{ist}>0\}} \sum_{it} \widetilde{\log p}_{ist}$ and $\overline{\log q}_s = \frac{1}{\sum_t \sum_{i \in \mathscr{G}_t} \mathbb{I}\{q_{ist}>0\}} \sum_{it} \widetilde{\log q}_{ist}$, where $\widetilde{\log p}_{ist} = \log p_{ist} - \frac{1}{S_{i??}} \sum_{s \in \mathscr{S}_{it}} \log p_{ist}$ and $\widetilde{\log q}_{ist} = \log q_{ist} - \frac{1}{S_{it}} \sum_{s \in \mathscr{S}_{it}} \log q_{ist}$. The solid line represents linear fit. We keep only observations with at least two sellers on a given date for a good (to ensure variation in log price deviations) and with at least one seller having obtained more than one click (to ensure variation in log clicks deviations). The figure only plots deviations within one log point around zero.

2.3 Price Stickiness in Online Markets

2.3.1 Methodological Issues

Posted and Regular Prices It has been documented that prices are much more flexible at high frequencies, while low frequency fluctuations may be more relevant for non-neutrality of nominal shocks.[16] Unlike in the literature that uses BLS Research Dataset, we do not have information on whether a particular item was on sale on a given date. Hence, we resort to using $\vee$-shaped sales filters.[17] We consider a price change to be transitory if after a change the price returns to its original level within one or two weeks. Eichenbaum, Jaimovich, and Rebelo (2011) point out that not only sales may be less relevant for macroeconomic implications, but also that high frequency fluctuations are more likely to represent idiosyncratic shocks. Hence, we use both $\vee$- and $\wedge$-shaped filters.

We refer to prices in our dataset as posted prices. A posted price is temporary if the price returns to its previous level within a specified number of periods (either one or two weeks). If a price is not temporary, we refer to it as a regular price. It is crucial to distinguish between regular and temporary prices, as well as permanent and transitory changes when analyzing response to macroeconomic shocks. Hence, we report the results for posted prices and regular prices separately.

Price Relevance and the Number of Clicks Virtually every study dedicated to price flexibility demonstrates tremendous heterogeneity in price stickiness. This implies that the way to convert the measure of price stickiness at the micro level into macro aggregate may significantly influence the outcome. We argue that different quote-lines have unequal relevance for aggregate price stickiness since in each category a relatively small number of prices receive a disproportionately big number of clicks. We document that taking this information into account implies that prices are stickier than when such information is omitted. Hence, we report several measures of the frequency of price changes. The first one computes the average and median frequency for each quote line. Those are averaged over sellers first and then over goods. We refer to this measure as the "no weights" frequency. The second approach takes into account that there is significant heterogeneity in prices for the same good and that some prices are not relevant as few people buy from the corresponding sellers (approximated by the number of clicks). Hence, for each good we compute weighted average of the frequency of price changes across sellers taking the number of clicks as weights and then take the raw average over goods. This procedure is referred to as "within-good weighting". Generally, this measure produces similar results since most goods in the data have a small number of sellers. However, for individual goods with many sellers and significant price dispersion, the two differ drastically. To recognize that some goods have more influence on aggregates than others, we also report "between-good weighted" results, which obtained by setting each

[16] See Klenow and Malin (2010) for an overview.

[17] See Nakamura and Steinsson (2008) and Kehoe and Midrigan (2012) for examples and discussion.

good's weight to be proportional to the number of clicks it receives. The construction of this measure is analogous to aggregating individual price series into a price index and, hence, represents our preferred statistics.

2.3.2 Frequency of Price Adjustment and Implied Duration of Spells

We compute the frequency of price adjustment per quote line as the number of non-zero price changes divided by the number of observed price changes. This measure is in line with the previous research by Bils and Klenow (2004), Klenow and Kryvtsov (2008), and Nakamura and Steinsson (2008).[18] A price change is defined based on consecutive observations since the prevalence of non-observable price quotes makes the imputation problematic. We think of price changes smaller than 0.1 percent as of no price change. Since a lot of quote lines do not have many observations on price changes, we only consider those that have at least five. The frequency of price changes for a quote line is aggregated to a good level and the distribution is reported. Based on the frequency of price adjustment, we compute the implied duration of price spells under the assumption of constant hazards.

Denote $\varphi_{ist} = \mathbb{I}\left\{q_{is,t} > 0\right\}\mathbb{I}\{q_{is,t-1} > 0\}$ the indicator function that a price change (either zero or not) based on *consecutive* observations is observed. Denote $\Pi_{is} = \sum_t \varphi_{ist}$ the number of observed price changes per quote-line. Finally, denote $\chi_{ist} = \mathbb{I}\left\{\left|\Delta \log p_{ist}\right| > 0.001\right\}$ the indicator function of a non-zero price change. The frequency of price adjustment, *in percent*, per quote-line is the number of non-zero price changes over the number of observed price changes.

$$f_{is} = \frac{\sum_t \chi_{ist}}{\Pi_{is}} \cdot 100$$

We aggregate this measure to a good level by taking raw ($\overline{f}_i$) or clicks-weighted ($\overline{f}_i^w$) averages across quote-lines with *at least five* observations for a price change:

$$\overline{f}_i = \frac{1}{\sum_{s\in\mathscr{S}_i} \mathbb{I}\{\Pi_{is} > 4\}} \sum_{s\in\mathscr{S}_i} f_{is}\mathbb{I}\left\{\Pi_{is} > 4\right\} \tag{2.2}$$

and

$$\overline{f}_i^w = \frac{\sum_s f_{is}\mathbb{I}\left\{\Pi_{is} > 4\right\}Q_{is}^{\varphi}}{\sum_s \mathbb{I}\{\Pi_{is} > 4\}Q_{is}^{\varphi}} \tag{2.3}$$

where $Q_{is}^{\varphi} = \sum_t q_{ist}\varphi_{ist}$. The former measure is referred to as "No weights" and the latter as "Within-good weights", respectively. The "Between-good" measure reports the distribution across goods of $\overline{f}_i^w$ with $W_i = \frac{Q_i^{\Pi}}{\sum_{i\in\mathscr{G}} Q_i^{\Pi}}$ as weights, where $Q_i^{\Pi} = \sum_{s\in\mathscr{S}_i} \mathbb{I}\{\Pi_{is} > 4\}Q_{is}^{\varphi}$.

[18] Alternatively, one can follow Gorodnichenko and Talavera (2012) or Li and Hong (2013) to estimate the average duration of price spells directly. However, our dataset contains nontrivial amount of truncated spells due to limited length of time series, which would lead to substantial bias were the alternative methodology applied.

The median implied duration of a price spell is computed as

$$\overline{d}_i = -\frac{1}{\ln(1-0.01\overline{f}_i)} \tag{2.4}$$

The sales filters are based on *consecutive* observations. The filtered observations are simply dropped from the computation, while the first observation after a transitory change is assigned the no-change value.

Table 2.8 presents the results on mean, median, dispersion, 25^{th} and 75^{th} percentiles, number of quote-lines, and the correlation between the "not-weighted" and "within-good weighted" measures of the frequency of price adjustment for the raw data, three filters, and three weighting schemes described above. The first conclusion that stands out is that clicks matter. Taking information on clicks into account decreases median duration of price spells by third. This means that once only relevant prices are considered (for sellers and goods that attract more customers), the estimated price rigidity appears significantly lower.

In the US the median implied duration of price spells varies from seven to twelve weeks when no weights are applied, from six to ten weeks when weights across sellers only are applied and from five to seven weeks when we use weights both across sellers and goods. Correlation between not weighted and weighted series is high as a lot of goods have only one seller. Filtering out transitory price changes leads to conclusion that even in online markets regular prices do not change often, while temporary changes are ubiquitous.

Excluding categories with the number of observations smaller than 50, one can the prices are the stickiest in "Arts and Entertainment", "Apparel and Accessories", "Cameras and Optics", "Software", and "Vehicles and Parts".

Our next step is to find determinants of frequency of price adjustment. As there is a lot of heterogeneity between goods and sellers, we concentrate on estimating determinants of probability that seller s of good i will change its price. One important factor is clearly competitor's prices. Since most of the clicks happen around the minimum price, we measure it with the distance of the current price from the minimum price charged by competitors, $\widetilde{\log p}_{ist}$. The number of sellers is included as a proxy for competition. Finally, we approximate seller's market share by the ratio of the number of clicks to all clicks received by the given good. We include quote-line and time-specific fixed effects. Also, since shocks that affect probability of price change may exhibit serial correlation, while errors can correlate between different quote-lines if shocks are industry- or seller-specific, we use Driscoll and Kraay (1998) standard errors, which are robust in the presence of autocorrelation, heteroscedasticity, and between-group correlation. The resulting specification looks like

$$\mathbb{I}\{\Delta p_{ist}=1\} = c+\alpha_{is}+\gamma_t+\beta_p\widetilde{\log p}_{ist}+\beta_S S_{ist}+\beta_Q \log\frac{q_{ist}}{Q_{ist}}+u_{ist}$$

Table 2.9 presents the results.

TABLE 2.8. FREQUENCY OF PRICE ADJUSTMENT AND IMPLIED DURATION

	Duration, weeks	Frequency, %								
	Median (1)	Corr. (2)	Mean (3)	St.Dev. (4)	p5 (5)	p25 (6)	Median (7)	p75 (8)	p95 (9)	N (10)
Panel A: USA										
No filter										
No weights	6.6	0.95	17.8	17.4	0.0	4.9	14.0	25.0	52.9	14,483
Within-good	5.5		19.7	17.9	0.0	5.3	16.7	28.9	53.8	
Between-good	4.7		19.8	11.2	2.8	11.8	19.3	26.4	40.0	
∨*-shaped, 1 week*										
No weights	7.3	0.95	16.8	16.8	0.0	4.3	12.8	23.4	50.0	14,458
Within-good	6.0		18.5	17.2	0.0	4.8	15.4	27.1	50.0	
Between-good	5.2		18.1	10.5	2.5	10.5	17.4	24.2	37.0	
∨*- and* ∧*-shaped, 1 week*										
No weights	10.9	0.94	12.3	14.0	0.0	0.4	8.8	17.3	40.0	16,332
Within-good	8.7		13.9	14.6	0.0	0.4	10.8	20.0	40.2	
Between-good	6.4		15.4	9.5	1.3	8.7	14.5	21.5	32.0	
∨*- and* ∧*-shaped, 2 weeks*										
No weights	12.2	0.95	11.7	13.9	0.0	0.0	7.9	16.7	40.0	16,110
Within-good	10.0		13.0	14.3	0.0	0.0	9.5	19.4	40.0	
Between-good	7.2		13.9	9.1	1.0	7.5	13.0	19.9	29.7	
Panel B: UK										
No filter										
No weights	7.3	0.98	20.4	24.1	0.0	0.0	12.8	28.6	80.0	6,623
Within-good	7.2		20.7	24.3	0.0	0.0	13.0	30.0	80.0	
Between-good	4.5		20.4	13.8	0.0	9.8	20.0	28.3	42.7	
∨*-shaped, 1 week*										
No weights	7.7	0.98	19.5	23.6	0.0	0.0	12.2	27.7	76.9	6,601
Within-good	7.8		19.7	23.7	0.0	0.0	12.0	28.6	77.8	
Between-good	4.8		19.1	13.3	0.0	8.3	18.8	26.3	41.2	
∨*- and* ∧*-shaped, 1 week*										
No weights	12.5	0.98	15.2	21.1	0.0	0.0	7.7	20.0	66.7	7,738
Within-good	12.5		15.5	21.3	0.0	0.0	7.7	20.1	66.7	
Between-good	5.8		16.7	12.6	0.0	6.6	15.8	23.3	37.9	
∨*- and* ∧*-shaped, 2 weeks*										
No weights	13.5	0.98	14.7	20.8	0.0	0.0	7.1	20.0	66.7	7,582
Within-good	13.5		14.9	21.0	0.0	0.0	7.1	20.0	66.7	
Between-good	6.2		15.8	12.2	0.0	6.4	15.0	22.4	36.6	

Notes: Columns (3)-(9) report moments of the distribution of the frequency of price adjustment across goods. We compute the frequency of price adjustment for a good when no filter is applied in the following way. Denote $\varphi_{ist} = \mathbb{I}\left\{q_{is,t} > 0\right\}\mathbb{I}\{q_{is,t-1} > 0\}$ the indicator function that a price change (either zero or not) measured based on *consecutive* observations is observed. Denote $\Pi_{is} = \sum_t \varphi_{ist}$ the number of observed such price changes per quote-line. Finally, denote $\chi_{ist} = \mathbb{I}\left\{\left|\Delta \log p_{ist}\right| > 0.001\right\}$ the indicator function of a non-zero price change. As the first step, we compute the frequency of price adjustment, *in percent*, per quote-line as a number of non-zero price changes over the number of observed price changes, $f_{is} = \frac{\sum_t \chi_{ist}}{\Pi_{is}} \cdot 100$. As the second step, we aggregate this measure by good by taking raw $(\overline{f}_i)$ or clicks-weighted $(\overline{f}_i^w)$ averages across quote-lines with *at least five* observations for a price change: $\overline{f}_i = \frac{1}{\sum_{s\in\mathscr{S}_i}\mathbb{I}\{\Pi_{is}>4\}}\sum_{s\in\mathscr{S}_i} f_{is}\mathbb{I}\{\Pi_{is} > 4\}$ and $\overline{f}_i^w = \frac{\sum_s f_{is}\mathbb{I}\{\Pi_{is}>4\}Q_{is}^{\varphi}}{\sum_s \mathbb{I}\{\Pi_{is}>4\}Q_{is}^{\varphi}}$, where $Q_{is}^{\varphi} = \sum_t q_{ist}\varphi_{ist}$. The former measure is referred to as "No weights" and the latter as "Within-good" weights, respectively. The "Between-good" rows report the distribution across goods of $\overline{f}_i^w$ with $W_i = \frac{Q_i^{\Pi}}{\sum_{i\in\mathscr{G}} Q_i^{\Pi}}$ as weights, where $Q_i^{\Pi} = \sum_{s\in\mathscr{S}_i}\mathbb{I}\{\Pi_{is} > 4\}Q_{is}^{\varphi}$. Column (10) reports the number of goods for which the frequency of price adjustment is defined. Column (2) reports the correlation coefficient between the raw and weighted frequencies, $r = corr_i(\overline{f}_i, \overline{f}_i^w)$. Column (1) reports the median implied duration of a price spell computed as $\overline{d}_i = -\frac{1}{\ln(1-0.01\overline{f}_i)}$. The three filters are based on *consecutive* observations with *a missing price quote treated as infinitely high price*. The filtered observations are simply dropped from the computation, while the first observation after a transitory change is assigned the no-price-change value.

TABLE 2.9. THE DETERMINANTS OF FREQUENCY AND SIZE OF PRICE CHANGES

	Frequency of			Size of		
Covariates	Changes (1)	Increases (2)	Decreases (3)	Changes (4)	Increases (5)	Decr., abs. (6)
Panel A: USA						
Log Deviation from the min price	-0.88^{***}	-4.23^{***}	3.35^{***}	-2.73^{***}	-1.26^{***}	1.48^{***}
	(0.28)	(0.38)	(0.32)	(0.23)	(0.14)	(0.13)
Log Number of Sellers with clicks	-1.77^{***}	0.52^{***}	-2.29^{***}	0.75^{***}	0.27^{***}	-0.48^{***}
	(0.22)	(0.16)	(0.19)	(0.07)	(0.04)	(0.04)
Log Market Share	-3.69^{***}	-0.28^{***}	-3.41^{***}	0.55^{***}	0.05^{**}	-0.50^{***}
	(0.12)	(0.10)	(0.10)	(0.04)	(0.02)	(0.02)
R^2	0.36	0.24	0.27	0.17	0.25	0.23
Obs.	273,903	273,903	273,903	273,903	273,903	273,903
Panel B: UK						
Log Deviation from the min price	-0.36	-2.91^{***}	2.54^{***}	-1.52^{***}	-0.72^{***}	0.80^{***}
	(0.58)	(0.92)	(0.67)	(0.41)	(0.20)	(0.23)
Log Number of Sellers with clicks	-1.84^{***}	1.12^{**}	-2.96^{***}	0.80^{***}	0.32^{***}	-0.48^{***}
	(0.68)	(0.51)	(0.58)	(0.12)	(0.07)	(0.07)
Log Market Share	-4.70^{***}	0.13	-4.84^{***}	0.77^{***}	0.18^{***}	-0.59^{***}
	(0.30)	(0.25)	(0.32)	(0.07)	(0.04)	(0.04)
R^2	0.42	0.3	0.29	0.21	0.29	0.25
Obs.	62,244	62,244	62,244	62,244	62,244	62,244

Notes: Columns (1)-(3) presents estimates from regressing the indicator function of a price change, $\mathbb{I}\{\Delta p_{ist}=1\}$, increase, or decrease on log deviation of price from the minimum over sellers, $\widetilde{\log p}_{ist}=\log p_{ist}-\frac{1}{S_{it}}\sum_{s\in\mathscr{S}_{it}}\log p_{ist}$, log number of sellers, S_{ist}, and log market share measured with clicks, $\frac{q_{ist}}{Q_{ist}}$. Quote-line and time fixed effects are included. Driscoll-Kraay standard errors are in parentheses. Columns (4)-(6) report estimates from the similar regression when the absolute size of price changes, increases, and decreases are used as the left-hand side variable. *, **, and *** represent 10%, 5%, and 1% significance level, respectively.

2.3.3 The Size of Price Changes

As above, let $\Delta\log p_{ist}=\log p_{is,t}-\log p_{is,t-1}$ be the log-difference of prices and $\chi_{ist}=\mathbb{I}\left\{\left|\Delta\log p_{ist}\right|>0.001\right\}$ be the indicator function for a price change. Then the average price change for good i can be written as

$$\overline{\Delta\log p}_i=\frac{1}{\sum_{s\in\mathscr{S}_i}\sum_t\chi_{ist}}\sum_{s\in\mathscr{S}_i}\sum_t\Delta\log p_{ist}\cdot\chi_{ist}$$

Now denote the total number of clicks within a good for observations when a price change occurred as $Q_i^{\chi}=\sum_{s\in\mathscr{S}_i}\sum_t q_{ist}\chi_{ist}$. Then within-good weighted average price can be written as

$$\overline{\Delta\log p}_i^{\mathrm{w}}=\sum_{s\in\mathscr{S}_i}\sum_t\frac{q_{ist}}{Q_i^{\chi}}\Delta\log p_{ist}\cdot\chi_{ist}$$

Note that within-good weights here are $w_{ist}=\frac{q_{ist}}{Q_i^{\chi}}\chi_{ist}$.

Finally, between-good weighted results represent the weighted distribution of $\overline{\Delta\log p}_i^{\mathrm{w}}$

with weights $W_i = \frac{Q_i^{\chi}}{\sum_{i \in \mathscr{G}} Q_i^{\chi}}$ implemented in a similar fashion as in the case of the frequency of price adjustment.

Table 2.10 reports the size of price change with a breakdown by type (increases vs. decreases). When sellers change their prices, they on average do so by about 22%. However, if only goods with a lot of clicks are considered this number falls to 17%. This implies that sellers that actively trade their goods online review their prices more often and change them by a smaller amount. Regular and temporary changes are approximately of the same size. The size of price increases slightly exceeds that of price decreases, but in the US the decreases were more likely to occur. Overall, the intensive and extensive margins roughly offset each other. The between-good weighted change is slightly negative, which reflects the fact that goods that are frequently sold online (e.g., in "Electronics") tend to quickly become obsolete, therefore, producing downward trend in prices.

The distribution of price changes, depicted in Figure 2.2, is symmetric and has non-trivial mass around zero, which does not confirm earlier findings of bimodal distribution of price changes.[19] Lack of evidence of bimodal distribution supports time-dependent pricing against the state-dependent models of adjustment. In fact, state-dependent price adjustment and bimodal distribution of price changes are usually derived from the menu cost assumption. As we argue above, there is little menu cost to adjust a price on the Google Shopping Platform as a seller can do so anytime by simply logging in to its account and setting a new price quote free of charge.

Categories with stickier prices tend to have larger mean size of absolute price changes, although there are notable exceptions. This relationship is highlighted in Figure 2.3. The finding is consistent with the Calvo model, in which firms that have to wait longer for an opportunity to reset the price accumulate more shocks and, hence, if the shocks are persistent, change the price by a bigger amount.

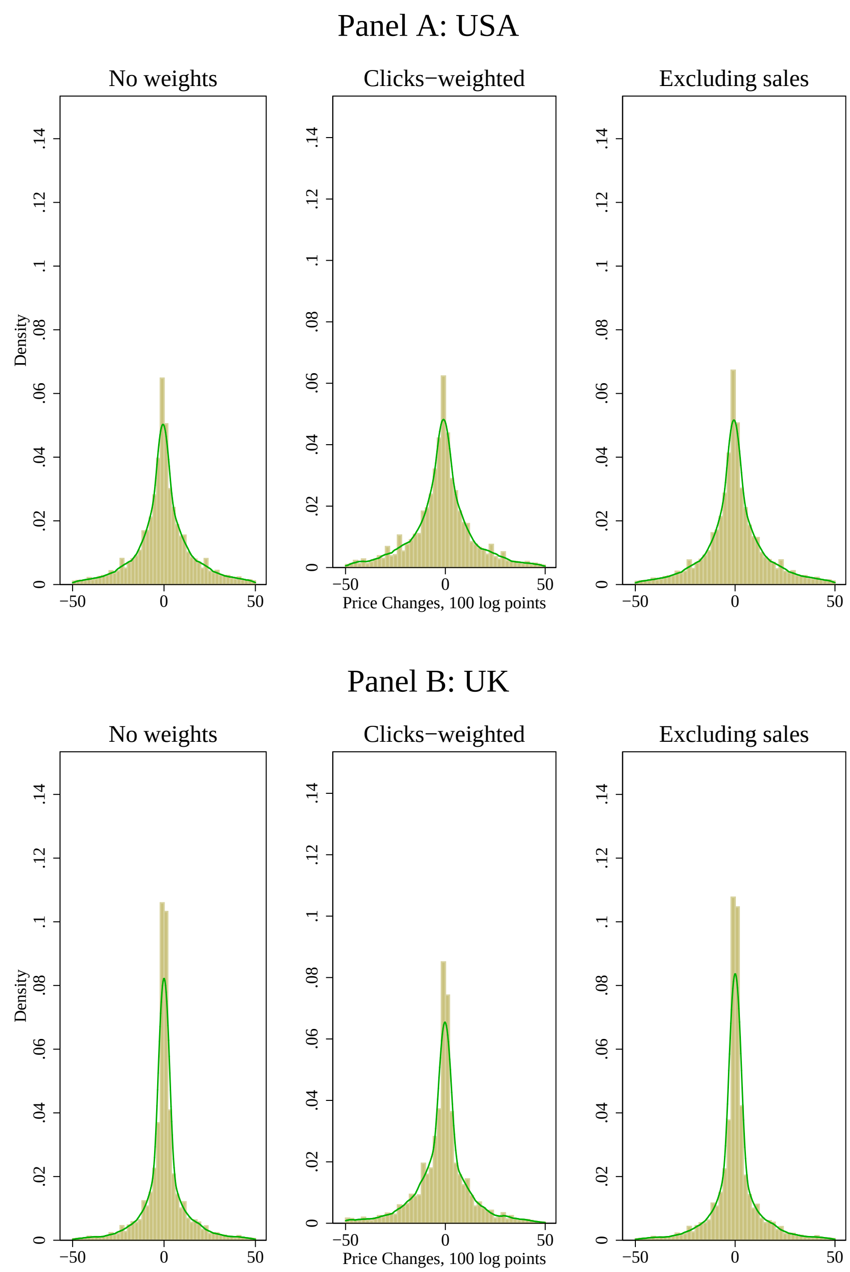
2.3.4 Synchronization

Within Goods We define synchronization within a good as the share of competitors that adjust their price quotes in response to a price change. Since we observe time changes within a period simultaneously, we cannot differentiate who changed the price first. Hence, our measure randomly assigns one price change a role of originating one. That is if A is the number of price changes for a good in a given period, and B is the number of all prices by different sellers of that good in that period, we define synchronization as $(A-1)/(B-1)$ if $A > 0$. Note that if $B = 1$, then regardless of A, synchronization is not defined. Otherwise, the synchronization rate is zero when $A = 1$, i.e. no one follows the originating price change. If $A = B > 1$ (every competitor follows the price change) the rate of synchronization is one. Every other case produces the synchronization rate between zero and one.

The actual way to compute synchronization is a bit trickier than that and requires some further notation. Denote $\psi_{it} = \mathbb{I}\{\sum_{s \in \mathscr{S}_{it}} \chi_{ist} > 0\}\mathbb{I}\{S_{it} > 0\}$ the indicator function

[19] See Cavallo (2012) and Cavallo and Rigobon (2011).

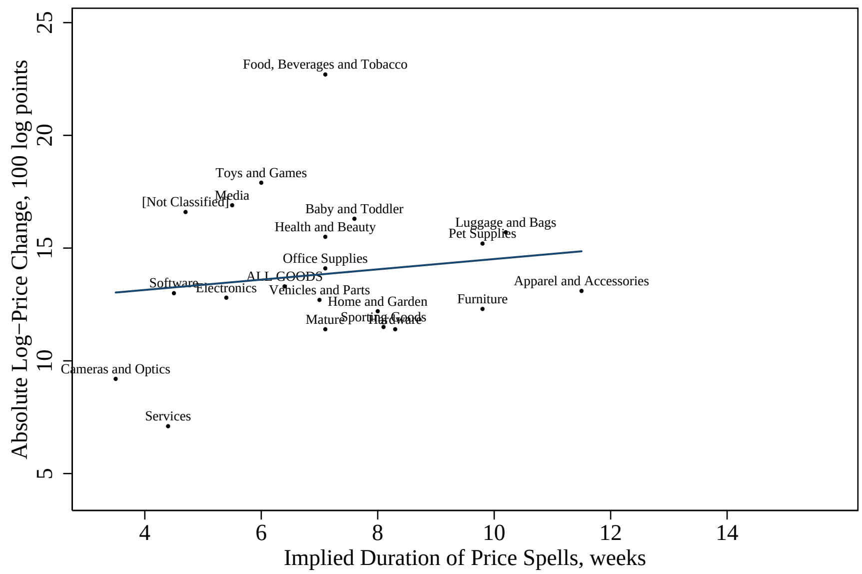
FIGURE 2.2. THE DISTRIBUTION OF THE SIZE OF PRICE CHANGES, WEEKLY FREQUENCY



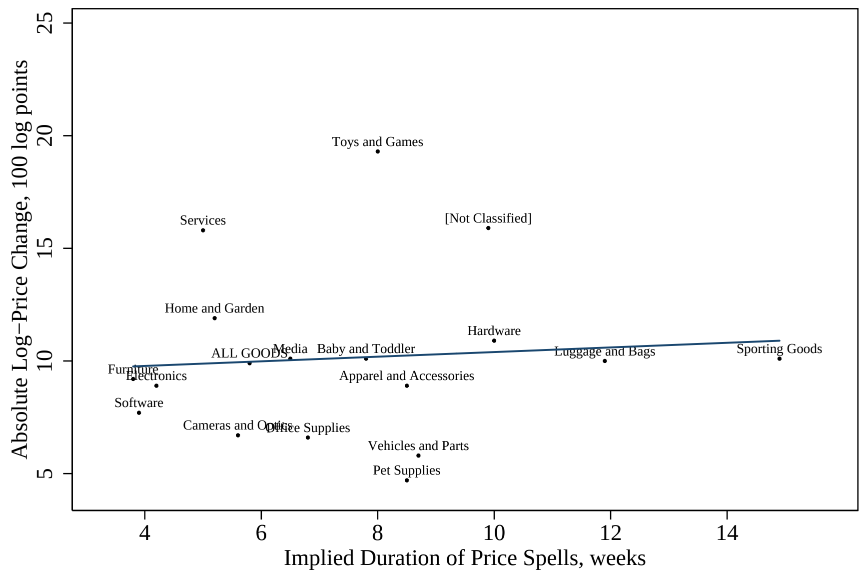
Notes: The left panel shows the distribution of the size of price changes in the raw data. The middle panel weights each price change by the number of clicks it receives. The right panel excludes two-side one-week sales with no weights applied. Price changes are truncated at 50% to improve visibility.

FIGURE 2.3. DURATION OF PRICE SPELLS VS. ABSOLUTE PRICE CHANGE, BY CATEGORY

Panel A: USA



Panel B: UK



Notes: Horizontal axis: weighted (across goods) median implied duration of price spells with two-sided 1-week sales filter, in weeks. Vertical axis: weighted (across goods) mean log-price change with two-side 1-week filter, in 100 log points. Each dot represents the statistics within a given top-level category.

TABLE 2.10. THE SIZE OF LOG-PRICE CHANGES, 100 LOG POINTS

	Corr. (1)	Mean (2)	St.Dev. (3)	p5 (4)	p25 (5)	Median (6)	p75 (7)	p95 (8)	*N* (9)
Panel A: USA									
All Changes									
No weights	0.97	0.6	17.6	−21.9	−3.5	0.0	3.9	26.0	17,053
Within-good		0.2	18.2	−22.9	−4.5	−0.3	4.0	26.8	
Between-good		−2.0	6.6	−10.9	−3.9	−1.6	0.3	5.8	
Absolute Value									
No weights	0.98	16.3	17.2	1.0	5.4	11.0	20.4	51.3	17,053
Within-good		16.3	17.4	1.0	5.2	10.7	20.5	52.2	
Between-good		13.7	9.8	4.2	7.5	11.2	16.7	30.6	
Price Increases									
No weights	0.98	17.5	18.3	1.0	5.7	11.8	22.2	55.0	13,795
Within-good		17.3	18.6	1.0	5.4	11.3	22.0	56.4	
Between-good		13.9	10.7	3.7	7.2	11.2	17.1	33.3	
Price Decreases									
No weights	0.98	15.4	17.0	0.9	4.9	10.3	19.3	49.6	14,023
Within-good		15.6	17.4	0.9	4.7	10.1	19.7	50.9	
Between-good		13.6	10.4	3.6	7.3	10.8	16.4	32.3	
Panel B: UK									
All Changes									
No weights	0.97	0.5	13.2	−15.2	−1.8	0.2	2.6	17.5	9,092
Within-good		0.2	13.8	−16.6	−2.4	0.1	2.5	18.2	
Between-good		−1.3	6.2	−9.7	−3.4	−0.6	0.7	5.5	
Absolute Value									
No weights	0.98	9.5	13.2	0.4	1.7	5.1	11.8	35.2	9,092
Within-good		9.7	13.5	0.4	1.7	5.0	11.8	35.9	
Between-good		10.1	8.0	1.8	4.6	8.5	14.0	23.6	
Price Increases									
No weights	0.98	9.9	13.6	0.4	1.7	5.3	12.3	35.2	6,983
Within-good		9.9	13.8	0.4	1.7	5.1	12.1	35.7	
Between-good		9.8	8.6	1.4	4.0	8.0	13.3	26.4	
Price Decreases									
No weights	0.98	9.4	13.5	0.4	1.6	4.7	11.3	34.8	6,717
Within-good		9.6	13.9	0.4	1.5	4.7	11.7	36.3	
Between-good		10.4	8.6	1.6	4.9	7.7	14.8	23.2	

Notes: Columns (2)-(8) report moments of the distribution across goods of average log-price change. "No" refers to simple average change, $\overline{\Delta \log p}_i = \frac{1}{\sum_{s\in\mathscr{S}_i}\sum_t \chi_{ist}} \sum_{s\in\mathscr{S}_i}\sum_t \Delta\log p_{ist}\cdot\chi_{ist}$, where $\chi_{ist} = \mathbb{I}\{\Delta\log p_{ist} > 0.001\}$. "Within-good" refers to changes weighted by the number of clicks across seller-time, $\overline{\Delta \log p}_i^{w} = \sum_{s\in\mathscr{S}_i}\sum_t \frac{q_{ist}}{Q_i^\chi}\Delta\log p_{ist}\cdot\chi_{ist}$, where $Q_i^\chi = \sum_{s\in\mathscr{S}_i}\sum_t q_{ist}\chi_{ist}$. Column (1) refers to cross-good correlation of the two, $r = corr_i(\overline{\Delta\log p}_i, \overline{\Delta\log p}_i^{w})$. "Between-good" refers to the weighted distribution of $\overline{\Delta\log p}_i^{w}$ with analytic weights taken as $W_i = \frac{Q_i^\chi}{\sum_i Q_i^\chi}$. A negligible number of price changes are windsorized at 100%.

that the number of sellers of good i at time t that changed the price is non-zero and that the synchronization rate is well defined (more than one seller). Here $\mathscr{S}_{it} \subseteq \mathscr{S}$ is the set of sellers that offer good i in period t. Then the rate of synchronization for a good on a given date is defined as

$$z_{it} = \frac{\left(\sum_{s\in\mathscr{S}_{it}}\chi_{ist}\right) - 1}{S_{it} - 1}\psi_{it}$$

where $S_{it} = \#\mathscr{S}_{it} \leq S$ is the number of sellers of good i on date t. Note that $z_{it} = 0$ may indicate that either the synchronization rate is zero or that it is undefined. Since we never report on it week-by-week, we will correct this ambiguity later. Now we define the synchronization rate for good i as a time average

$$\bar{z}_i = \frac{1}{\sum_t \psi_{it}} \sum_t z_{it}$$

Note that all observations for which the rate is undefined are omitted from both the numerator and the denominator (by setting them to be zero summands).

To compute the weighted average rate we need to have information on which seller originated the price change. But since we observe all price changes at the same time, this information is latent. To deal with this issue, we simply take the average of weights for each seller that changes the price. Denote the average number of clicks over sellers that change the price as $\bar{q}_{it}^{\chi} = \frac{1}{\sum_{s\in\mathcal{S}_{it}} \chi_{ist}} \sum_{s\in\mathcal{S}_{it}} q_{ist}\chi_{ist}$ and the average number of clicks over all sellers of a good at a time as $\bar{q}_{it} = \frac{1}{S_{it}} \sum_{s\in\mathcal{S}_{it}} q_{ist}$, then the synchronization rate for a good on a given date is measured as

$$z_{it}^{w} = \frac{\left(\sum_{s\in\mathcal{S}_{it}} q_{ist}\chi_{ist}\right) - \bar{q}_{it}^{\chi}}{\left(\sum_{s\in\mathcal{S}_{it}} q_{ist}\right) - \bar{q}_{it}^{\chi}}$$

Finally, we aggregate this measure to a good level in a usual way

$$\bar{z}_i^{w} = \sum_t \frac{Q_{it}}{Q_i^{\psi}} z_{it}^{w} \psi_{it}$$

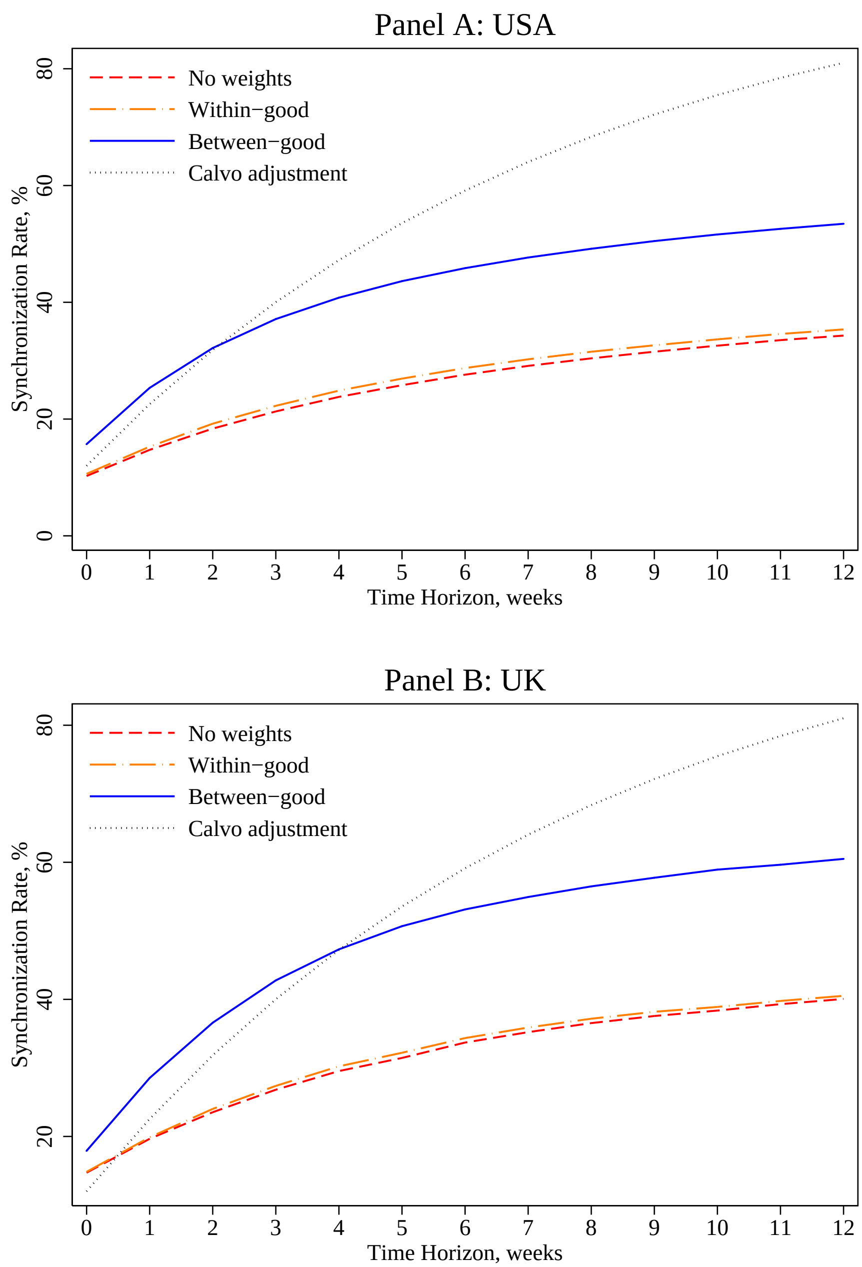
if $\psi_i = \max_t \psi_{it} > 0$, i.e. there is at least one episode when good's synchronization is defined. Here $Q_{it} = \sum_{s\in\mathcal{S}_{it}} q_{ist}$, as per usual, and $Q_i^{\psi} = \frac{1}{\sum_t \psi_{it}} \sum_t Q_{it}\psi_{it}$.

Finally, between-good weighted average is the weighted mean of $\bar{z}_i^{w}$ with the weights $W_i = \frac{Q_i^{\psi}\psi_i}{\sum_{i\in\mathcal{G}} Q_i^{\psi}\psi_i}$.

The results are in Table 2.11. We see that the cross-seller weights have little importance, while cross-good weights change the results a lot. In the US, about 10% of sellers adjust their price when one of their competitors makes a price change. The number is approximately the same when within-good weights are applied. However, for goods that are likely to have higher online circulation, the synchronization rate is about 15%. Crucially, if we consider median synchronization, the difference is even more significant as for the median good there is no synchronization at all. However, clicks-weighted synchronization is 15% suggesting that relevant sellers adjust their prices often while there are many sellers who barely review their prices.

We also track synchronization over time (see Figure 2.4). Synchronization triples within 12 weeks after the triggering price change. In case of no weights applied, it goes up from 10% to 35%, while for between-good weights, it increases from 15% to slightly above 50%. Still, it appears that about half of the sellers fail to react to their competitors' price change within a quarter.

FIGURE 2.4. MEAN (OVER GOODS) SYNCHRONIZATION RATE, BY TIME HORIZON



Notes: Synchronization at time-t horizon is measured as the share of sellers who adjust their price within t weeks after a competitor changes the price. Three series report the results for the cases with no weights across goods, with weights within goods (across sellers), and with weights both across sellers and goods. The black dotted line shows what the synchronization would be if sellers could adjust their price every period at random *a la* Calvo with exogenously given probability 12%. The latter number is based on the estimated frequency of price adjustment.

TABLE 2.11. SYNCHRONIZATION RATE, %

	Corr. (1)	Mean (2)	St.Dev. (3)	p25 (4)	Median (5)	p75 (6)	p95 (7)	N/S (8)
Panel A: USA								
Good								
No weights	0.97	10.2	18.6	0.0	0.0	13.5	50.0	9,937
Within-good		10.6	19.2	0.0	0.0	14.2	48.0	
Between-good		15.7	10.0	8.1	15.1	21.6	33.8	
Seller								
No weights	0.97	17.2	27.4	0.0	1.6	25.0	100.0	2,344
Within-good		17.6	28.3	0.0	1.2	23.7	100.0	
Between-good		22.5	11.6	12.1	24.9	31.4	31.4	
Panel B: UK								
Good								
No weights	0.97	14.7	24.8	0.0	0.0	20.0	96.3	3,867
Within-good		14.8	25.2	0.0	0.0	19.6	96.3	
Between-good		17.9	11.1	9.8	17.9	25.7	35.8	
Seller								
No weights	0.96	19.7	26.5	0.0	8.2	30.0	83.3	1,258
Within-good		19.3	26.8	0.0	8.3	26.9	85.9	
Between-good		26.1	16.7	12.9	26.0	34.4	57.0	

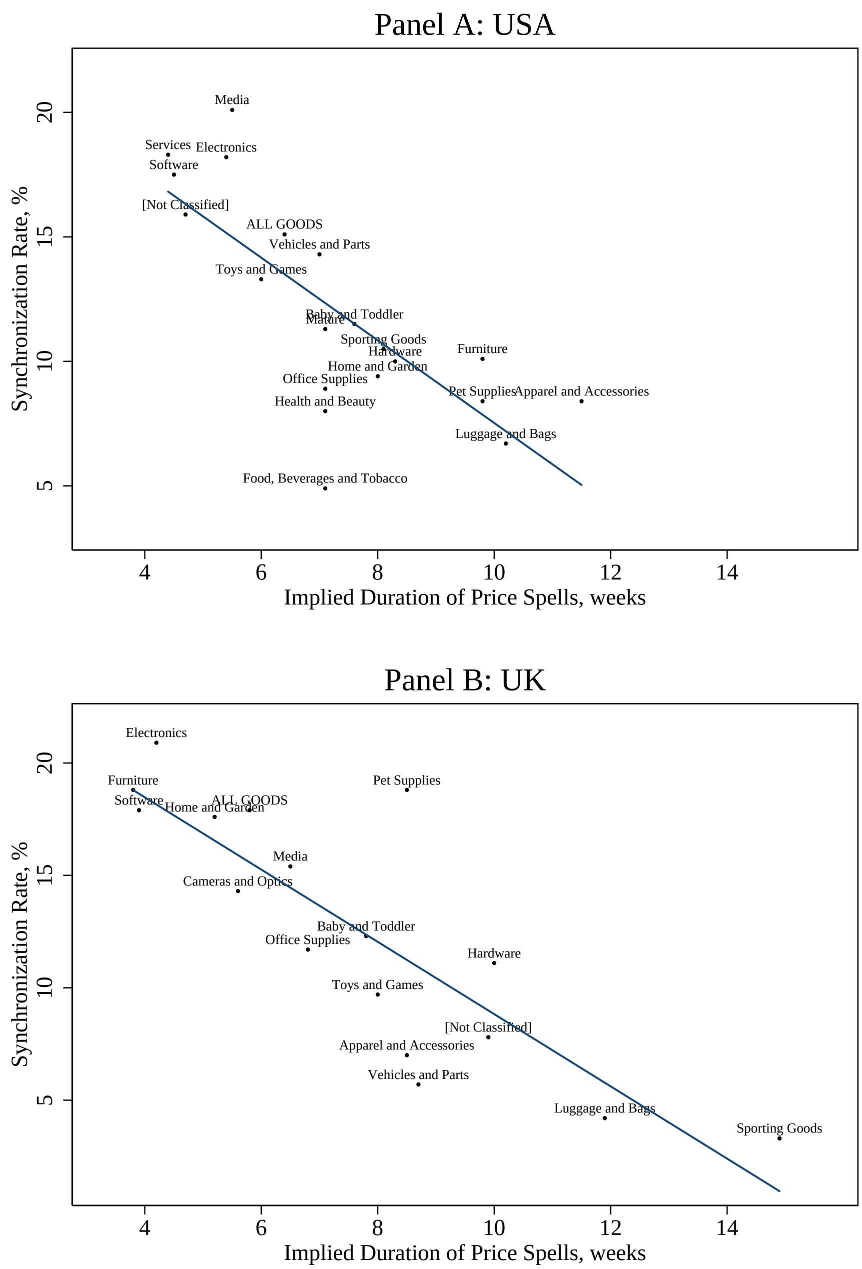
Notes: Columns (2)-(7) report moments of the distribution across goods (sellers) of the synchronization rate. For the case of synchronization of sellers within a good ("Good"), "No" refers to the simple average rate, $\overline{z}_i = \frac{1}{\sum_t \psi_{it}} \sum_t z_{it}$ where $\psi_{it} = \mathbb{I}\left\{\sum_{s\in\mathscr{S}_{it}} \chi_{ist} > 0\right\} \mathbb{I}\left\{S_{it} > 0\right\}$ with $\chi_{ist} = \mathbb{I}\left\{\Delta log p_{ist} > 0.001\right\}$ and $z_{it} = \frac{\left(\sum_{s\in\mathscr{S}_{it}} \chi_{ist}\right)-1}{S_{it}-1}\psi_{it}$. "Within-good" refers to the rate weighted by the number of clicks across time, $\overline{z}_i^w = \sum_t \frac{Q_{it}}{Q_i^\psi} z_{it}^w \psi_{it}$, where $Q_i^\psi = \frac{1}{\sum_t \psi_{it}} \sum_t Q_{it}\psi_{it}$ and $z_{it}^w = \frac{\left(\sum_{s\in\mathscr{S}_{it}} q_{ist}\chi_{ist}\right)-\overline{q}_{it}^\chi}{\left(\sum_{s\in\mathscr{S}_{it}} q_{ist}\right)-\overline{q}_{it}^\chi}$ with $\overline{q}_{it}^\chi = \frac{1}{\sum_{s\in\mathscr{S}_{it}} \chi_{ist}} \sum_{s\in\mathscr{S}_{it}} q_{ist}\chi_{ist}$. Column (1) refers to cross-sectional correlation of the two, $r = corr_i(\overline{z}_i, \overline{z}_i^w)$. "Between-good" refers to the weighted distribution of $\overline{z}_i^w$ with analytic weights taken as $W_i = \frac{Q_i^\psi \psi_i}{\sum_{i\in\mathscr{G}} Q_i^\psi \psi_i}$ with $\psi_i = \max_t \psi_{it}$. Synchronization rate of goods within a seller ("Seller") can be obtained in a straightforward way by interchanging indexes s and i. Column (8) refers to the total number of goods (sellers) available for the computation.

It is interesting to see if the pattern that emerges is similar to how synchronization would evolve over time if every period a seller was to change its price with an exogenously given probability *a la* Calvo. We calibrate such probability from our previous estimates of the frequency of price adjustment and compute synchronization rates at various horizons in the setting. As Figure 4 shows, Calvo model overshoots synchronization at longer horizons, implying heterogeneity of frequency of price adjustment across sellers.

Synchronization by category is broadly consistent with the result for all goods. Note that synchronization is higher in categories with shorter duration of price spells (see Figure 2.5).

In the previous analysis we talk about the frequency of price changes and synchronization as if sellers behave in a similar fashion with respect to price increases and decreases. It could be, however, that in a competitive environment sellers find it much easier to decrease the price than to increase it and more compelled to follow a fall in competitor's price rather than a rise. Hence, Table 2.12 presents a break-down of the results for price changes by the type (increase vs. decrease). Frequency and synchronization are slightly bigger for price decreases, however, the difference is not consequential, generally less

FIGURE 2.5. DURATION OF PRICE SPELLS VS. SYNCHRONIZATION RATE, BY CATEGORY



Notes: Horizontal axis: weighted (across goods) median implied duration of price spells with two-sided 1-week sales filter, in weeks. Vertical axis: weighted (across goods) median synchronization rate, %. Each dot represents the statistics within a given top-level category.

TABLE 2.12. FREQUENCY AND SYNCHRONIZATION BY TYPE OF PRICE ADJUSTMENT

	No weights			Between-good			
	Mean (1)	St.Dev. (2)	Median (3)	Mean (4)	St.Dev. (5)	Median (6)	N (7)
Panel A: USA							
Frequency of							
Price Changes	12.3	14.0	8.8	15.4	9.5	14.5	16,332
Price Increases	5.7	7.9	3.3	6.8	4.4	6.4	16,332
Price Decreases	6.6	9.1	3.7	8.6	6.1	7.7	16,332
Synchronization of							
Price Changes	10.2	18.6	0.0	15.7	10.0	15.1	9,937
Price Increases	5.4	14.4	0.0	6.6	5.5	6.3	8,281
Price Decreases	5.9	14.7	0.0	9.8	7.2	10.3	8,365
Panel B: UK							
Frequency of							
Price Changes	15.2	21.1	7.7	16.7	12.6	15.8	7,738
Price Increases	7.8	12.6	2.3	8.0	6.6	7.2	7,738
Price Decreases	7.4	11.6	1.7	8.7	7.2	8.1	7,738
Synchronization of							
Price Changes	14.7	24.8	0.0	17.9	11.1	17.9	3,867
Price Increases	8.7	19.2	0.0	8.3	7.1	8.1	3,122
Price Decreases	8.4	19.1	0.0	11.1	8.8	10.3	3,066

Notes: The table reproduces the results from Table 2.8 and Table 2.11 and gives the breakdown by type of price change.

than a percentage point.

Within Sellers Here we measure if a seller changes prices of many goods at once when changing at least one price. It is defined analogously to within-good synchronization. We omit laying down formulas as they can be obtained from those above in a straightforward way by interchanging indexes s and i.

The pattern is very similar here to the previous case. Conditional on one change, a seller is likely to change 17% of other price quotes. Within-seller weights do not matter much here (the correlation between weighted and raw series is 0.97), but sellers that obtain more clicks are likely to review larger share of their goods at once. The between-seller weighted synchronization reaches 23%.

2.3.5 Price Setting and Duration of Product Life

Previous literature provides some insights that many goods change their price during product substitution.[20] If this is the case, we are likely to observe a lot of goods with a short life and no price change. Since our data does not allow tracking product substitution, we rely on comparison between goods with a constant price throughout their life and the rest. Table 2.13 suggests that in the US only 12% of goods exhibit no price changes throughout their life. This is significantly lower than in the previous findings. Moreover, goods that never change their price account for only 1% of total clicks. Such discrepancy between the share in terms of number of goods and clicks could be due to

[20] See, for example, Nakamura and Steinsson (2012) or Cavallo, Neiman, and Rigobon (2012).

TABLE 2.13. GOODS WITH NO PRICE CHANGE

	$\max\lvert dp\rvert = 0$ (1)	$\max\lvert dp\rvert > 0$ (2)
Panel A: USA		
Share, %	11.9	88.1
Total Clicks Share, %	1.3	98.7
Average Clicks, per quote	1.5	1.7
Price Quotes, #	9.1	12.2
Sellers, #	1.3	5.1
Product Life, wks	36.2	57.2
not truncated	32.2	43.3
N	3,119	23,060
Panel B: UK		
Share, %	17.0	83.0
Total Clicks Share, %	3.3	96.7
Average Clicks, per quote	1.8	1.7
Price Quotes, #	8.7	10.8
Sellers, #	1.2	3.4
Product Life, wks	28.5	45.3
not truncated	26.0	35.7
N	2,467	12,005

Notes: The table compares goods with no changes in observed price for each seller, Column (1), with goods with at least one price change for a seller, Column (2). Only quote lines with at least five quotes are considered. "Share, %" reports the share of the number of goods for each group. "Total Clicks Share, %" represents the share of total number of clicks. "Average Clicks, per quote" shows the mean number of clicks a price quote receives in each group. "Price Quotes, #" reflects on the average number of price quotes observed for a seller in the group. "Sellers, #" shows the average number of sellers for a good in each group. "Duration, wks" reports product life duration in weeks as observed in the dataset, while "not truncated" only considers goods that enter the dataset from the fifth week on and exit before the fourth last week. "*N*" stands for the total number of goods in each category.

four factors: average number of clicks on a price quote, product life, number of quotes with a click, or a number of sellers. As the further break-down in the table shows all but the average number of clicks are important. Goods with at least one price change span over 57 weeks, have twelve price quotes, and five sellers as opposed to 36 weeks, nine quotes, and one seller for goods with no price changes.

As the dataset spans over a short period of time to consistently estimate entry, exit, and duration of life and in recognition that a lot of goods may potentially live longer than two years, we resolve to estimating the lower bound of the duration. To do this, we split the sample into goods with truncated entry and exit and those that are not. We consider an entry (exit) to be truncated if the good emerges in (disappears from) our sample within the first (last) five weeks. We then estimate the duration of not truncated goods and the lower bound of duration for all goods in the following way. Let s_c and s_{hc} be the share of truncated and half-truncated (from one side only) goods, $\overline{d}_{hc}$ and $\overline{d}_u$ be the mean life durations of such goods, and T be the total number of weeks observed in the data. The lower bound of life duration is then computed by simply taking the weighted mean across averages for the three types of goods:

$$\overline{d}_{l.b.} = s_c T + s_{hc}\overline{d}_{hc} + \left(1 - s_c - s_{hc}\right)\overline{d}_u$$

Table 2.14 presents the results. In the US, the average not truncated good lives around

TABLE 2.14. DURATION OF PRODUCT LIFE, WEEKS

	Truncated	Half-Truncated			Not Truncated				
Category, j	Share,% (1)	Share,% (2)	Mean (3)	St.Dev. (4)	Mean (5)	St.Dev. (6)	Median (7)	Mean l.b. (8)	N (9)
Panel A: USA									
Apparel and Accessories	0.1	42.1	51.8	22.0	26.3	21.9	24	37.1	2,645
Arts and Entertainment	0.4	48.9	54.0	22.7	26.5	22.9	23	40.2	2,873
Baby and Toddler	10.6	50.6	45.6	24.1	14.7	16.6	9	38.7	160
Business and Industrial	3.0	31.3	44.5	23.7	16.7	22.4	2	27.7	67
Cameras and Optics	7.7	48.6	54.8	26.1	29.3	23.7	26	46.5	978
Electronics	13.7	40.7	50.0	28.2	24.4	22.9	18	44.2	7,606
Food, Beverages and Tobacco	0.0	59.7	25.5	21.8	22.4	26.5	4	24.2	67
Furniture	8.1	52.4	53.6	25.4	29.4	24.9	30	47.2	334
Hardware	10.1	39.9	52.8	25.8	23.3	23.9	14	42.1	2,831
Health and Beauty	0.3	53.5	53.8	22.5	28.7	22.8	28	42.3	4,425
Home and Garden	8.5	47.7	48.0	25.9	25.4	22.8	21	41.9	5,150
Luggage and Bags	1.3	34.4	42.6	26.2	27.9	22.1	24	33.8	1,077
Mature	16.3	48.8	58.9	23.1	28.4	27.3	28	53.8	43
Media	11.3	31.4	57.3	27.4	25.2	26.3	15	42.9	14,370
Office Supplies	4.1	47.5	49.0	25.8	28.6	23.1	32	41.0	849
Pet Supplies	28.2	44.3	58.1	26.0	33.7	27.5	33	61.3	1,106
Services	11.5	34.6	55.6	31.5	26.3	22.6	28	44.1	26
Software	10.3	39.9	48.0	27.3	22.9	23.5	14	40.1	506
Sporting Goods	2.3	48.8	41.0	27.0	17.5	19.9	9	30.7	2,335
Toys and Games	12.5	46.5	52.9	24.7	26.9	24.1	21	47.2	2,777
Vehicles and Parts	7.0	42.4	50.0	25.2	25.4	23.9	19	40.5	575
Not Classified	5.5	44.5	43.9	23.9	22.5	21.2	17	35.9	1,976
All Goods	***8.5***	***41.5***	***51.7***	***26.2***	***25.3***	***24.1***	***19***	***42.1***	***52,776***
Panel B: UK									
Apparel and Accessories	0.0	32.1	40.3	24.4	16.3	18.8	7	24.0	2,761
Arts and Entertainment	0.3	32.1	36.7	25.7	13.1	17.9	1	20.9	2,945
Baby and Toddler	4.1	57.4	37.8	26.2	16.3	17.2	9	31.9	169
Business and Industrial	0.0	47.9	27.7	23.8	8.0	10.1	1	17.5	48
Cameras and Optics	5.1	37.8	41.0	24.8	16.4	18.1	10	29.6	978
Electronics	7.4	36.0	42.0	28.5	18.4	21.4	8	32.4	7,693
Food, Beverages and Tobacco	0.0	50.7	25.6	16.2	13.2	15.8	3	19.5	69
Furniture	0.3	43.5	26.4	21.6	13.5	18.2	5	19.4	338
Hardware	1.4	36.5	41.2	26.6	16.5	20.5	4	26.6	2,770
Health and Beauty	0.0	44.8	39.0	24.1	16.3	19.0	7	26.5	4,425
Home and Garden	1.0	33.8	34.7	26.5	13.2	18.0	3	21.3	5,311
Luggage and Bags	1.4	30.5	30.3	23.6	17.2	18.3	10	22.2	1,037
Mature	0.0	26.7	10.8	19.9	9.4	13.1	2	9.7	30
Media	0.1	18.9	41.6	27.1	14.5	20.0	1	19.8	14,197
Office Supplies	2.5	28.7	31.2	24.4	15.0	17.8	6	21.6	792
Pet Supplies	2.4	34.8	38.8	31.5	15.8	23.4	2	25.7	1,145
Services	8.0	24.0	41.4	26.8	13.8	19.3	2	26.7	50
Software	7.3	34.9	46.2	28.3	17.1	21.3	5	32.8	545
Sporting Goods	0.6	44.2	30.9	21.4	16.3	17.1	10	23.2	2,392
Toys and Games	0.7	31.8	39.1	25.8	19.3	21.9	9	26.1	3,179
Vehicles and Parts	0.8	30.2	32.4	23.1	11.2	15.3	1	18.3	620
Not Classified	0.3	35.3	27.6	22.4	13.2	16.8	4	18.6	1,273
All Goods	***1.7***	***31.5***	***38.3***	***26.3***	***15.5***	***19.7***	***4***	***24.0***	***52,767***

Notes: Column (1) reports the percentage of observations that are truncated both from the right and left. An observation is considered truncated if it appears (disappears) with the first (last) five weeks. Column (2) reports the percentage of observations truncated from either side, while Columns (3) and (4) report their mean and standard deviation of duration of life, respectively. Columns (5)-(7) show mean, standard deviation, and median duration of life for observations that are not truncated. Column (8) presents the lower bound of the mean life duration computed as $\overline{d}_{l.b.} = s_c T + s_{hc}\overline{d}_{hc} + (1 - s_c - s_{hc})\,\overline{d}_u$, where s_c and s_{hc} are the share of truncated and half-truncated goods, $\overline{d}_{hc}$ and $\overline{d}_u$ are mean life durations of half-truncated and not truncated goods, and T is the total number of weeks observed in the data. Column (9) refers to the total number of goods.

TABLE 2.15. PRICE STICKINESS BY DURATION OF PRODUCT LIFE

	No weights				Clicks-weighted				
	Frequency				Frequency				
	Mean	St.Dev.	Median	Duration	Mean	St.Dev.	Median	Duration	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: USA									
< 6 months	18.4	22.9	12.0	7.8	20.6	14.6	22.7	3.9	1,263
6–12 months	17.8	18.7	13.6	6.8	18.5	13.1	17.4	5.2	1,962
> 1 year	17.9	17.4	14.1	6.6	18.2	11.1	18.0	5.1	1,594
Panel B: UK									
< 6 months	22.6	29.1	11.1	8.5	17.0	21.4	7.1	13.5	989
6–12 months	20.7	25.5	12.1	7.7	21.3	16.6	22.0	4.0	914
> 1 year	19.8	21.6	13.0	7.2	22.1	13.5	23.3	3.8	461

Notes: The table reproduces results from Table 2.18 by duration of product life computed as in Table 2.14 based on observations that are not truncated.

25 weeks, and the lower bound of duration is 42 weeks. Note that only a quarter of goods in the dataset are not truncated, so actual duration could be much longer.

We finally compare frequency of price adjustment and duration of spells for goods that differ in their product life. We use only not truncated goods since product life is estimated more precisely for them and split the sample into goods that live less than six months, six months to a year, and more than a year. The results in Table 2.15 suggest that there is little difference in price adjustment once a good lives longer than six months. Goods that live less than that have a median duration of spells one-week longer, though the difference changes once clicks are taken into account.

2.4 Prices and Clicks in Cross Section

In this section we examine if the distribution of prices for goods that are actively traded online is different from that for the prices that do not receive many clicks. Since prices vary across goods, sellers, and time, we examine the role of each of these dimensions. First, we consider cross-sectional variation across goods by taking the raw and clicks-weighted averages across sellers and time. Second, we consider time-series of cross-seller variation by zooming in on prices of a specific good that gets a lot of clicks. Then we average over goods and examine pure time-series properties of prices. Third, we examine potential time dependence in price setting. We conclude the section by looking at the relation between clicks and price dispersion.

2.4.1 Distribution across Goods

To examine cross-sectional variation of prices, we aggregate them at the good level. For each good on a given date, we compute raw and weighted mean price over sellers. Then for each good we take the average over time. We report the distribution of raw and weighted means across goods, in addition, applying between-good weights for the latter distribution.

To be more specific, the mean price is computed as

$$\overline{p}_i^{mean} = \frac{1}{T_i} \sum_t \frac{1}{S_{it}} \sum_{s \in \mathscr{S}_{it}} p_{ist} \tag{2.5}$$

while the weighted mean price is

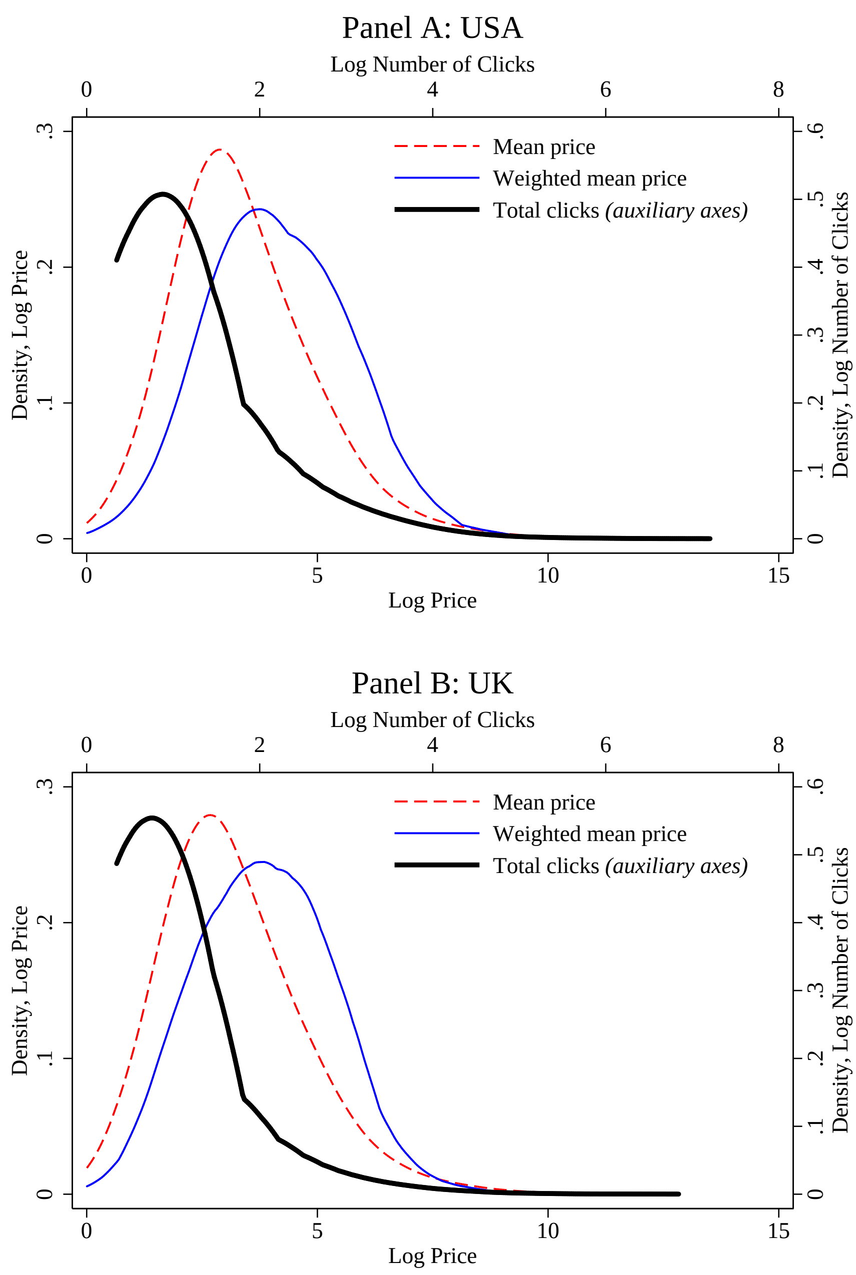
$$\overline{p}_i^{wms} = \frac{1}{T_i} \sum_{s \in \mathscr{S}_{it},\ t} \frac{q_{ist}}{Q_{it}} p_{ist} \tag{2.6}$$

with $W_i = \frac{Q_i}{Q}$ used as weights. In addition, we report the average log number of clicks computed as

$$\overline{\log Q_i} = \frac{1}{T_i} \sum_t \log \left(\sum_{s \in \mathscr{S}_{it}} q_{ist} \right)$$

Figure 2.6 reports the corresponding distributions. First, the distribution of prices for goods that get a lot of clicks is very different. It is more dispersed and the average price is higher due to the composition effect. Second, we observe a fat right tail in the distribution. As for the number of clicks, there is huge mass at zero cut from the graph to enhance visibility. Most of the goods get only a few clicks on average, but there are a small number of goods that get a disproportionately big number of clicks (fat right tail).

FIGURE 2.6. THE DISTRIBUTION OF LOG PRICES AND THE NUMBER OF CLICKS ACROSS GOODS



Notes: "Mean price" is the average price of goods for all sellers, $\overline{p}_i^{mean} = \frac{1}{T_i}\sum_t \frac{1}{S_{it}}\sum_{s\in\mathscr{S}_{it}} p_{ist}$, "Weighted mean price" refers to the weighted average with weights across sellers, $\overline{p}_i^{wms} = \frac{1}{T_i}\sum_{s\in\mathscr{S}_{it},\ t} \frac{q_{ist}}{Q_{it}} p_{ist}$, with additional cross-good weights $W_i = \frac{Q_i}{Q}$. "Total clicks" stands for the average (across time) log number of total (across sellers) clicks measured as $\overline{\log Q_i} = \frac{1}{T_i}\sum_t \log\left(\sum_{s\in\mathscr{S}_{it}} q_{ist}\right)$. To enhance visibility we show only goods that get more than one click in median.

2.4.2 Price Dispersion across Sellers

We start by documenting the amount of price dispersion in the data. There is no unique measure of price dispersion as thoroughly discussed in Baye, Morgan, and Scholten (2010). Since it is very important for us to distinguish between price dispersion that occurs around the minimum price from that at the upper percentiles of the distribution, we use five different measures that in our view complement each other rather than substitute. The two of them, *the coefficient of variation* (CV) and "*the range*", capture the whole spectrum of prices for a given good. The former is computed as $CV = \widehat{\sigma}_p/\overline{p}$, where $\widehat{\sigma}_p$ stands for sample standard deviation of prices for good i at time t, and $\overline{p}$ is the average price, while the latter is simply the log difference between the biggest and the smallest prices, $Range = \log p^{max} - \log p^{min}$. The other two, "*the gap*" and *the value of information* (VI), instead capture the price dispersion at the left tail. The gap represents the log difference between the two smallest prices[21] and the value of information is the log difference between the average and minimum prices, $VI = \log \overline{p} \; - \log p^{min}$. The latter can be interpreted as a maximum mark-up a risk-neutral consumer would be willing to pay to obtain information on the seller with the best price versus buying from a seller picked at random (Varian 1980). As measures based either on the whole spectrum of prices or on minimum prices are sensitive to extreme values, we also find it useful to compute *the interquartile range* (IQR), $IQR = \log p^{p75} - \log p^{p25}$, as a measure of price dispersion around the median price.

Table 2.16 documents the amount of price dispersion based on each measure by category of goods. Strikingly enough, the average gap between the smallest two prices constitute 28 log points, while the range is 41 log points. Together with the fact that, on average, the value of information is smaller than the gap, it suggests that there is more mass in the left tail than in the right one.

The previous result comes as no surprise. In the model of "loyals" and "shoppers" sellers have an opportunity to jack up profits if they can segment the market into bargain-hunters, who look for the smallest price, and customers with strong brand preferences (Baye and Morgan 2009, Morgan, Orzen, and Sefton 2006). Ideally, a seller wants to offer the lowest price for the first group and the reservation price for the second.[22] If each seller can post only one price, then the most efficient one will target shoppers, while every other seller acts as a monopolist to extract premium from loyals.

We then look if price dispersion mainly occurs at the good's introduction or develops over time, and if with the certain amount of time passed it disappears. The latter would be the case if price dispersion is due to incomplete nominal adjustment and informational frictions on the seller's side, e.g. a seller cannot perfectly monitor competitors' prices.

[21] See Baye, Morgan, and Scholten (2004) for further discussion.

[22] Or, alternatively, if consumers face ex ante different information sets, like in Varian (1980), i.e. some consumers are "informed" about the price distribution while others are "uninformed" and purchase from a seller at random, and firms are heterogeneous in marginal costs, then the most efficient firm will be charging at the marginal costs of the most efficient competitor to attract informed customers, while every other firm will charge the monopoly price to extract the whole surplus from uninformed customers in their markets.

TABLE 2.16. AVERAGE PRICE DISPERSION, BY CATEGORY

	No weights					Clicks-weighted					
Measure	CV (1)	Gap (2)	VI (3)	IQR (4)	Range (5)	CV (6)	Gap (7)	VI (8)	IQR (9)	Range (10)	*N* (11)
Panel A: USA											
Apparel and Accessories	15.6	17.8	15.3	23.4	27.9	16.5	15.3	18.8	23.8	34.8	1,599
Arts and Entertainment	18.8	23.4	20.3	29.9	34.3	17.3	19.2	21.2	25.8	36.1	1,718
Baby and Toddler	15.6	19.2	17.6	23.6	30.7	16.1	14.3	22.4	20.8	41.3	88
Business and Industrial	18.5	18.1	19.2	29.5	34.4	18.8	19.2	22.6	29.1	39.2	29
Cameras and Optics	13.2	17.7	15.9	21.0	26.4	13.1	12.3	24.2	15.9	45.1	631
Electronics	20.6	26.0	24.3	32.9	40.9	19.2	18.8	31.4	27.1	54.1	4,581
Food, Beverages and Tobacco	28.4	36.9	31.5	48.1	51.7	26.6	31.8	27.3	43.2	47.0	35
Furniture	15.2	15.9	16.3	22.7	29.7	15.7	12.7	20.2	22.0	37.6	232
Hardware	20.5	25.2	22.6	32.5	38.7	20.8	21.9	26.0	30.7	45.7	1,475
Health and Beauty	17.1	20.4	18.1	26.3	31.9	19.5	18.0	23.9	27.7	43.9	2,920
Home and Garden	18.7	21.5	19.4	28.3	34.5	19.1	17.0	24.1	26.1	44.4	3,016
Luggage and Bags	17.3	21.8	18.0	27.3	31.2	17.2	17.8	21.1	26.0	37.4	526
Mature	22.0	28.7	26.7	35.6	45.1	19.6	19.3	24.1	28.2	45.3	36
Media	29.6	41.9	36.1	50.4	57.0	33.4	41.1	46.2	50.4	76.3	7,016
Office Supplies	22.8	28.6	26.1	36.6	43.9	25.3	26.5	33.9	36.2	58.8	515
Pet Supplies	21.9	25.1	22.9	33.8	40.6	21.5	20.4	25.0	30.5	46.0	843
Services	10.1	8.6	8.6	15.4	17.9	12.6	8.1	11.4	18.1	25.1	14
Software	18.8	24.6	21.3	30.6	35.3	16.1	16.3	26.9	23.6	45.8	263
Sporting Goods	16.0	19.1	16.6	24.5	29.5	16.4	14.8	19.9	23.2	37.3	1,014
Toys and Games	20.7	27.6	23.5	33.5	39.1	21.8	28.8	32.3	33.5	51.8	1,814
Vehicles and Parts	20.4	23.0	21.9	31.5	38.6	21.1	20.7	27.5	30.4	47.5	328
Not Classified	20.9	26.2	22.3	33.6	38.0	21.4	22.0	24.8	32.6	43.8	1,058
All Goods	***21.5***	***27.6***	***24.4***	***34.6***	***40.7***	***20.5***	***21.1***	***28.7***	***29.4***	***50.1***	***29,751***
Panel B: UK											
Apparel and Accessories	15.9	20.4	15.1	25.0	27.0	15.8	19.3	16.4	25.0	29.2	991
Arts and Entertainment	17.7	23.6	16.5	27.4	28.7	15.2	18.8	14.8	22.7	26.1	779
Baby and Toddler	17.5	20.7	18.6	26.2	33.0	18.4	18.9	21.2	26.5	38.8	90
Business and Industrial	26.1	35.8	24.2	39.5	42.5	24.5	29.9	24.5	36.1	44.7	12
Cameras and Optics	17.4	22.7	17.6	27.1	30.6	14.4	15.1	16.9	20.8	31.2	387
Electronics	18.7	24.8	20.2	29.8	34.4	17.8	20.1	24.5	26.3	41.9	3,320
Food, Beverages and Tobacco	19.9	25.4	18.4	30.5	32.9	17.4	16.8	17.5	26.2	33.7	24
Furniture	19.7	26.5	18.8	29.9	33.0	16.3	15.8	17.0	21.8	34.3	78
Hardware	21.1	27.3	21.0	33.1	36.4	19.6	22.6	21.2	30.0	37.8	771
Health and Beauty	16.5	22.7	16.8	26.4	28.6	24.0	17.5	23.2	27.3	46.6	2,003
Home and Garden	24.9	34.8	25.5	39.8	42.6	22.6	36.9	38.8	33.6	59.6	1,192
Luggage and Bags	19.1	25.6	17.2	29.2	30.6	19.0	22.9	18.0	28.7	32.9	334
Mature	50.7	73.0	55.8	90.9	90.9	50.7	73.0	55.8	90.9	90.9	1
Media	20.3	29.8	23.7	34.7	38.1	21.4	29.4	27.2	34.0	45.0	4,488
Office Supplies	31.6	43.7	32.4	50.6	53.7	30.8	44.9	37.0	49.2	59.3	191
Pet Supplies	34.0	48.4	33.5	52.7	55.3	34.9	44.3	35.3	53.2	59.2	232
Services	14.2	14.4	14.7	21.6	26.5	17.6	13.0	17.6	27.8	33.2	19
Software	12.5	14.9	12.2	18.8	22.5	12.5	9.6	18.0	15.6	36.4	201
Sporting Goods	14.3	18.8	13.2	21.7	23.6	14.4	16.1	15.0	21.5	27.2	957
Toys and Games	20.8	28.6	20.9	33.1	35.1	20.9	27.2	23.6	33.0	39.3	1,158
Vehicles and Parts	22.8	30.0	21.9	35.7	38.0	20.5	25.3	20.1	31.5	35.3	133
Not Classified	20.7	28.7	20.6	32.2	35.1	19.8	23.4	22.2	30.1	38.4	354
All Goods	***19.4***	***26.7***	***20.4***	***31.3***	***34.3***	***19.5***	***23.0***	***24.1***	***28.5***	***41.8***	***17,715***

Notes: Columns (1)-(5) report mean over time and goods of five measures of price dispersion. $CV = \widehat{\sigma}_p/\overline{p}$ is the coefficient of variation, where $\widehat{\sigma}_p$ stands for sample standard deviation of prices for good i at time t, and $\overline{p}$ is the average price. Gap is the log-difference between the two smallest prices, $VI = \log \overline{p} - \log p^{min}$ is the value of information, $Range = \log p^{max} - \log p^{min}$ is the range of prices, and $IQR = \log p^{p75} - \log p^{p25}$ is the interquartile range measured as the log-difference between 75^{th} and 25^{th} percentile of price distribution across sellers for a given good at a given date. Columns (6)-(10) report clicks-weighted mean across goods. Column (11) reports the number of goods.

The price dispersion does not disappear if it is due to frictions on consumers' side as described above. Figure 2.7 clearly shows that, if anything, price dispersion rises with the time since the good was introduced. This can be due to a composition effect, for example, which does not take away from the conclusion that price convergence in online markets should be strongly rejected.

Another question we look at is whether price dispersion is "spatial" or "temporal" as distinguished by Varian (1980). The former implies that firms that charge low (high) prices do so persistently. This finding is consistent with Reinganum (1979), MacMinn (1980), or Spulber (1995) models, but is critiqued by Varian, who argues that over time consumers learn if a firm is high- or low-price, which should eliminate price dispersion. Temporal price dispersion, which means a seller can charge different prices each period but takes on any possible place in price distribution, also arises in Burdett and Judd (1983) model.[23] Temporal price dispersion is empirically supported by Lach (2002) who uses data on month-to-month store level data.

To tackle this question we calculate how likely it is for a seller that charges a price in the lowest quartile to charge a price in the highest quartile at some point in the future, and vice versa. Spatial price dispersion implies that sellers never jump from the lowest to the highest quartile or in the opposite direction. Temporal price dispersion implies that either of the extreme pricing episodes is equally likely. Figure 2.8 clearly favors spatial price dispersion to temporal one.

So, what explains the differences in price dispersion? We suspect that the number of clicks, sellers, and the level of price can all contribute to the differences in price dispersion.

There are a few reasons to believe goods that obtain more clicks exhibit higher degree of price dispersion. First, bigger markets create more opportunities for price discrimination, which implies positive relationship between clicks and price dispersion. Second, bigger markets imply higher return on precision of the demand elasticity estimates and, thus, firms are more likely to resort to price experimentation (Baye et al. 2007). The two channels are akin to spatial and temporal price dispersion.

The number of sellers is a proxy for market competitiveness. A more competitive market may imply a reduction in market power and, as a result, price convergence. On the other hand, more sellers can segment the market more efficiently and build a bigger number of loyal-customer groups, which increases price dispersion.

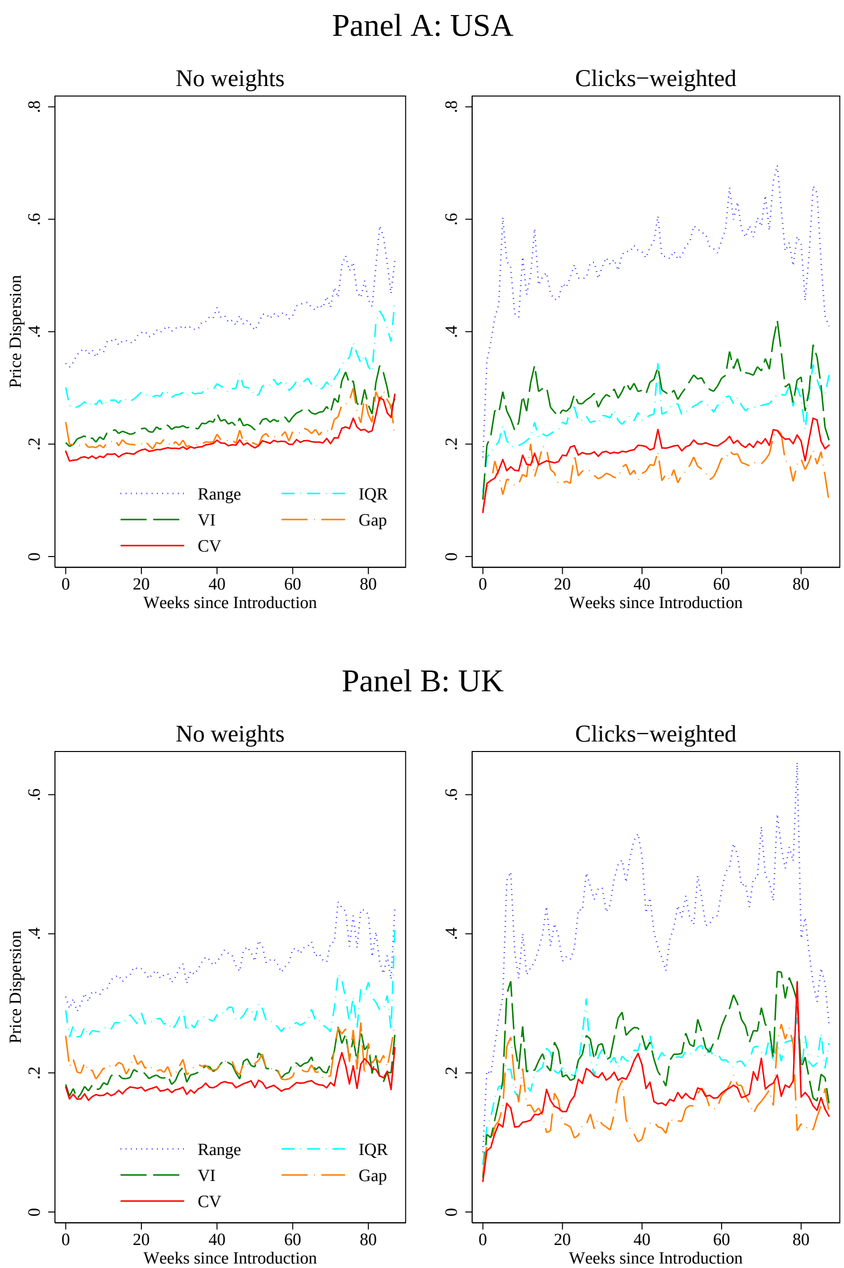
Finally, more expensive goods usually represent larger share in consumer's budget, which increases returns on search. This effect should tighten the price distribution.

Let $\widetilde{\sigma}_{it}$ be a measure of price dispersion, Q_{it} be the total (over sellers) number of clicks good i receives in period t, S_{it} be the number of sellers, and $\overline{p}_{it}$ be the average price over sellers. We estimate the following specification.

$$\widetilde{\sigma}_{it} = c + \alpha_i + \beta_t + \gamma_1 \log Q_{it} + \gamma_2 \log S_{it} + \gamma_3 \log \overline{p}_{it} + \varepsilon_{it} \tag{2.7}$$

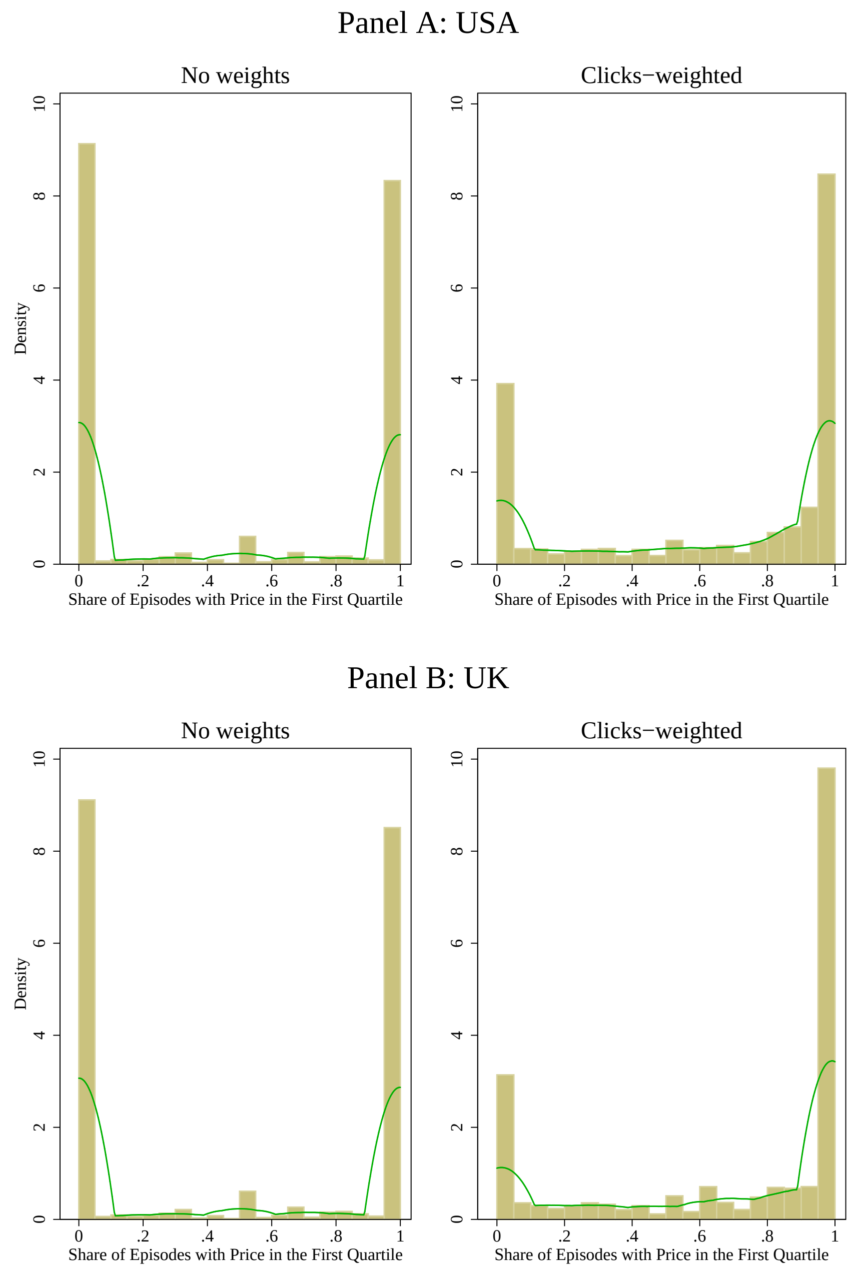
[23] See Baye, Morgan, and Scholten (2010) for a comprehensive overview of search models that generate price dispersion.

FIGURE 2.7. PRICE DISPERSION SINCE PRODUCT INTRODUCTION



Notes: The figure reports raw and clicks-weighted means over goods of five measures of price dispersion by the time passed since the good introduction. Goods introduced during the first five weeks are cut off to account for truncated observations. The measures of price dispersion are defined as in Table 2.17.

FIGURE 2.8. SHARE OF EPISODES WITH PRICE IN THE FIRST OR FOURTH QUARTILE



Notes: The figure reports the share of episodes when a price offered by seller s of good i is in the first quartile of the cross-seller price distribution in the number of episodes when a price is either in the first or fourth quartile. Episodes when the price is within the interquartile range are omitted. Spatial price dispersion implies that the share should be either zero or one, while temporal price dispersion suggests a peak at 0.5.

Columns (1)-(5) of Table 2.17 report the estimates for each of the measures of price dispersion. In accordance with our priors, the number of clicks and the average price have positive and significant effect on each measure. As we discussed before, the number of sellers can have two opposite effects. For the measures that capture the whole distribution, such as the coefficient of variation or the range, the market segmentation effect dominates and price dispersion increases with an additional seller. However, for the gap, which captures the amount of price competition in the segment of shoppers, the competition effect dominates and price dispersion falls with more sellers.

In addition, we test for σ-convergence in online markets more formally. If the convergence is the case in online markets, we would expect price dispersion follow an AR(1) process with coefficient smaller than 1. We estimate the specification

$$\widetilde{\sigma}_{i,t} = c + \alpha_i + \beta\widetilde{\sigma}_{i,t-1} + \varepsilon_{i,t}$$

and formally test the convergence hypothesis of $\beta < 1$. We can see from Columns (6)-(7) in Table 2.17 that unity is outside of the 95-percent confidence interval displaying a strong sign of σ-convergence in prices over time.

TABLE 2.17. DETERMINANTS OF PRICE DISPERSION AND σ-CONVERGENCE

	Regression					AR(1)	
Measure	$\log Q_{it}$ (1)	$\log S_{it}$ (2)	$\log \bar{p}_{it}$ (3)	R^2 (4)	Obs. (5)	Lag (6)	Obs. (7)
Panel A: USA							
CV	0.019***	0.017***	0.188***	0.49	460,369	0.086***	293,529
	(0.001)	(0.002)	(0.014)			(0.012)	
Gap	0.032***	−0.128***	0.113***	0.37		0.274***	293,529
	(0.002)	(0.004)	(0.017)			(0.022)	
VI	0.033***	0.121***	0.213***	0.45		0.326***	293,529
	(0.002)	(0.005)	(0.024)			(0.024)	
Range	0.048***	0.244***	0.357***	0.50		0.234***	293,529
	(0.003)	(0.006)	(0.034)			(0.017)	
IQR	0.032***	−0.041***	0.272***	0.44		0.130***	293,529
	(0.002)	(0.003)	(0.025)			(0.016)	
Panel B: UK							
CV	0.024***	0.003	0.198***	0.54	147,300	0.194***	83,419
	(0.001)	(0.002)	(0.030)			(0.021)	
Gap	0.036***	−0.116***	0.112*	0.46		0.312***	83,419
	(0.003)	(0.006)	(0.058)			(0.061)	
VI	0.039***	0.079***	0.252***	0.46		0.360***	83,419
	(0.003)	(0.008)	(0.086)			(0.057)	
Range	0.057***	0.173***	0.399***	0.51		0.298***	83,419
	(0.004)	(0.009)	(0.101)			(0.044)	
IQR	0.040***	−0.042***	0.328***	0.50		0.171***	83,419
	(0.004)	(0.007)	(0.088)			(0.042)	

Notes: Columns (1)-(3) report coefficients from multivariate regressions of five measures of price dispersion (rows) on log number of clicks, log number of sellers, and log mean price. Columns (4) and (5) report R^2 and the number of observations from those regressions. Good and time fixed effects are included. Standard errors (in parentheses) are clustered by time. Columns (6) and (7) report the coefficient and number of observations from the panel AR(1) regression with first lag of price dispersion instrumented by the second lag to account for potential measurement error. $CV = \widehat{\sigma}_p/\overline{p}$ is the coefficient of variation, where $\widehat{\sigma}_p$ stands for sample standard deviation of prices for good i at time t, and $\overline{p}$ is the average price. Gap is the log-difference between the two smallest prices, $VI = \log\overline{p} - \log p^{min}$ is the value of information, $Range = \log p^{max} - \log p^{min}$ is the range of prices, and $IQR = \log p^{p75} - \log p^{p25}$ is the interquartile range measured as the log-difference between 75^{th} and 25^{th} percentile of price distribution across sellers for a given good at a given date. *, **, and *** represent 10%, 5%, and 1% significance level, respectively.

2.5 Price Adjustment over Time

2.5.1 Price Setting Patterns around Sales Seasons

To see how a price of a good evolves over time, Figure 2.9 depicts time-series variation of price for a good with the biggest number of clicks. The good picked belongs to the category "Headphones", which is no surprise as goods in "Electronics" category seem to better suit online trade. The figure reports mean price over sellers for a given date, $\overline{p}_{\tilde{\imath}t}^{mean} = \frac{1}{S_{\tilde{\imath}t}} \sum_{s \in \mathscr{S}_{\tilde{\imath}t}} p_{\tilde{\imath}st}$, clicks-weighted mean price, $\overline{p}_{\tilde{\imath}t}^{wms} = \sum_{s \in \mathscr{S}_{\tilde{\imath}t}} \frac{q_{\tilde{\imath}st}}{Q_{\tilde{\imath}t}} p_{\tilde{\imath}st}$, the minimum price over sellers, $\overline{p}_{\tilde{\imath}t}^{min} = \min_{s \in \mathscr{S}_{\tilde{\imath}t}} p_{\tilde{\imath}st}$, and the log total number of clicks, $\log Q_{\tilde{\imath}t} = \log(\sum_{s \in \mathscr{S}_{\tilde{\imath}t}} q_{\tilde{\imath}st})$.

The minimum price line lies significantly below the other ones indicating that the good has multiple sellers and significant price dispersion. The clicks-weighted line lies in between the minimum and the mean prices. It indicates that sellers with minimum prices obtain more clicks than other sellers. We argue that clicks-weighted price is the best price quote because it takes into account consumers swing toward best prices (something that the mean price does not) and, at the same time, it accounts for other popular sellers that get clicks because of their reputation, promotions, etc. (which is not picked by the minimum price alone). Hence, in our data clicks-weighted index is the closest analog to the CPI in the offline world.

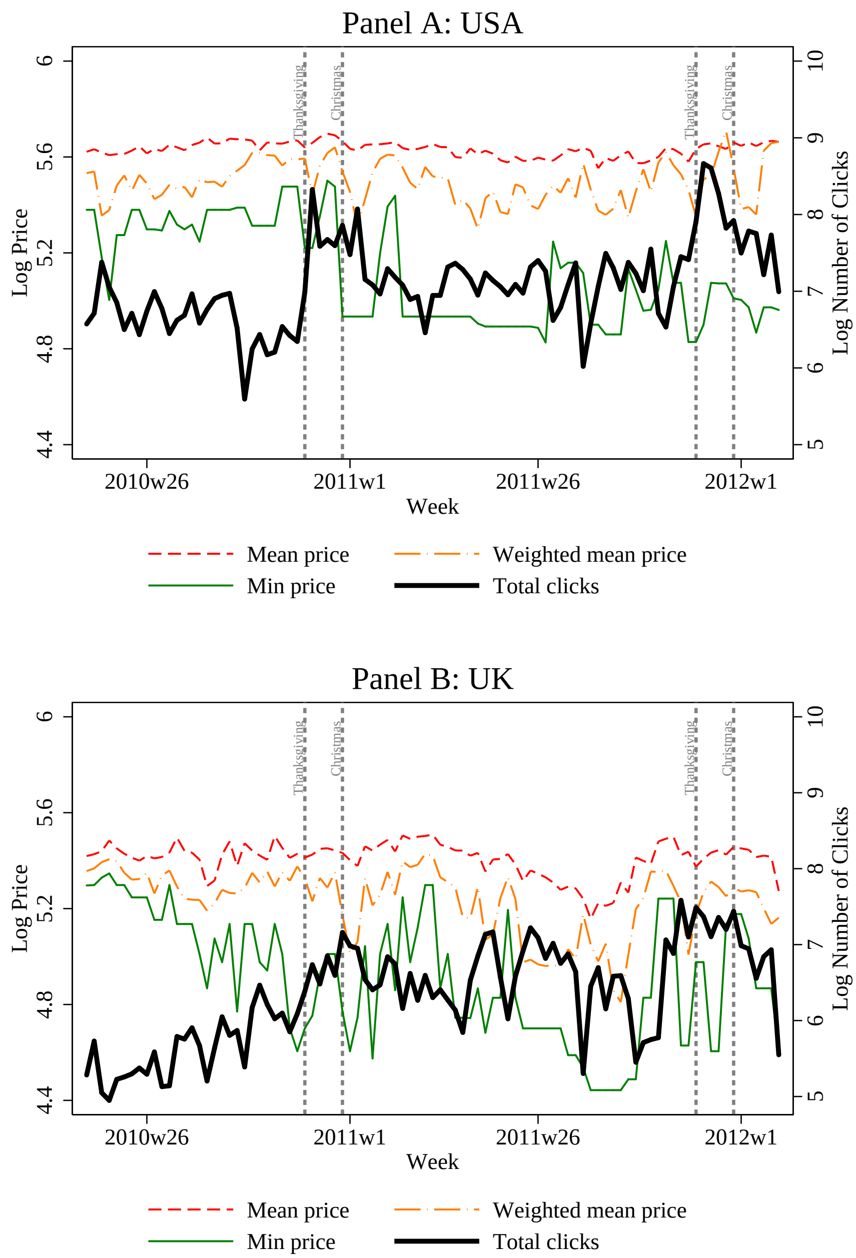
For the US data the mean price does not show Thanksgiving and Christmas sales, but the clicks-weighted one does. Both in 2010 and 2011 clicks are going up while prices are going down during the holiday sales. We observe a similar pattern in the UK. Although the UK does not celebrate Thanksgiving, the late November is usually the time when people start Christmas shopping. After sales prices do not go back exactly to their presale level but rather settle somewhere below it. More research needs to be done, but this fact can be an indication that sellers use shopping seasons to permanently reset prices.

This picture also highlights some peculiarities of sales in online markets. In the US the minimum price drops after Christmas then spikes for a week and then goes back to its lower level. A possible explanation is that a seller that offers the best price runs out of stock quickly, does not offer the good online for a week replenishing the stock, and then comes back with the original price. This is consistent with Warner and Barsky (1995) who find that sellers tend to time their price mark-downs during periods of high-intensity demand.

The findings above are true for one particular good that belongs to the narrow category "Headphones". However, this pattern is similar for many goods that are actively traded online. We aggregate over all goods in our sample to see if the difference between the raw and weighted means would persist there. Note that since most of the goods do not have a lot of within variation, mean, cross-seller weighted mean, and minimum prices are similar, something that is not true for goods with many clicks. Hence, it is reasonable to compare raw and cross-good weighted means only.

The exact computation works in the following way. "Mean price" is the average price for all goods and sellers, $\overline{p}_{t}^{mean} = \frac{1}{N_t} \sum_{i \in \mathscr{G}_t} \frac{1}{S_{it}} \sum_{s \in \mathscr{S}_{it}} p_{ist}$, "Weighted mean price" refers

FIGURE 2.9. TIME-SERIES OF LOG PRICE OF A GOOD: "HEADPHONES"



Notes: This graph is for the good with the biggest number of clicks. Such a good belongs to the category "Headphones" and is indexed by $\tilde{\imath}$. "Min" refers to the good's minimum price across sellers, $\overline{p}_{\tilde{\imath}t}^{min} = \min_{s\in\mathscr{S}_{\tilde{\imath}t}} p_{\tilde{\imath}st}$, "Mean" is the average price for all sellers, $\overline{p}_{\tilde{\imath}t}^{mean} = \frac{1}{S_{\tilde{\imath}t}} \sum_{s\in\mathscr{S}_{\tilde{\imath}t}} p_{\tilde{\imath}st}$, and "Weighted mean" refers to the weighted average with weights across sellers, $\overline{p}_{\tilde{\imath}t}^{wms} = \sum_{s\in\mathscr{S}_{\tilde{\imath}t}} \frac{q_{\tilde{\imath}st}}{Q_{\tilde{\imath}t}} p_{\tilde{\imath}st}$. "Total clicks" stands for the log number of clicks measured as $\log Q_{\tilde{\imath}t} = \log(\sum_{s\in\mathscr{S}_{\tilde{\imath}t}} q_{\tilde{\imath}st})$.

to the weighted average across sellers and goods, $\overline{p}_t^{wmg} = \sum_{i\in\mathscr{G}_t,\, s\in\mathscr{S}_{it}} \frac{q_{ist}}{Q_t} p_{ist}$, and "Total clicks" stands for the average (across goods) log number of total (across sellers) clicks measured as $\overline{\log Q_t} = \frac{1}{N_t}\sum_{i\in\mathscr{G}_t} \log(\sum_{s\in\mathscr{S}_{it}} q_{ist})$.

We observe more variation in the weighted average price than in the raw average price. The former captures conventional sales periods better and exhibits higher correlation with the number of clicks, which generally confirms our previous findings.

We also look at variation of frequency of price adjustment by type, the fraction of goods with a price change, and the absolute value of price changes over time. All three variables vary a lot over time. Although the frequency and the fraction jump up around the sales seasons, they tend to go down right before with the following jump simply offsetting the previous fall. We conclude that there although many price changes are timed for the sales seasons, the effect comes at the expense of relative inattention in the preceding periods.

We also look at the series for price dispersion over time and note there is consistent changes in price dispersion around the sales seasons. Moreover, except for the range between the maximum and minimum prices, other measures of price dispersion do not appear to fluctuate much.

Figure 2.10 shows that firms that offer better prices do so consistently. The same argument is true for firms with prices in the top quartile. This evidence is against the (S,s)-pricing mechanism implied by models with fixed menu costs.

2.5.2 Within-Week and -Month Variation

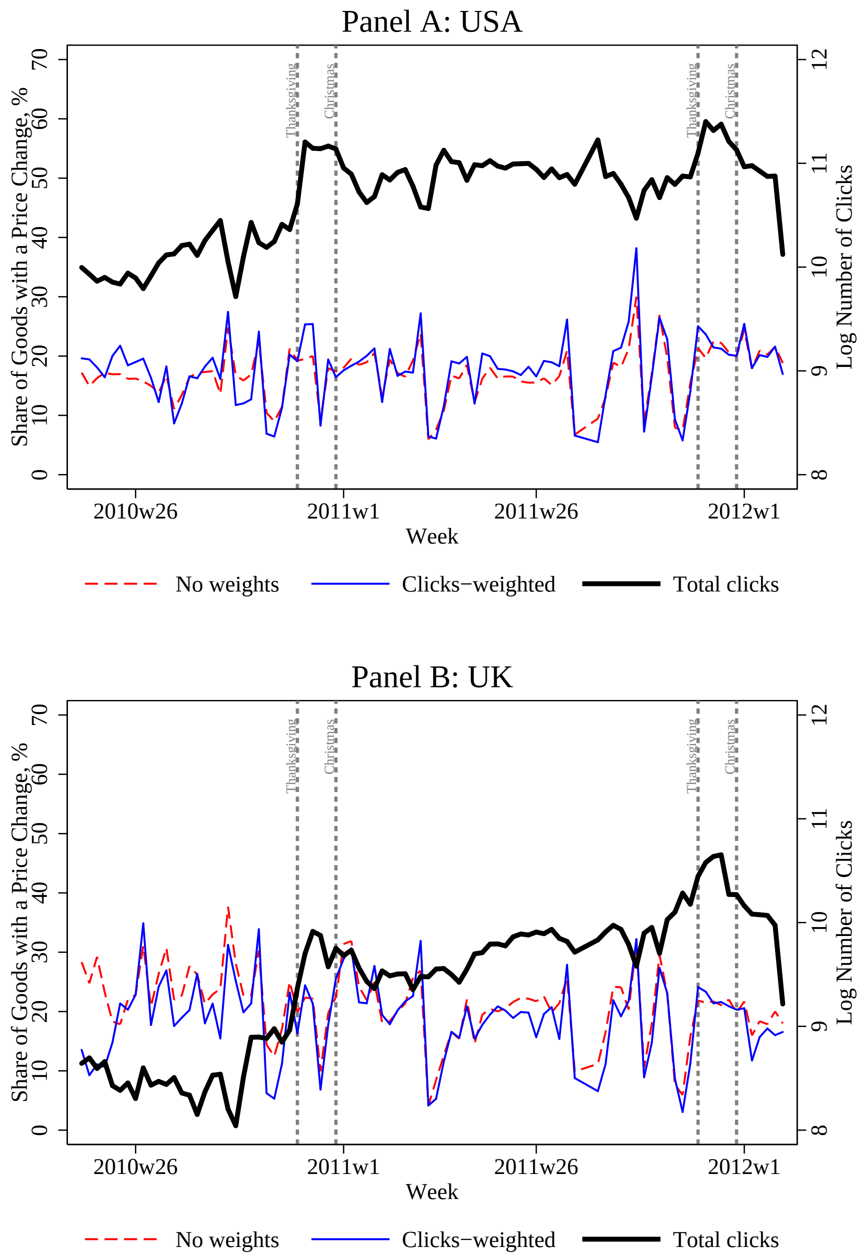
It is an important question if firms are more likely to adjust their prices on specific days, as well as if people shop more on certain days, which would make firms more attentive to changes in fundamentals, hence changing their price in the aftermath.

An example could be that people are more likely to shop at the beginning of the month when they receive a paycheck (and in the middle of the month if they are paid biweekly). At the same time, they might prefer to make bigger spending in certain months (in January if they receive annual bonuses like a thirteenth salary, or in April-May after filing or receiving a tax return, etc.) Firms might want to review their prices due to these spikes in consumer activity (as in Warner and Barsky 1995) or various management practices honored by firms (reviewing subset of prices at the beginning of the month or the full set of prices at the beginning of the year, etc.)

The macroeconomic implication of such time dependence is that prices are more flexible in some parts of the year (or month) than in others. According to Olivei and Tenreyro (2007), the effect of monetary policy shocks on output depends on the timing of the shock due to uneven staggering of wage contracts across quarters. Shocks that occur in the first two quarters of the year are more likely to have sizeable and persistent effect on output. Such time dependence may, in principle, be also due to producers adjusting their prices on specific dates.

Such findings can give rise to the idea of time-dependent monetary policy, i.e. introducing policy innovations when prices or wages are likely to be stickier. Of course,

FIGURE 2.10. FREQUENCY OF PRICE ADJUSTMENT OVER TIME



Notes: The figure reports time-series for the frequency of price adjustment defined as in Table 2.8 and the log number of total clicks.

TABLE 2.18. CLICKS SHARE AND LOG PRICE, BY DAY OF THE WEEK

	Clicks	Log Price	
Week Day	Share, %	Mean	Weighted Mean
	(1)	(2)	(3)
Panel A: USA			
Monday	16.4	3.76	4.15
Tuesday	15.6	3.77	4.15
Wednesday	14.7	3.78	4.14
Thursday	14.2	3.78	4.16
Friday	13.3	3.79	4.18
Saturday	12.1	3.74	4.15
Sunday	13.8	3.72	4.14
All Days	***100***	***3.76***	***4.15***
Panel B: UK			
Monday	16.2	3.57	3.82
Tuesday	15.8	3.58	3.84
Wednesday	14.9	3.59	3.84
Thursday	14.7	3.60	3.85
Friday	13.0	3.62	3.87
Saturday	11.8	3.56	3.83
Sunday	13.6	3.53	3.80
All Days	***100***	***3.58***	***3.83***

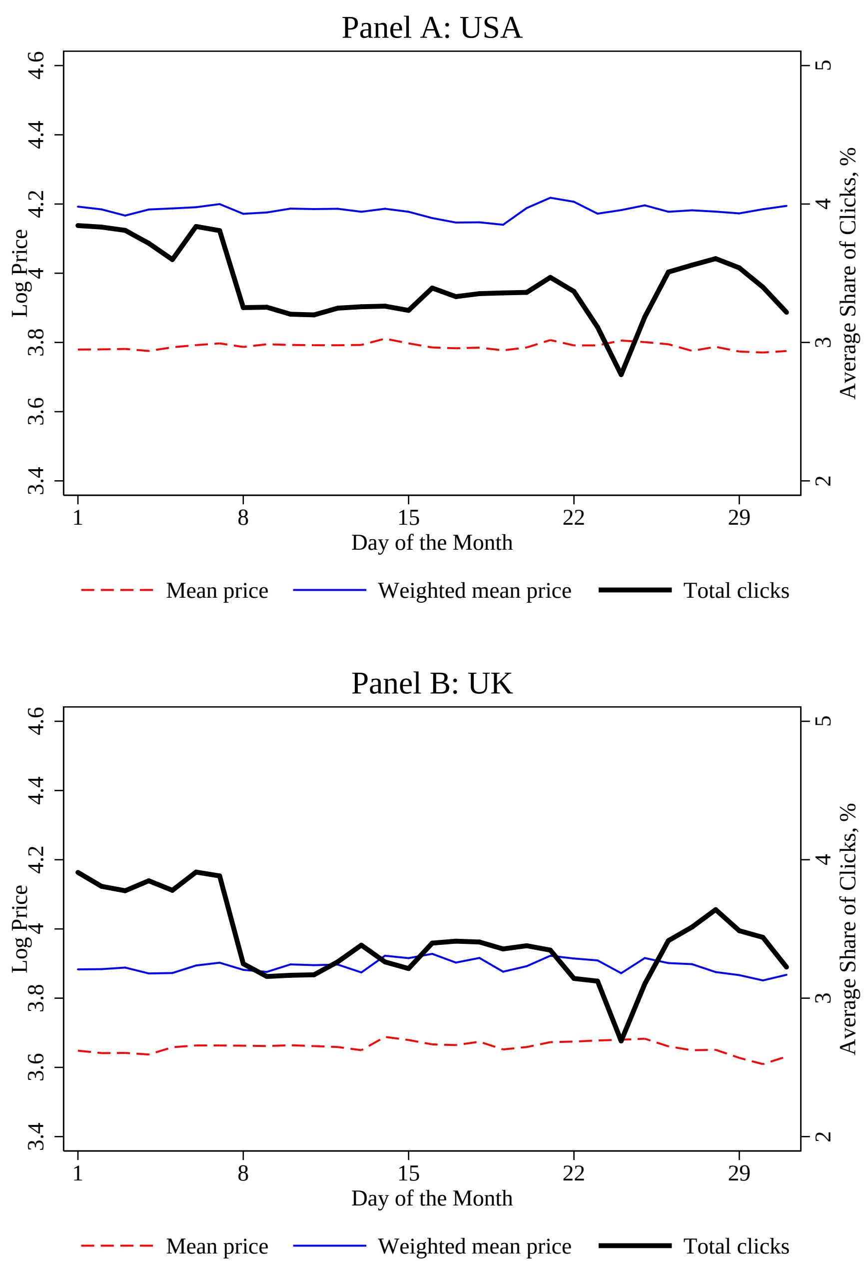
Notes: Column (1) reports the clicks share by day of the week, d, computed as $\frac{Q_d}{Q}$, where $Q_d = \sum_{i,s,t\in\mathscr{T}_d} q_{ist}$ with $\mathscr{T}_d$ being the set of days that fall on a given day of the week. Column (2) reports the average (across goods, sellers, and time) price, $\overline{p}_d^{mean} = \frac{1}{\#_{i,t\in\mathscr{T}_d}} \sum_{i,t\in\mathscr{T}_d} \frac{1}{S_{it}} \sum_s p_{ist}$. Column (3) reports weighted (across sellers and goods) average price, $\overline{p}_d^{wmg} = \frac{1}{\#_{t\in\mathscr{T}_d}} \sum_{i,s,t\in\mathscr{T}_d} \frac{Q_{ist}}{Q_t} p_{ist}$.

this recommendation would raise time consistency concern, which is that firm decisions would likely be dependent on such practices too. Our dataset does not span over many years to address the question whether firms review their prices in certain months. Even if such relationship is found across firms within one year, it could well be due to an aggregate shock they faced. More low-frequency time-series variation is needed. What we do instead is tracking firms and customers behavior within the week or month. If firms have reasons to review their prices on certain days of the month, they might have similar reasons to do so throughout the year.

Table 2.18 reports the average price and share of clicks by day of the week, while Figure 2.11 does a similar thing by day of the month. More specifically, the clicks share by day of the week (month), d, is computed as $\frac{Q_d}{Q}$, where $Q_d = \sum_{i,s,t\in\mathscr{T}_d} q_{ist}$ with $\mathscr{T}_d$ being the set of days that fall on a given day of the week (month). The average (across goods, sellers, and time) price is computed as $\overline{p}_d^{mean} = \frac{1}{\#_{i,t\in\mathscr{T}_d}} \sum_{i,t\in\mathscr{T}_d} \frac{1}{\mathscr{S}_{it}} \sum_s p_{ist}$, while the weighted (across sellers and goods) average price is $\overline{p}_d^{wmg} = \frac{1}{\#_{t\in\mathscr{T}_d}} \sum_{i,s,t\in\mathscr{T}_d} \frac{Q_{ist}}{Q_t} p_{ist}$.

The results suggest that there is little variation in prices within a week or month. At the same time, we observe that people are more likely to shop on Mondays or Tuesdays and are less likely to do so on Fridays or Saturdays. This can be so because people get recommendations what to buy or realize what they need during weekends when they spend more time with family and friends. It could also be that a lot of online shopping is

FIGURE 2.11. MEAN LOG PRICE AND CLICKS, BY DAY OF THE MONTH



Notes: "Mean price" is the average price for all goods and sellers, $\overline{p}_d^{mean} = \frac{1}{\#_{i,t\in\mathcal{T}_d}} \sum_{i,t\in\mathcal{T}_d} \frac{1}{\mathcal{S}_{it}} \sum_s p_{ist}$, "Weighted mean price" refers to the weighted average across sellers and goods, $\overline{p}_d^{wmg} = \frac{1}{\#_{t\in\mathcal{T}_d}} \sum_{i,s,t\in\mathcal{T}_d} \frac{Q_{ist}}{Q_t} p_{ist}$. "Total clicks" stands for log of the total number of clicks measured as $\log Q_d = \log(\sum_{i,s,t\in\mathcal{T}_d} q_{ist})$ with $\mathcal{T}_d$ being the set of days that fall on a given day of the month.

done by office workers in the working time. People may experience a "weekend is over" fatigue on Mondays and shopping may make them feel better. Delivery may play some role too as ordering something on Monday may ensure having it on the porch within the same week.

Shopping pattern also varies within a month. Clicks are numerous during the first 5-7 days of the month when paychecks have just been received, then drop a bit to a steady level maintained till the last week of the month, then the number drops significantly (the end of the month is the time to tighten belts) and spikes back in the last few days in anticipation of a new paycheck. This spike might not necessarily represent an increase in sales but rather be due to consumers looking for goods to buy at the beginning of the next month. We also observe a small spike in the middle of the month, possibly, reflecting consumers that are paid biweekly.

2.5.3 Reaction to Unforecasted Changes in Aggregate Variables

In this section we explore how frequency of price adjustment reacts to unforeseen changes in macro aggregates. Those changes are likely to represent some exogenous shocks or policy innovations. Although we cannot identify what shocks contribute to the changes, it is still important to know if measures of price stickiness respond to them or not. If prices become more flexible during the time of increased volatility, then theories that rely on exogenous and time-invariant nominal rigidities need to be modified to account for the finding.

We use HAVER data that provides monthly observations on actual realization of macroeconomic variables and the median forecast. Although an observation comes in once a month only, we observe the day on which the announcement was made, which allows us to produce a weekly proxy for macroeconomic shocks described below.

We use the data on capacity utilization, consumer confidence, CPI core, employment cost index, GDP, initial claims, the Institute of Supply Management (ISM) manufacturing composite index, leading indicators, new home sales, non-farm sales, PPI core, retail sales, retail sales excluding motor vehicles, and unemployment—14 series in total. For each of the series i, we compute the shock in the following way

$$shock_t^{(i)} = actual_t^{(i)} - forecast_t^{(i)} \tag{2.8}$$

where $actual_t^{(i)}$ is the realization of series i in week t and $forecast_t^i$ is the median forecast for series i in week t.

To aggregate 14 separate series into one proxy for the aggregate shock, we estimate how each of these loads on monthly change in consumption. We estimate the following regression

$$\Delta C_t = \alpha + \sum_{i=1}^{14} \beta_i shock_t^{(i)} + \varepsilon_t \tag{2.9}$$

at the monthly frequency using data from 1993 to 2012. We then compute predicted values from this regression at the daily frequency, $\Delta\hat{C}_t$, setting $shock_t^{(i)} = 0$ if it is not observed on day t.

Let f_t and f_t^w be the raw and clicks-weighted frequency of price adjustment on day t, respectively. Let $f2_t^{(w)} = \frac{1}{14}\sum_{\tau=0}^{13} f_{t+\tau}^{(w)}$ be the average raw (weighted) frequency of price adjustment within two weeks since realization of the shock. To see if online sellers react to macroeconomic shocks, we run the following regressions. First, we regress frequency (raw, weighted, and within two weeks) on each individual shock separately.

$$\phi_t = \alpha + \beta_i shock_t^{(i)} + DoW_t + DoM_t + \varepsilon_t \tag{2.10}$$

where $\phi_t = \left\{f_t,\ f_t^w,\ f2_t,\ f2_t^w\right\}$, DoW_t—dummies for days of the week, and DoM_t—dummies for days of the month. To account for possible serial correlation in residuals, the standard errors are corrected using Newey-West estimator.

Finally, we estimate the sensitivity of frequency of price adjustment to changes in our shock proxy. The following regressions are estimated.

$$\phi_t = \alpha + \beta\Delta\hat{C}_t + DoW_t + DoM_t + \varepsilon_t$$

with variables defined as above.

Table 2.19 reports the estimates for the case when frequency of price adjustment is used as dependent variable. We see that unanticipated changes in the initial claims and PPI core correlate with price stickiness on impact and the effect remains significant within two weeks. New home sales, non-farm payrolls, and CPI core shocks have an immediate effect which vanishes over the course of two weeks. Changes in consumer confidence do not have a significant effect on impact but do correlate with the frequency within two weeks.

Our interpretation of the results is the following. As sellers obtain news about economic developments, they factor in the obtained information and adjust their prices, which affects the frequency on impact. If it takes time to obtain the new information or if the effect comes from the economic environment rather than news *per se*, we observe a change in frequency of price adjustment in the future but not on impact.

Table 2.20 reports the results for the number of clicks. Clicks do not correlate with news, except marginally for the GDP series, possibly because consumers are much less attentive than businesspeople, so it takes them longer to take the new information into account when making consumption decisions.

Table 2.19. Reaction of Frequency of Price Adjustment to Shocks

	Impact		2-weeks ahead	
Shock	No weights (1)	Clicks-weighted (2)	No weights (3)	Clicks-weighted (4)
Capacity utilization	0.42	0.05	−0.33	−1.00
	(4.57)	(5.40)	(2.05)	(2.58)
Consumer confidence	0.09	0.18	0.24^{***}	0.28^{***}
	(0.23)	(0.26)	(0.07)	(0.09)
CPI core	-56.03^{**}	-58.09^{**}	-22.53^{*}	−23.83
	(26.72)	(29.22)	(12.17)	(15.97)
Employment cost index	14.40	14.10	3.39	4.20
	(15.84)	(21.10)	(7.44)	(10.37)
GDP	3.23	7.65	1.15	2.89
	(7.17)	(9.24)	(2.66)	(3.68)
Initial claims	-0.09^{**}	-0.11^{**}	-0.04^{***}	-0.05^{**}
	(0.04)	(0.04)	(0.02)	(0.02)
ISM mfg composite index	0.19	0.31	0.11	0.22
	(0.48)	(0.57)	(0.21)	(0.23)
Leading indicators	5.59	8.99	1.52	1.99
	(7.40)	(8.93)	(2.41)	(2.96)
New home sales	-0.05^{**}	-0.07^{**}	0.00	−0.01
	(0.02)	(0.04)	(0.01)	(0.02)
Non-farm payrolls	0.03^{***}	0.04^{***}	0.00	−0.01
	(0.01)	(0.01)	(0.01)	(0.01)
PPI core	-13.67^{***}	-15.38^{***}	-13.45^{***}	-18.88^{***}
	(4.24)	(5.05)	(3.58)	(5.20)
Retail sales	2.51	2.92	4.41	4.77
	(3.01)	(3.32)	(2.89)	(3.76)
Retail sales exclude motor vehicles	0.88	0.58	1.77	1.19
	(2.09)	(2.31)	(1.32)	(1.45)
Unemployment	1.15	5.21	−2.64	−1.81
	(3.83)	(4.15)	(2.46)	(2.61)
Total Shock Proxy	***0.02***	***-0.01***	***0.00***	***0.00***
	(0.04)	***(0.04)***	***(0.01)***	***(0.01)***

Notes: The table presents coefficients from regressing frequency of price adjustment and the average frequency with the next two weeks, both raw and clicks-weighted, (columns) on each of the measures of innovations in aggregate variables (rows) controlling for day of the week and month. Newey-West standard errors are in parentheses. The total shock proxy is measured as fitted values from regressing changes in consumption on all shocks simultaneously. *, **, and *** represent 10%, 5%, and 1% significance level, respectively.

Table 2.20. Reaction of Clicks to Shocks

Shock	Impact (1)	2-weeks ahead (2)
Capacity utilization	0.00	0.22
	(0.07)	(0.14)
Consumer confidence	0.00	0.00
	(0.00)	(0.00)
CPI core	−0.16	0.03
	(0.36)	(0.32)
Employment cost index	0.19	0.27
	(0.25)	(0.17)
GDP	0.41^{**}	0.17
	(0.19)	(0.11)
Initial claims	0.00	0.00
	(0.00)	(0.00)
ISM mfg composite	−0.01	0.00
	(0.01)	(0.01)
Leading indicators	−0.08	0.09
	(0.09)	(0.10)
New home sales	0.00	0.00
	(0.00)	(0.00)
Non-farm payrolls	0.00	0.00
	(0.00)	(0.00)
PPI core	0.05	−0.10
	(0.09)	(0.16)
Retail sales	0.02	0.04
	(0.04)	(0.06)
Retail sales exclude motor vehicles	0.13	0.13
	(0.09)	(0.11)
Unemployment	0.04	0.13
	(0.12)	(0.11)
Total Shock Proxy	***0.00***	***0.00***
	(0.00)	***(0.00)***

Notes: The table presents coefficients from regressions analogous to those in Table 2.19 with the log number of clicks as dependent variable.

2.6 Concluding Remarks

This paper is a first stab to understand micro pricing properties using the dataset similar to those for brick-and-mortar stores. However, the dataset suffers from a number of limitations. First, the number of clicks is only a proxy for sales. Information on actual sales and costs would improve quality of the results. Second, we only have data from one particular site. We hope that in the future there will be more data to compare results across different platforms. Third, we know little about the relationship between sellers and the platform. Do they advertise on other platforms? Do they offer their products offline? As more data become available, we expect more research on pricing in online markets.

Chapter 3

Evidence on the Size of Fiscal Multipliers from International Military Spending Data

3.1 Introduction

One of the key questions in macroeconomics is the effect of fiscal policy on economic performance. Quantitatively, this question often boils down to the size of fiscal multiplier, i.e. by how much real GDP rises when government spending increases or taxes are reduced. At the same time, studies dedicated to effectiveness of fiscal policy make an implicit assumption that the size of fiscal multiplier is independent of what the government spends on. Indeed, as theoretical justification often goes back to traditional Keynesian models, the key amplification mechanism of expansionary fiscal policy comes from providing additional income to consumers who, in turn, spend it on other goods and services generating multiplicative effect. The result holds in the neoclassical framework too, in which the effect on consumption is negative through the "wealth channel" associated with future tax increases; in both strands of literature, however, the size of the multiplier is independent of which sectors are targeted .

The microfounded models–both neoclassical and New Keynesian–imply that amplification and persistence of demand shocks depend crucially on the speed of price responses to those shocks, a parameter that varies across sectors. Such variability in price responses could generate a possibility that the size of fiscal multiplier depends on what the government spends on. Another important aspect is a difference in intertemporal elasticity of substitution across industries, which affects consumption smoothing behavior of agents. The works of Carvalho (2006), Mankiw and Reis (2003), Benigno (2004), and, especially, Barsky, House, and Kimball (2007) show that these two factors are important for monetary policy, hence, leaving us with a reasonable guess that these findings can be generalized to any demand shock–the question that is outside the scope of this paper.

This paper analyzes how the government's decision to spend on durables or nondurables and services affects the size of spending multiplier. There are a few reasons to believe that the durables multiplier is larger. First, the durables sector is usually more volatile, hence, hit harder during recession. The simple logic here is that under imperfect goods or factor mobility, the government is better off by offsetting demand shocks in sectors that are disproportionately affected. Second, durables exhibit higher intertemporal elasticity of substitution, which leads to disproportionate effect of demand shocks. As for price flexibility, it is not yet clear which of the sectors exhibits more rigidity, so further research is needed.

Estimation of sectoral fiscal multipliers stumbles upon the same challenge as that for total spending–to identify "exogenous" movements in government spending. As government actions are likely to respond to economic developments, it is important to catch the effect of fiscal policy on economic performance, and not the response of the government to changes in economic environment. Literature provides a number of methods to deal with this problem including using military expenditure as a proxy for government spending (Hall 2009), extracting cross-state variation (Nakamura and Steinsson 2011), as well as narrative approach (Ramey 2011, Romer and Romer 2010). In this paper, I adopt the first approach mostly due to data availability. It is, however, essential to examine robustness of the results using other approaches.

Here I use the data compiled from UN, NATO, and the Stockholm International Peace Research Institute (SIPRI) that contains information on disaggregated military expenditure across 69 countries within 1950-1997 period. The data allows grouping spending into that on durables versus nondurables and services consistently across countries and years. It has not been used to estimate any sort of fiscal multipliers so far, which makes it interesting to use as a litmus test by comparing the estimates of fiscal multipliers with those available in the literature. I combine these data with those on countries' economic performance from the Penn World Tables.

My empirical strategy mimics that of Hall (2009) simply extending it to the panel of countries and two types of spending, i.e., I regress real GDP growth on the change in sectoral spending relative to lagged output, controlling for country- and year-specific fixed effects, as well as for some other covariates. To get a better sense of the data, the paper examines in detail what is in there by analyzing pairwise correlations and overall, within and between countries and years variations. I also visualize the relationship between real GDP growth and the growth of spending on durables partialled-out from that of total spending. This should be the closest visual representation of my quantitative results (although it does not take into account possible influence of other control variables).

Visualizing the raw data, within and between countries and years variation, examining pairwise correlations, as well applying more standard regression analysis mostly imply that the size of the durables multiplier appears to be larger than that of the nondurables multiplier. Quantitatively, the former could be up to four times as big as the latter. Applying the same methodology to analyze the total spending multiplier and comparing the results to the existing literature suggests the multiplier of about 1 ranging from 0.6 to 1.3 depending on a group of countries considered. However, due to imprecision of the obtained results and reliance on military data exclusively, further research is encouraged, especially one that utilizes other identification strategies.

The paper proceeds as follows. Section 3.2 gives the detailed description of the data together with some descriptive statistics. Section 3.3 presents empirical strategy including the visualization of “within” and “between” variations in the data, together with a way to partial out the effect of durables from that of total spending. Section 3.4 lets the data speak by examining pairwise correlations and visual patterns in the raw data, as well as aforementioned within and between countries and years relationships. Section 3.5 quantifies the size of fiscal multiplier for durables and nondurables and conducts a litmus test by estimating total spending multiplier. Section 3.6 concludes.

3.2 Data

The data I use to document a potential difference in fiscal multipliers come from three sources.[1] The first one, previously used in Ball (1988), contains an unbalanced panel of developing countries during 1950-1980 period. I further refer to this dataset as that of Less Developed Countries (LDC). The representation varies from only 3 countries included for 1950 to 31 countries for 1973. The median year contains data on 21 of them. To get a sense of what countries are included, I just mention the countries with the data closest to the balanced panel. The data on Chile are available for 30 years, those for India or Pakistan for 29 years, the Philippines or Sri Lanka for 26 years. Other countries in the dataset have less than 25 annual entries. The complete list of countries and years available in the dataset is described in Table B.1 of Section B.1. I should mention that the list of countries in LDC dataset represents nearly exclusively developing world, with the only exception of Singapore included by the IMF to the list of advanced economies.

The second dataset uses data obtained from the UN for some of the member states for 1978-1996. It is a combination of developed and developing countries (see Table B.1 for details). The number of countries within a year varies from 2 in 1996 to 31 in 1993, with the median year of 21 countries. It should be noted that the data on advanced economies contains fewer missing observations than those for less developed countries. Thus, the most represented are Canada (17 years of data), Austria, the Netherlands, and Norway (16 years each), Australia, Finland, and New Zealand (15 years each), with all the other countries having fewer than 15 years. For less developed countries, except of Turkey (12 years) and Chile (10 years), all other countries have data on 6 years (Hungary and Romania) or less (5 – Thailand, 4 – Argentina, Barbados, and Mexico, etc.) I naturally call this dataset UN, while I refer to its subsamples of IMF advanced economies and the rest as “UN, IMF advanced economies” and “UN, LDC”, respectively.

Finally, my last piece of data comes from the Stockholm International Peace Research Institute (SIPRI) and NATO, which is referred to as SIPRI/NATO dataset. It contains a balanced panel on 11 advanced economies (Table B.1) and Turkey for 1985-1997, as well as some data with missing observations on Germany and Spain. This is probably the

[1] See Gartzke (2001) for more details on how the data were compiled.

TABLE 3.1. COUNTRY REPRESENTATION

Dataset	Time Span	Represented Countries					
		Min		Max		Mean	Median
		#	year	#	year		
LDC	1950-80	3	1950	31	1973	19	21
UN	1978-96	2	1996	31	1993	19	21
SIPRI/NATO	1985-97	13	multiple	14	1987-90	13	13
Pooled	1950-97	3	1950	44	1993	24	26

most reliable dataset out of those available, although it suffers from low representation both country- and time-wise.

Table 3.1 summarizes this information for the three datasets, as well as provides some insights on what is available in the pooled dataset, which includes data for 1950-1997 with country representation varying from as low as 3 in 1950 to as high as 44 in 1993 and 26 countries in the median year. The fact that the average number of countries is 24 suggests that the distribution is skewed towards years with fewer countries represented.

I have the data on the following variables: country's real GDP, y, total military spending, g, proxies for spending on durables, g^d, and that on nondurables and services, g^n. LDC and UN datasets also contain a dummy on whether civilian defence expenditure is included or not, $civil$, (although there is little variation as it is always excluded in LDC dataset and mostly excluded–92% of the cases–in the UN dataset) and the type of fiscal year used to report military expenditure, $fytype$. The latter does not vary much either, with 2/3 of the cases being standard January to December years, while 15% and 13% of observations use April to March and July to June definitions, respectively. As I work with annual data, it is important to control for this whenever data lags half a year. I also control for the development level using dummies on whether a country belongs to IMF advanced economies list, adv_IMF, and for being at war, war. The information is taken from the Correlates of War Project that collects information on the history of non-state, intrastate, and interstate wars including countries-participants, duration, number of casualties, etc.

Table 3.2 reports descriptive statistics for the main variables used in the regression analysis. Those are some transformations of the original data that result in real GDP growth, $\frac{\Delta^t\ y_{i,\ t}}{y_{i,\ t-1}}$, the change in total military expenditure relative to the size of the economy, $\frac{\Delta^t\ g_{i,\ t}}{y_{i,\ t-1}}$, as well as its breakdown into durables and nondurables/services components, $\frac{\Delta^t g^d_{i,\ t}}{y_{i,\ t-1}}$ and $\frac{\Delta^t g^n_{i,\ t}}{y_{i,\ t-1}}$, respectively. I use Δ^t to denote a standard one-period lag operator. I also report the share of durables in total military expenditure, $\phi_{i,\ t} \equiv \frac{g^d_{i,\ t}}{g_{i,\ t}}$, as well as the annual change in that share, $\Delta^t\phi_{i,\ t}$. The reason why a change in military spending is normalized by the lagged real GDP is twofold. The first one is to make it independent from measurement units, hence, easy to interpret and compare between countries. Second, to make the coefficient in regression estimated later interpretable as usual fis-

TABLE 3.2. DESCRIPTIVE STATISTICS, POOLED DATA

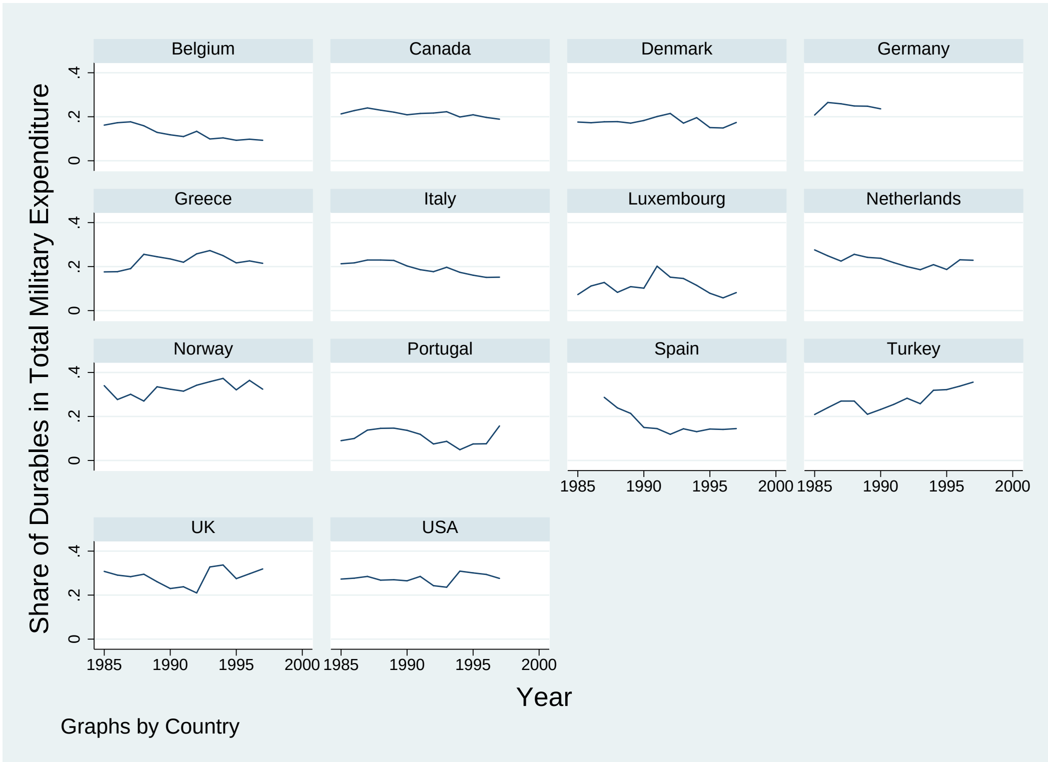
Variable	Mean	Std. Dev.			N	n	$\bar{T}$
		overall	between	within			
$\frac{\Delta^t y_{i,\,t}}{y_{i,\,t-1}}$	.042	.061	.034	.055	914	87	10
$\frac{\Delta^t g_{i,\,t}}{y_{i,\,t-1}}$	.008	.079	.052	.064	856	86	10
$\frac{\Delta^t g^d_{i,\,t}}{y_{i,\,t-1}}$	.002	.019	.008	.018	856	86	10
$\frac{\Delta^t g^n_{i,\,t}}{y_{i,\,t-1}}$	.006	.068	.045	.056	856	86	10
$\phi_{i,\,t} \equiv \frac{g^d_{i,\,t}}{g_{i,\,t}}$	.182	.155	.161	.083	1079	106	10
$\Delta^t \phi_{i,\,t}$	.001	.089	.062	.084	897	91	10

cal multiplier (that is why I normalize the change in military spending by lagged output rather than by lagged military spending). In general, this approach simply extends Hall's (2009) specification to the spending composition case.

To get a systematic breakdown of spending into durables and nondurables categories, I follow Gartzke (2001) and use grouping of the expenditure into four categories: "personnel", "other expenditure" (operational and intelligence), "equipment", and "infrastructure". The total military spending then can be further broken into operational spending (mostly labor force contributions associated with military services) and capital spending (on durable goods). The first group is used as a proxy for spending on nondurables and services, while the second one as that for durables.

The descriptive statistics suggests that an average country in an average year grew at 4.2% with a standard deviation of 6 p.p. There is quite a lot of variation both within and between countries. The average change in total military expenditure was 0.8% of the last year's GDP, most of which (0.6%) comes from the change in spending on nondurables and services rather than from that on durables (0.2%). This should not be interpreted, however, as a sign that durables did not matter or that changes were small, but rather as an indicator of a difference in time-series properties of these variables. Changes in spending on non-durables and services are usually more persistent as they are related to the overall size of the army. Hence, positive changes in one year are likely to be followed by positive changes in subsequent years, producing positive mean changes in the growth rate. On the other hand, spending on durables is typically implemented through a one-time program, producing a year with a large positive growth in spending on durables followed by that with the large negative growth resulting from returning to the usual spending pattern. This could explain why the average change in spending on durables is close to zero even though the estimated standard deviation suggests there was quite a variation in it. As we look at the share of durables, the mean change is close to zero, but the variation is relatively high, even within countries, which confirms that movements in spending composition take place regularly. At the same time between countries variation in durables share is about twice as high as that within countries. To verify that these results are not sample-specific, Tables B.2 and B.3 of Section B.1 provide a breakdown

FIGURE 3.1. SHARE OF DURABLES IN TOTAL MILITARY EXPENDITURE, SIPRI/NATO DATASET



by data source and the level of development.

The fact that there is enough variation in the share of durables is important to make identification of potential differences between the durables and nondurables multipliers possible. To visualize the data, Figure 3.1 shows the time-series of spending composition for SIPRI/NATO sample. I choose this sample because the dataset appears to be the most reliable and the set of countries is relatively homogenous in terms of economic development. Figures B.1 and B.2 in Section B.1 depict the pattern for two other datasets and generally support the argument. It can be seen that for the set of developed countries in relatively peaceful times, the variation within the range of 10-15 p.p. is not uncommon. This range can be much wider for developing countries and during wars.

3.3 Empirical Strategy

My empirical strategy consists of two parts. First, I examine correlations between key variables along various dimensions (mainly, the data source and the level of development) and see wether the correlation between the measure of economic activity and various measures of military spending can shed any light on heterogeneity of fiscal multipliers. I also let the data speak and plot simple scatterplots with linear fits of $\frac{\Delta^t y_{i,\ t}}{y_{i,\ t-1}}$

against $\frac{\Delta^t g^d_{i,\ t}}{y_{i,\ t-1}}$ and $\frac{\Delta^t g^n_{i,\ t}}{y_{i,\ t-1}}$ across different subsamples and levels of development. As I recognize there could be substantial country- and year-specific fixed effects, I also consider a few modifications described below. The second part deals with estimating the spending composition multiplier quantitatively. As an intermediate step, I examine scatterplots of output growth against spending on durables partialled out from the total spending effect. I argue below that such scatterplots can be a simple visual tool to compare durables and nondurables multipliers. I proceed with explaining how I deal with country-specific and time-specific effects first.

Country-Specific Effects Denote $\tilde{y}_{i,\ t} \equiv \frac{\Delta^t y_{i,\ t}}{y_{i,\ t-1}}$ and $z_{i,\ t} \equiv \left\{\frac{\Delta^t g_{i,\ t}}{y_{i,\ t-1}}, \frac{\Delta^t g^d_{i,\ t}}{y_{i,\ t-1}}, \frac{\Delta^t g^n_{i,\ t}}{y_{i,\ t-1}}\right\}$. Assuming that there is a country-specific fixed effect, let the relationship between the economic performance and one of the proxies for spending look like

$$\tilde{y}_{i,\ t} = c + \alpha_i + m_z z_{i,\ t} + \varepsilon_{i,\ t} \tag{3.1}$$

Here α_i represents country-specific fixed effects. If $\alpha_i \equiv 0$ for all i, I can recover the relationship between a spending proxy and the output growth by simply plotting one against the other and estimating linear fit. However, if $\alpha_i \neq 0$ for some i, my linear fit will produce an indistinguishable mix of two effects: country-specific one and fiscal policy response. Let M^t be the mean operator over the time dimension, i.e. $M^t x_{i,\ t} \equiv \sum_t x_{i,\ t}/T$. Note that $M^t x_{i,\ t}$ depends on i only, and not on t. Applying the mean operator to both sides of Equation (3.1) gives us

$$\underbrace{M^t \tilde{y}_{i,\ t}}_{\bar{\tilde{y}}_i} = c + m_z \underbrace{M^t z_{i,\ t}}_{\bar{z}_i} + \underbrace{\alpha_i + M^t \varepsilon_{i,\ t}}_{u_i} \tag{3.2}$$

Note that as long as α_i is not correlated with $\bar{z}_i$, plotting the time-averages across countries and recovering linear fit produces consistent estimates of the coefficient of interest m_z. I call the resulting scatterplots "between countries" variation.

Of course, in real life it could be that the two are correlated. In fact, fiscal policy within a country can be constrained by a number of factors including but not limited to individual characteristics of political process, the level of success of historical instances of fiscal or military expansion, coordination with monetary authorities, etc. To take this correlation into account, consider the demean operator over time defined as $D^t x_{i,\ t} \equiv x_{i,\ t} - M^t x_{i,\ t}$. Applying this demean operator to both sides of Equation (3.1) gives us the following.

$$D^t \tilde{y}_{i,\ t} = m_z D^t z_{i,\ t} + D^t \varepsilon_{i,\ t} \tag{3.3}$$

It is easy to see that if $\varepsilon_{i,\ t}$ is a classical error term, so is $D^t \varepsilon_{i,\ t}$. And hence, plotting demeaned over time variables against each other lets us compare different fiscal multipliers. I call those "within countries" scatterplots.

Time-Specific Effects Similarly, time-specific fixed effects that make the model look like

$$\tilde{y}_{i,\,t} = c + \beta_t + m_z z_{i,\,t} + \varepsilon_{i,\,t} \tag{3.4}$$

can be dealt with by applying mean operator over countries ($M^i x_{i,\,t} \equiv \sum_i x_{i,\,t}/n$) to our variables to get "between years" scatterplots if time fixed effects are not correlated with spending proxies. International coordination of fiscal policy through various international organizations, ideas spillover, and correlation of business cycles, and especially international cooperation that affects military spending across countries in a systematic way laid down through means of the UN and NATO, for example, may give rise to correlation between time-specific fixed effects and military spending. Analogously, demeaning over countries ($D^i x_{i,\,t} \equiv x_{i,\,t} - M^i x_{i,\,t}$) and reporting "within years" scatterplots solve this issue. In Section 3.4 I report and discuss these scatterplots separately for the spending composition (durables versus nondurables) and the overall spending level.

Partialled-Out Spending on Durables Finally, to produce a simple visualization of the difference between the durables and nondurables multiplier, I examine the relationship between output growth and spending on durables net of the interaction with that on nondurables. I use partialling-out framework similar to that used to estimate a slope in the multivariate regression by means of the bivariate one. Thus, in the first stage I regress spending on durables on total spending:

$$\frac{\Delta^t g^d_{i,\,t}}{y_{i,\,t-1}} = c + b\frac{\Delta^t g_{i,\,t}}{y_{i,\,t-1}} + u_{i,\,t}. \tag{3.5}$$

I then plot $\tilde{y}_{i,\,t}$ against residuals obtained from that regression, $\hat{u}_{i,\,t}$. The fitting line in this scatterplot corresponds to slope d in the following regression

$$\tilde{y}_{i,\,t} = c' + d\frac{\Delta^t g^d_{i,\,t}}{y_{i,\,t-1}} + a\frac{\Delta^t g_{i,\,t}}{y_{i,\,t-1}} + e_{i,\,t}, \tag{3.6}$$

which, as argued next, is the composition multiplier. Hence, upward sloping fit indicates that the durables multiplier is larger than that for nondurables. It is straightforward to combine partialling-out with "within" and "between" variations. Graphical results are presented in the next section.

Quantitative Analysis I start from the model that allows for heterogeneity in fiscal multipliers, country-specific and time-specific fixed effects.

$$\frac{\Delta^t y_{i,\,t}}{y_{i,\,t-1}} = c + \alpha_i + \beta_t + m_n\frac{\Delta^t g^n_{i,\,t}}{y_{i,\,t-1}} + m_d\frac{\Delta^t g^d_{i,\,t}}{y_{i,\,t-1}} + \varepsilon_{i,\,t} \tag{3.7}$$

In this framework m_n is government-spending multiplier associated with spending on nondurables and services, and m_d is that for durables. The key question is wether $m_n = m_d$ or not, and how big the potential difference could be. To make a specification even easier to interpret, I rewrite it in the following form.

$$\frac{\Delta^t y_{i,\ t}}{y_{i,\ t-1}} = c + \alpha_i + \beta_t + m_n \frac{\Delta^t g_{i,\ t}}{y_{i,\ t-1}} + \underbrace{(m_d - m_n)}_{m_c} \frac{\Delta^t g^d_{i,\ t}}{y_{i,\ t-1}} + \varepsilon_{i,\ t} \tag{3.8}$$

There are a few practical advantages of this specification. First, it allows to test the hypothesis of whether $m_d = m_n$ by simply testing that of $m_c = 0$. Second, it nests the specification used to estimate standard fiscal multiplier in the literature, like that in Hall (2009). If there is no statistical difference between multipliers on durables and non-durables ($m_d = m_n$), i.e., m_c is indistinguishable from zero, then the coefficient on total spending can be interpreted as the standard government spending multiplier ($m_n = m_g$). In Section 3.5 I report both estimates from Equation (3.8) for different subsamples and control variables, as well as estimates from the standard fiscal multiplier regression, which is obtained from the latter equation by dropping $\frac{\Delta^t g^d_{i,\ t}}{y_{i,\ t-1}}$ from the list of regressors. This is to serve as a litmus test of whether the current dataset stands on the upper or lower tail of the estimates available in the literature.

When estimating these regressions, I, in addition, control for $civil$, $fytype$, war (see Section 3.2 for definition), as well as two interaction variables: $war * \frac{\Delta^t g^d}{y_{-1}}$ and $\mathscr{I}\left\{\frac{\Delta^t y}{y_{-1}} < 0\right\} * \frac{\Delta^t g}{y_{-1}}$. The first interaction variable (between the war dummy and spending on durables) is to capture a change in spending composition due to wars, the second one (between being in recession and total military spending) is to capture fiscal policy constraints that developing countries at war may face.

3.4 Sectoral Composition of Military Spending

I report correlations between main variables in different subsamples first, and then move on to discus scatterplots: raw, within countries, between countries, within years, and between years separately for durables versus nondurables and for total spending. I then go over the partialled-out effect of spending on durables.

Table B.4 in Section B.1 reports pairwise correlations between variables overall and across different subsamples. First, let us look at the correlation between GDP growth and various types of spending. The correlations appear to be weak enough to find any correspondence between spending and well-being in the pooled sample. This could be due to substantial measurement error, heterogeneity of different samples, country- and time- specific fixed effects, influence of other factors, etc. The datasets that exhibit positive relationship are SIPRI/NATO and UN, LDC subsample. In the former we observe correlation between real GDP growth and change in overall spending of 0.20 (significant at 1%). Additional inference suggests that this correlation is due to spending on both durables (0.13 and significant at 10%) and nondurables (0.17, significant at 5%). In the latter sample we observe positive correlation with total spending (0.28, 10% significance level) and spending on durables (0.31, 10% significance level). It is quantitatively smaller and statistically insignificant for nondurables.

If we look at the pooled data, there is negative correlation between GDP growth and the share of durables and, occasionally, positive one between the former and the change in the share of durables (UN sample). The first finding could be interpreted as the fact that countries that spend a lot on military equipment were experiencing smaller GDP growth, which could be due to them being at war, making an adverse choice for guns relative to butter in some militarized developing countries, or simply because large military purchases of durables are undertaken by richer countries that have slower growth rates. More importantly, the second finding serves as somewhat an evidence that increasing the share of durables in expenditure over time may have benign effects on growth.

Also it comes as no surprise that there is large and positive correlation between spending on durables, nondurables, and overall spending. The correlation coefficient between overall spending and that on nondurables being close to one suggests that there is more systematic relationship between the two than between overall spending and that on durables. Of course, these pairwise correlations do not take into account fixed effects and influence of other variables that could affect military spending, its composition, and GDP growth.

Spending Composition I plot real GDP growth against spending on durables and that on nondurables. I trim the outliers by restricting my attention to observations for which the change in both components of spending is smaller than 10% of GDP. This helps me solve several problems. First, I get rid of the observations with obvious measurement errors. Second, I remove influential observations: even if the data on those observations is potentially valid, including them into sample reduces the weight of other observations to nearly zero. Third, I remove observations for countries participating in big wars as the effect of the war itself could contain unobservables that affect the economy in many other ways. Finally, I do not need to worry about losing important information as most of the time the proposed cutoff points are inside of 1% percentile from each side of the distribution, hence, I do not throw away information representative for the mean country in the mean year of the sample.

Figure 3.2 demonstrates the scatterplots for the raw data. Red circles and solid fitting line represent spending on durables, while blue diamonds and dashed fitting line represent that on nondurables and services. We can see from the graph that for most samples red solid line is steeper than the blue dashed one implying that spending on durables has stronger effect than that on nondurables. Assuming country-specific fixed effects that might correlate with the size of military spending, Figure 3.3 plots the time-demeaned data. The results are mostly confirmed, with an exception for the LDC data. The difference between the slopes, however, appears to be smaller once country-specific effects are taken into account.

Figure 3.2. Real GDP Growth vs Spending on Durables and Nondurables-Services: raw data

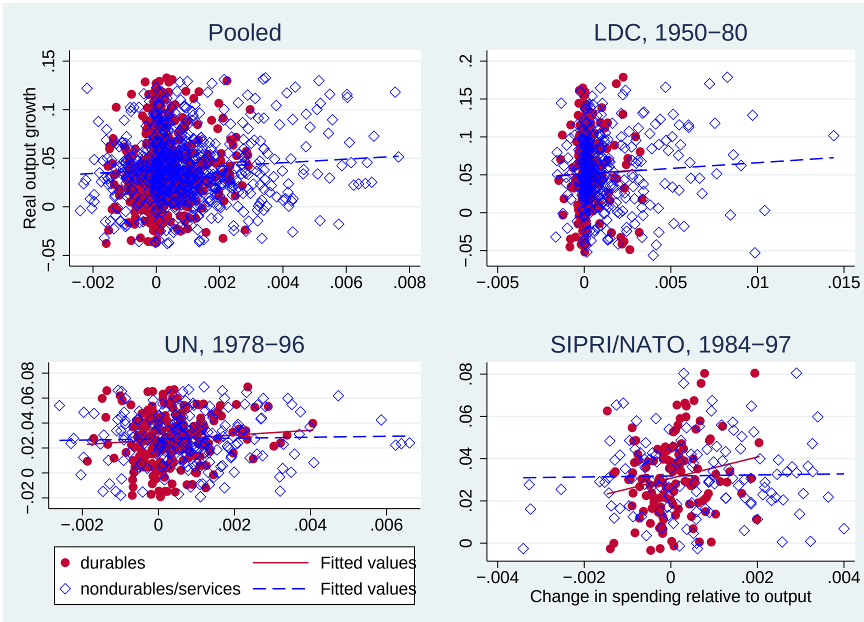
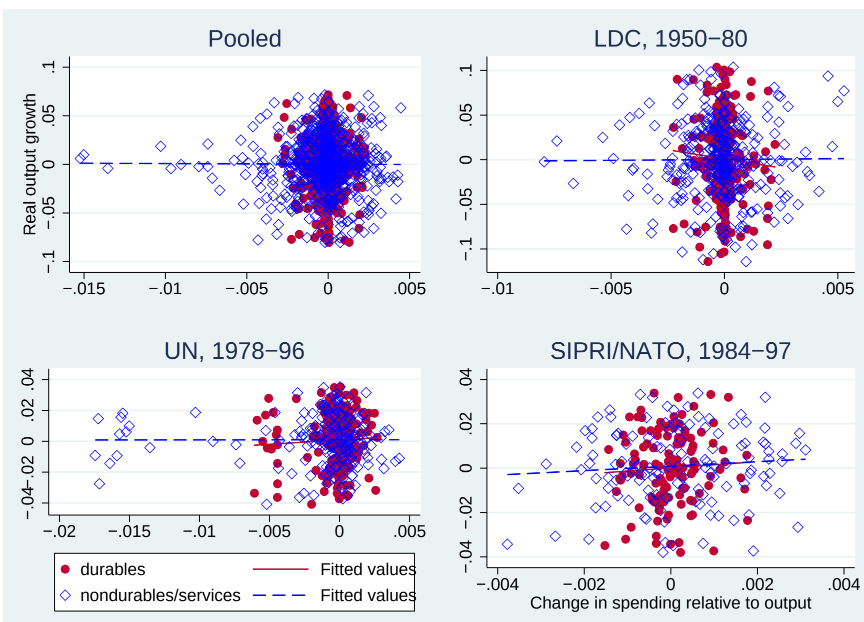


Figure 3.3. Real GDP Growth vs Spending on Durables and Nondurables-Services: "within countries"



Due to the lack of space, I do not report the whole set of graphs, which are available from the author upon request. However, to check the robustness of the results, in Section B.1 I plot “between countries”, “between years”, and “within years” scatterplots (Figures B.3 – B.5), as well as a breakdown of “within countries” scatterplot by UN subsamples (Figure B.6).

Total Spending Now I plot similar graphs for the total military spending. Figures 3.4 and 3.5 examine variations in the raw data and “within countries”, while Figure B.9 in Section B.1 does so “within years”. “Between countries” and “between years” graphs are available from the author upon request. The relationship is weakly positive for most of the samples and specifications. However, to assess statistical and economic significance of these results, one should run more formal analysis of the data, which I do in the next section.

Partialled-Out Spending on Durables Figures 3.6 and 3.7 show the relationship between output growth and partialled-out normalized spending on durables. For the raw data, all six scatterplots give a univocal suggestion that the durables multiplier is larger than that for nondurables. The results are qualitatively similar (but quantitatively smaller) when country-specific fixed effects are accounted for with the only exception of SIPRI dataset. The results are more ambiguous “between countries” or “within years” (see Figures B.7 and B.8 in Section B.1).

3.5 Quantitative Results

Spending Composition Table 3.3 presents estimates of Equation (3.8) for different subsamples. Country fixed effects are accounted for by demeaning the data over time, while year fixed effects are dealt with by including year dummies. The fiscal multipliers are positive and significant in 2 out of 3 samples and in 5 out of 6 specifications. In 3 out of 6 specifications the difference between durables and nondurables multipliers is both statistically and economically significant. In the rest of the specifications although the effect of the composition is statistically insignificant, the confidence intervals include a wide range of economically significant values. The results suggest that there could be a huge difference between fiscal multipliers that involve spending on durables versus nondurables, with the former being much larger than the latter.

Quantitatively the results stand on rather an upper tail of those provided in literature. The nondurables multiplier is in the range of 0.5 – 1.1. However, the quantitative estimate of the difference in multipliers is even more striking. It is around 3, when significant, with a confidence interval of approximately 0.3 to 5.7. Even in those specifications where the difference in multipliers is not significant, an upper end of confidence interval includes values as high as 5.

What can produce such large values for the durables multiplier? First, it could be that the durables multiplier is indeed large but the pass-through to the total spending

Figure 3.4. Real GDP Growth vs Total Spending: raw data

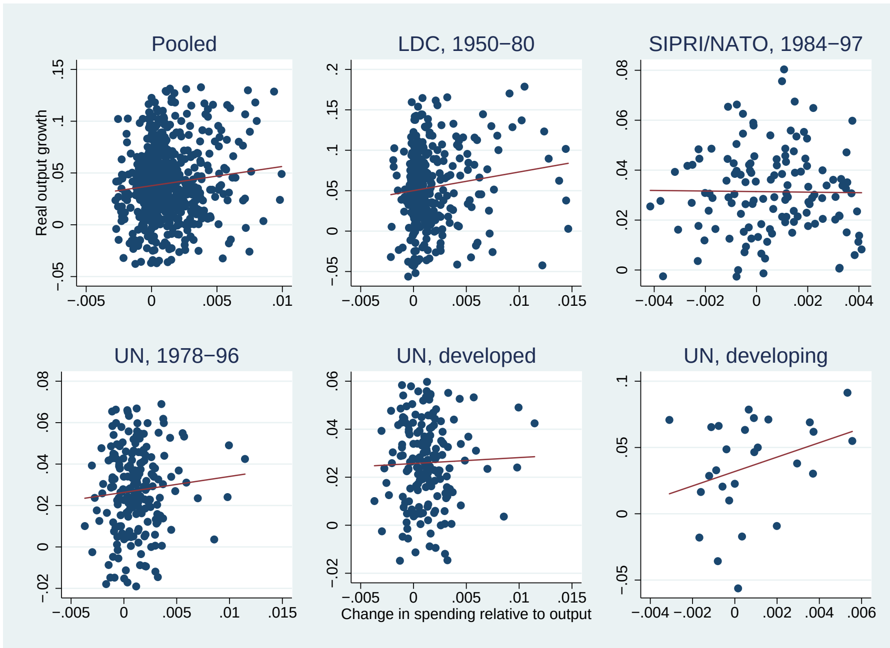


Figure 3.5. Real GDP Growth vs Total Spending: "within countries" variation

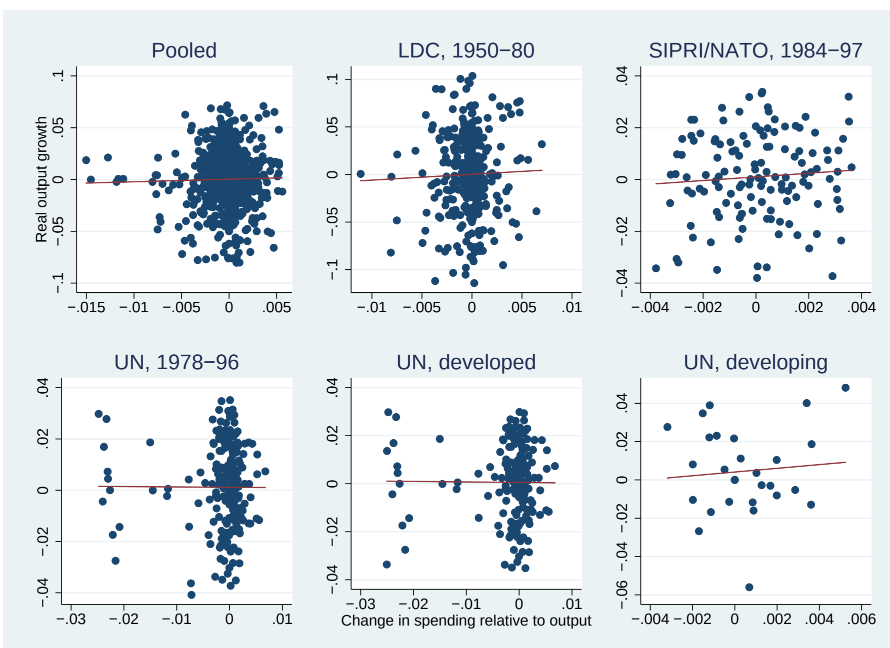


FIGURE 3.6. REAL GDP GROWTH VS PARTIALLED-OUT SPENDING ON DURABLES: RAW DATA

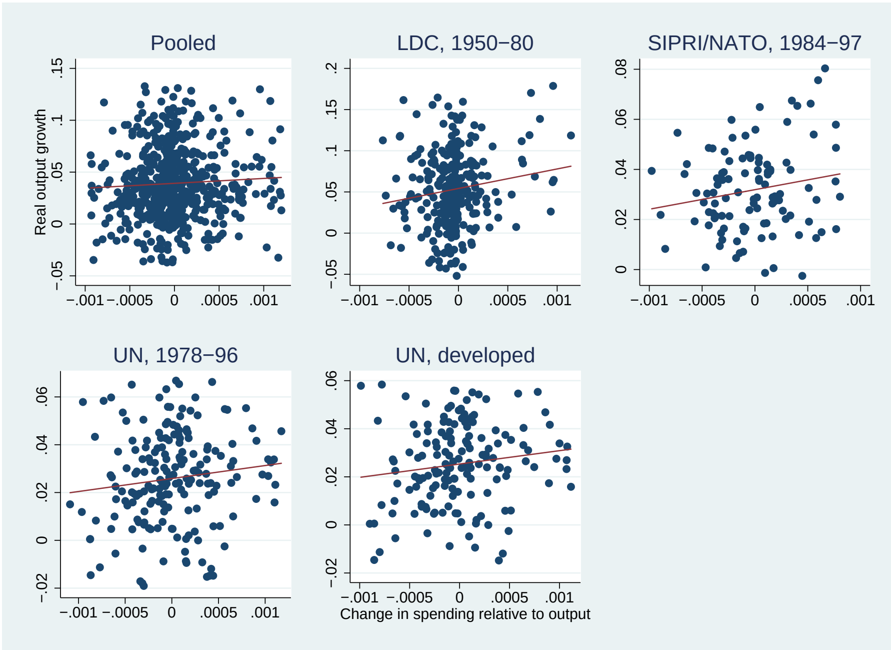


FIGURE 3.7. REAL GDP GROWTH VS PARTIALLED-OUT SPENDING ON DURABLES: "WITHIN COUNTRIES"

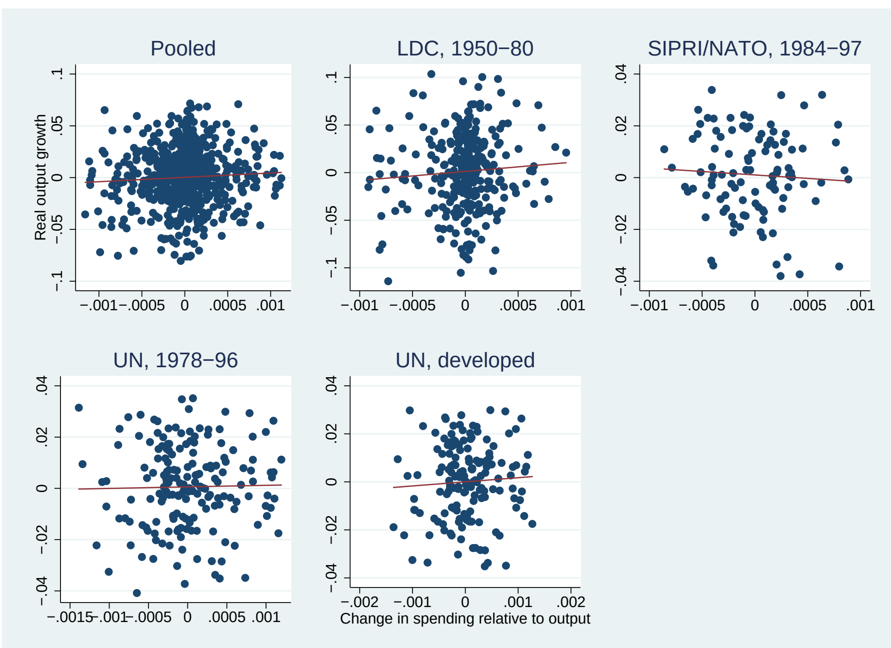


TABLE 3.3. FISCAL MULTIPLIERS FOR DURABLES VS NONDURABLES AND SERVICES

	Sample					
Coefficient	(1) Pooled	(2) UN+LDC	(3) LDC	(4) UN	(5) UN	(6) SIPRI
m_n	0.83$^{\bigstar}$	0.83*	1.12*	0.55*	0.55*	0.93
	(0.35)	(0.39)	(0.60)	(0.29)	(0.29)	(0.97)
$m_d - m_n$	2.52*	2.69*	3.25*	0.70	0.67	1.20
	(1.16)	(1.32)	(1.76)	(1.43)	(1.43)	(2.21)
N	838	679	426	253	253	159
n	85	71	34	37	37	14
$\bar{T}$	9.9	9.6	12.5	6.8	6.8	11.4
R^2_{within}	0.13	0.13	0.13	0.20	0.20	0.29
$civil$	No	Yes	No	No	Yes	No
$fytype$	No	No	No	No	Yes	No

Standard errors in parenthesis. Significance level: $\bigstar$ – 1%, $\star$ – 5%, $+$ – 10%.

Countries and years fixed effects included. Other controls: $war, war * \frac{\Delta^t g^d}{y_{-1}}, \mathscr{I}\left\{\frac{\Delta^t y}{y_{-1}} < 0\right\} * \frac{\Delta^t g}{y_{-1}}$.

multiplier is small as government buys durables only from time to time, and large positive changes are almost immediately offset by large negative changes in the subsequent period. If this is the case, a *persistent* increase in purchase of durables is needed during recessions to have a large effect on output. Second, it could be the case that since military durables have high intertemporal elasticity of substitution, the government decide to spend on durables only when the economy is on the rise, which produces an upward bias in my estimates. Third, it could be that spending on durables usually involves large projects that have potentially stronger influence on the economy. This would imply a nonlinearity in fiscal multipliers and being potentially on the different parts of the same curve when looking at durables versus nondurables.[2] Fourth, it could be that as spending on nondurables are more persistent, they are often financed by increased taxes and supplemented by leaning against the wind monetary policy, while one-time boost in durables spending is financed by borrowing and accommodated by monetary authorities. Another possibility is that countries at war are the ones that need to buy a lot of equipment, and most of the time wars are financed by debt, not taxation. Finally, there is a number of data limitations that could put the quantitative results to test. Hence, I conclude that further research is needed to check the reliability of the estimates, although there seems to be enough evidence of sectoral heterogeneity in fiscal multipliers, at least, at the qualitative level, with the durables multiplier being potentially larger.

Total Spending Another interesting question is to use this new piece of data to estimate standard fiscal multiplier and compare it with what is provided in the literature. I do this by dropping spending on durables from specification in Equation (3.8), which then reduces to Hall (2009) approach extended to multi-country data. The results are

[2]Michaillat (2012) and Parker (2011) discuss why fiscal multipliers may vary over the business cycle.

Table 3.4. Fiscal Multipliers for Total Military Spending

	Sample					
Coefficient	(1) Pooled	(2) UN+LDC	(3) LDC	(4) UN	(5) UN	(6) SIPRI
m_g	1.04$^{\bigstar}$	1.03$^{\bigstar}$	1.33*	0.62$^{\bigstar}$	0.61$^{\bigstar}$	1.18
	(0.33)	(0.37)	(0.59)	(0.25)	(0.25)	(0.85)
N	838	679	426	253	253	159
n	85	71	34	37	37	14
$\bar{T}$	9.9	9.6	12.5	6.8	6.8	11.4
R^2_{within}	0.12	0.56	0.13	0.20	0.20	0.28
$civil$	No	Yes	No	No	Yes	No
$fytype$	No	No	No	No	Yes	No

Standard errors in parenthesis. Significance level: $\bigstar$ – 1%, $\star$ – 5%, $+$ – 10%.

Countries and years fixed effects included. Other controls: $war, war*\frac{\Delta^t g^d}{y_{-1}}, \mathscr{I}\left\{\frac{\Delta^t y}{y_{-1}} < 0\right\}*\frac{\Delta^t g}{y_{-1}}$.

presented in Table 3.4. In all specifications the fiscal multiplier is significant and varies from 0.6 to 1.3. This is in accordance with estimates in the literature that suggest multipliers close to 1. Though it is likely that the composition multiplier is overestimated, the fact that standard fiscal multiplier estimates obtained from the new data encompass more or less conservative values of the multiplier that exist in the literature, together with another fact that even a lower end of the confidence interval produces large differences between the sectoral multipliers are comforting for our qualitative finding that the durables multiplier is potentially larger than that for nondurables.

3.6 Concluding Remarks

Due to data limitations, it would also be interesting to extend this approach to the U.S. state-level spending and control for states' fixed effects. First, it will tackle omitted-variable bias since it is unlikely that the federal government reacts to a change in economic conditions that occurs in a specific state. This is especially true for military expenditure. Second, it will control for a common trend in monetary policy, isolating fiscal effects from monetary accommodation. This will give us an extension of Nakamura and Steinsson's (2011) "open economy relative multiplier" to the sectoral level. Besides, as the quantitative results of this paper should be interpreted with caution, using other identification techniques and/or more reliable or homogeneous data could help reduce the width of the confidence intervals.

The other strand of prospective research could involve understanding of why the durables multiplier is larger than that for nondurables on the theoretical level. Indeed, all we know is that the differences in price rigidity and intertemporal elasticity of substitution across sectors possibly play some role. It is not clear, however, what the amplification and propagation mechanisms for the sectoral multiplier effects are and whether the multipliers are the same when recession is brought about by sectoral or aggregate shocks.

Finally, it would be interesting to move a few levels down the disaggregation ladder and estimate the difference not only between durables and nondurables multipliers, but also between sectoral multipliers at various disaggregation levels. This could provide policymakers with more specific targets for expansionary fiscal policy. Of course, any policy recommendations would be subject to Lucas critique as applying these findings in practice may change the way agents react to changes in economic environment. All these directions suggest that there is a large scope for prospective research on sectoral fiscal multipliers.

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Appendix A

Appendix to Chapter 1

A.1 Additional Results

Data for Markets and Categories The list of markets and categories of goods is presented in Table A.1. Most locations correspond to a Metropolitan Statistical Area (MSA). A few cases combine two MSAs situated close to each other (e.g., Birmingham/Montgomery, AL). Four markets represent areas generally larger than an MSA. Those markets are capitalized in the table.

Figure A.1 shows the scatterplot of average monthly inflation and price dispersion over categories of goods. Figure A.2 depicts a similar scatterplot across markets rather than categories. Two scatterplots are equivalent to Figure 1.2, with additional averaging across either markets or categories.

Robustness to Fixed Effects The main results specification controls for market-category and time fixed effects. I examine robustness of the result to alternative sets of fixed effects in Table A.2. The baseline specification includes market-category and time fixed effects; the results are reproduced in Column (8). Alternatively, Column (1) reports the results when neither cross-sectional nor time fixed effects are included. In Columns (2)-(4), I drop time fixed effects, but keep cross-sectional ones: market only, category only, and market-category, respectively. Columns (5)-(7) add time fixed effects to specifications in (2)-(4).

For the set of all prices, MSA fixed effects are the most important. They explain 42% of variation in price dispersion and are responsible for most of the coefficient change relative to the case with no fixed effects. For regular prices, MSA and category fixed effects are equally important explaining around 25% of the variation each.

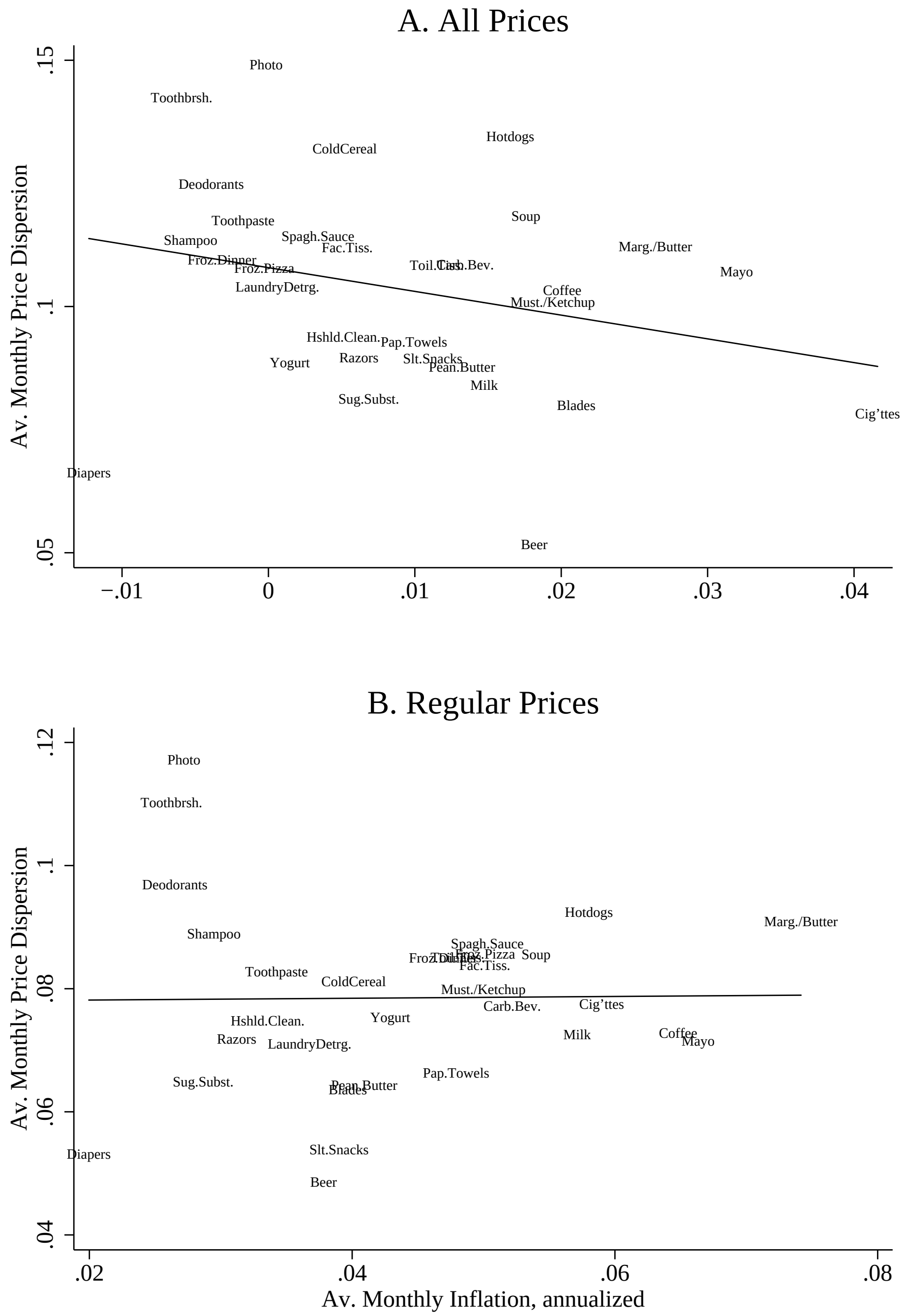
Despite significant variation in magnitude (up to four times), the qualitative finding remains intact for any set of fixed effects used confirming that the comovement is negative for all prices and positive for regular prices.

TABLE A.1. LIST OF MARKETS AND CATEGORIES OF GOODS

Markets (1)	Categories (2)
Atlanta, GA	Beer
Birmingham/Montgomery, AL	Blades
Boston, MA	Carbonated Beverages
Buffalo/Rochester, NY	Cigarettes
Charlotte, NC	Coffee
Chicago, IL	Cold Cereal
Cleveland, OH	Deodorants
Dallas, TX	Diapers
Des Moines, IA	Facial Tissues
Detroit, MI	Frozen Dinner
Eau Claire, WI	Frozen Pizza
Grand Rapids, MI	Hotdogs
Green Bay, WI	Household Cleaning
Harrisburg/Scranton, PA	Laundry Detergent
Hartford, CT	Margarine/Butter
Houston, TX	Mayo
Indianapolis, IN	Milk
Kansas City, MO	Mustard/Ketchup
Knoxville, TN	Paper Towels
Los Angeles, CA	Peanut Butter
Milwaukee, WI	Photo
Minneapolis/St. Paul, MN	Razors
MISSISSIPPI	Shampoo
NEW ENGLAND	Salty Snacks
New Orleans, LA	Soup
New York, NY	Spaghetti Sauce
Oklahoma City, OK	Sugar Substitutes
Omaha, NE	Toilet Tissues
Peoria/Springfield, IL	Toothbrush
Philadelphia, PA	Toothpaste
Phoenix, AZ	Yogurt
Pittsfield, MA	
Portland, OR	
Providence, RI	
Raleigh/Durham, NC	
Richmond/Norfolk, VA	
Roanoke, VA	
Sacramento, CA	
Salt Lake City, UT	
San Diego, CA	
San Francisco, CA	
Seattle/Tacoma, WA	
SOUTH CAROLINA	
Spokane, WA	
St. Louis, MO	
Syracuse, NY	
Toledo, OH	
Tulsa, OK	
Washington, DC	
WEST TEXAS/NEW MEXICO	

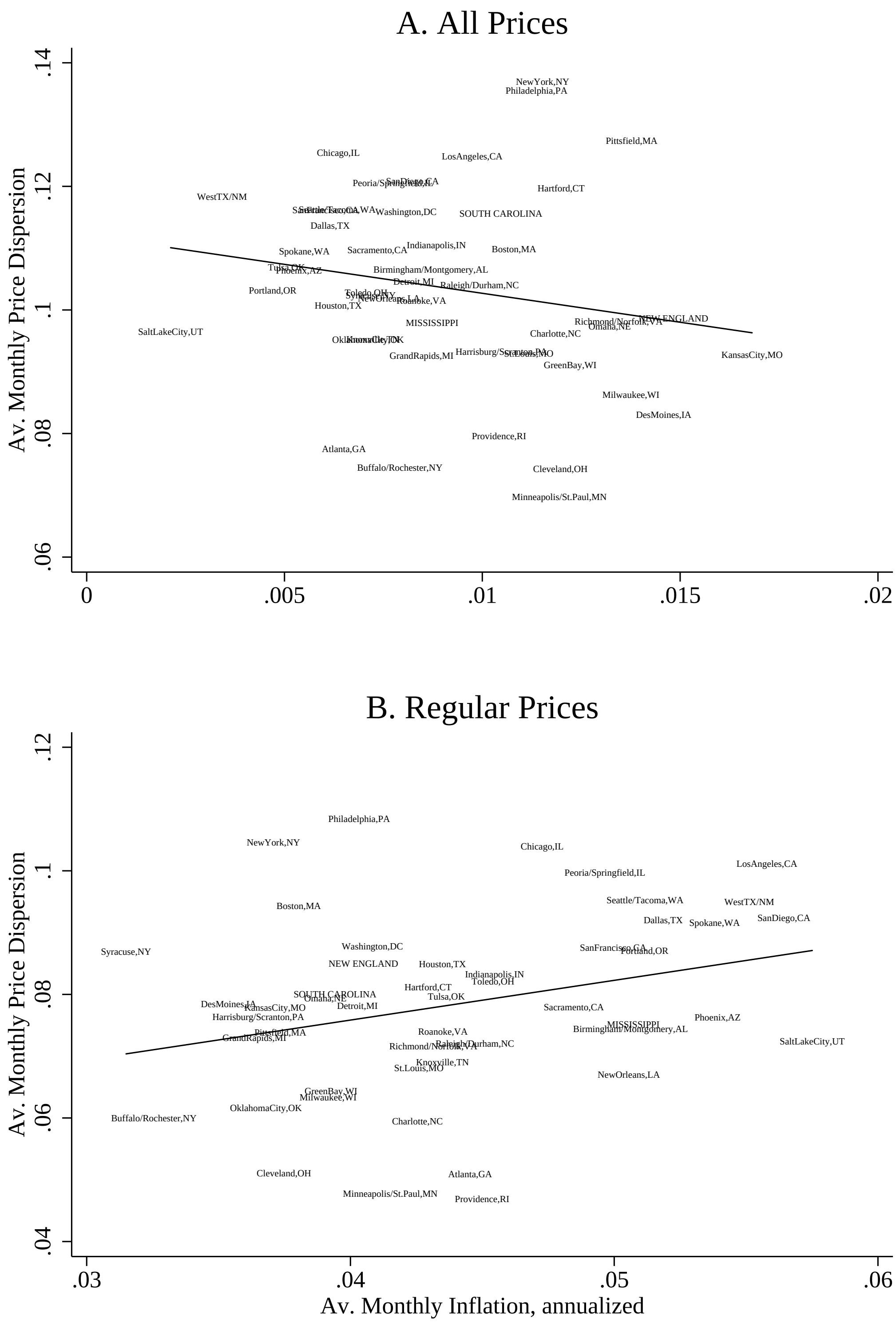
Notes: See Section 1.3.1 for details.

FIGURE A.1. AVERAGE MONTHLY DATA OVER CATEGORIES



Notes: "Regular Prices" do not include sales. See Section 1.3.1 for details.

FIGURE A.2. AVERAGE MONTHLY DATA OVER LOCAL MARKETS



Notes: "Regular Prices" do not include sales. See Section 1.3.1 for details.

TABLE A.2. ROBUSTNESS TO FIXED EFFECTS

Fixed Effects:	No (1)	Market (M) (2)	Category (C) (3)	M-C (4)	Time (T) (5)	M, T (6)	C, T (7)	M-C, T (8)
				A. ALL PRICES				
Inflation	-0.095^{***}	-0.039^{***}	-0.090^{***}	-0.025^{***}	-0.109^{***}	-0.047^{***}	-0.102^{***}	-0.029^{***}
	(0.013)	(0.006)	(0.014)	(0.008)	(0.014)	(0.009)	(0.015)	(0.010)
R^2	0.01	0.42	0.22	0.78	0.01	0.42	0.22	0.78
				B. REGULAR PRICES				
Inflation	0.097^{***}	0.113^{***}	0.072^{***}	0.061^{***}	0.082^{***}	0.097^{***}	0.054^{***}	0.034^{***}
	(0.023)	(0.018)	(0.020)	(0.010)	(0.022)	(0.017)	(0.018)	(0.006)
R^2	0.01	0.25	0.24	0.66	0.02	0.26	0.26	0.67

Notes: Each column represents coefficients from regression of price dispersion on inflation with a given set of fixed effects. "Regular Prices" do not include sales. Driscoll and Kraay (1998) standard errors are in parentheses. Serial correlation of up to 12 lags is allowed. Number of observations $N = 173,960$. $^{*}, ^{**}, ^{***}$ denote 10%, 5%, and 1% significance level, respectively. See Section 1.3.2 and Section A.1 for further details.

Positive vs. Negative Inflation The Calvo model without trend inflation suggests that price dispersion comoves with the squared inflation. To check this hypothesis, I first split my sample for cases of positive and negative inflation. If the Calvo model is correct, I should obtain coefficients of the same size, but opposite in sign. The results are in Columns (2) and (3) of Table A.3. For all prices, the coefficients are both negative and similar in size, suggesting that the data is inconsistent with the Calvo model. The two coefficients have the opposite sign for regular prices, but the effect of deflation is estimated rather imprecisely since the episodes of deflation in regular prices are rare.

I then regress price dispersion directly on squared inflation. Columns (4) and (5) present the results. Using squared inflation confirms qualitative statements about comovement of inflation and price dispersion: it is negative for all prices and positive for regular prices. For all prices the effect of squared inflation becomes statistically indistinguishable from zero once the level of inflation is controlled for. Overall, the results for the reduces-form equation are in line with those for the structural specification.

Trend Inflation and Price Dispersion The relationship between variables analyzed before takes business-cycle fluctuations into account. It is also important to see if price dispersion and inflation have trend relationship. This is because early search literature considers equilibrium models that do not allow for transitional dynamics, hence, a shock to inflation would not propagate over time, but rather lead to immediate adjustment in price dispersion.

In addition, welfare calculation in the Calvo model usually relies on approximating steady-state price dispersion with a parametric function of the steady-state inflation. The test below is a way to see if the steady-state relationship exists in the data.

I estimate the trend relationship using "between" regression. I compute average inflation and price dispersion over time for a given market-category, and then run cross-sectional regression. Since my data contain monthly observations for 11 years, I interpret time averages as steady-state values for a given market-category.

TABLE A.3. ROBUSTNESS OF THE REDUCED-FORM SPECIFICATION

	Baseline (1)	$\pi > 0$ (2)	$\pi < 0$ (3)	π^2 (4)	π, π^2 (5)
		A. ALL PRICES			
Inflation	-0.029^{***}	-0.026^{***}	-0.023		-0.027^{**}
	(0.010)	(0.008)	(0.014)		(0.011)
Inflation squared				-0.154^{***}	-0.048
				(0.048)	(0.043)
R^2, within	0.01	0.01	0.01	0.00	0.01
N	173,960	105,296	68,664	173,960	173,960
		B. REGULAR PRICES			
Inflation	0.034^{***}	0.039^{***}	-0.124^{***}		0.081^{***}
	(0.006)	(0.006)	(0.030)		(0.017)
Inflation squared				0.123^{***}	-0.335^{***}
				(0.036)	(0.109)
R^2, within	0.05	0.05	0.15	0.04	0.05
N	173,786	169,416	4,370	173,786	173,786

Notes: Each column presents coefficients from regression of price dispersion on inflation for different samples and variables. Column (1) is the baseline specification. Columns (2) and (3) restrict attention to either positive or negative inflation rates, respectively. Columns (4) and (5) add squared inflation into the reduced-form equation. "Regular Prices" do not include sales. Driscoll and Kraay (1998) standard errors are in parentheses. Serial correlation of up to 12 lags is allowed. Number of observations $N = 173,960$. $^{*},^{**},^{***}$ denote 10%, 5%, and 1% significance level, respectively. See Section 1.3.2 and Section A.1 for further details.

TABLE A.4. TREND INFLATION AND PRICE DISPERSION

	All Prices			Regular Prices		
	(1)	(2)	(3)	(4)	(5)	(6)
Inflation	-0.414^{***}		-0.213^{***}	0.213^{***}		0.780^{***}
	(0.055)		(0.062)	(0.038)		(0.097)
Inflation Squared		-5.264^{***}	-4.183^{***}		0.762^{***}	-4.614^{***}
		(0.556)	(0.636)		(0.290)	(0.725)
R^2	0.04	0.06	0.06	0.02	0.00	0.05
N	1,513	1,513	1,513	1,513	1,513	1,513

Notes: Coefficients from regression of trend price dispersion on trend inflation. Trends are computed as the averages over time for a given market category. "Regular Prices" do not include sales. $^{*},^{**},^{***}$ denote 10%, 5%, and 1% significance level, respectively. See Section A.1 for details.

As shown in Table A.4, the relationship between price dispersion and inflation is qualitatively similar, but quantitatively stronger than in the baseline. Hence, the negative comovement of inflation and price dispersion is a steady-state relationship as well.

Calvo Model Specification Finally, if Equation (1.11) is an accurate representation of the data-generating process, by iterating backward, one can obtain the following specification.

$$\sigma^2_{mc,t} = \beta_1 \pi^2_{mc,t} - \beta_2 \pi_{mc,t} + \Phi_1 (L)\, \pi_{mc,t-1} + \Phi_2 (L)\, \pi^2_{mc,t-1} + \gamma_{mc} + \tau_t + \varepsilon_{mc,t} \qquad \text{(A.1)}$$

where $\Phi_i (L)$ is the lag polynomial of an arbitrary-high order, $i = \{1, 2\}$. This simply means that the lag of price dispersion can be approximated by sufficiently many lags

TABLE A.5. EMPIRICAL ESTIMATES OF THE CALVO SPECIFICATION: INFLATION LAGS

	(1)	(2)	(3)	(4)
		A. ALL PRICES		
Lag Price Dispersion	0.909^{***}	0.544^{***}	0.545^{***}	
	(0.026)	(0.068)	(0.068)	
Inflation Squared	-0.013	0.006	0.002	-0.019^{***}
	(0.012)	(0.008)	(0.006)	(0.007)
Inflation	-0.002^{**}	-0.002^{**}	-0.003^{***}	-0.001
	(0.001)	(0.001)	(0.001)	(0.002)
Inflation Lags	N	N	N	Y
Market-Category FE	N	Y	Y	Y
Time FE	N	N	Y	Y
R^2, within	0.74	0.24	0.24	0.01
N	155,690	155,690	155,690	155,823
		B. REGULAR PRICES		
Lag Price Dispersion	0.856^{***}	0.537^{***}	0.527^{***}	
	(0.031)	(0.062)	(0.061)	
Inflation Squared	-0.041^{**}	-0.056^{***}	-0.049^{**}	-0.069^{***}
	(0.016)	(0.021)	(0.020)	(0.023)
Inflation	0.006^{**}	0.013^{***}	0.010^{***}	0.016^{***}
	(0.003)	(0.003)	(0.003)	(0.003)
Inflation Lags	N	N	N	Y
Market-Category FE	N	Y	Y	Y
Time FE	N	N	Y	Y
R^2, within	0.35	0.08	0.09	0.01
N	155,504	155,504	155,504	155,651

Notes: The table presents empirical estimates of the relationship between price dispersion and inflation suggested by the structural relationship in the Calvo model. Columns (1)-(3) reproduces the estimates for alternative sets of fixed effects in Table 1.3. Column (4) controls for 12 lags of inflation instead of lagged price dispersion. "Regular Prices" do not include sales. *,**,*** denote 10%, 5%, and 1% significance level, respectively. See Section 1.3.2 and Section A.1 for details.

of inflation and its square. I show estimates for this specification in Column (4) of Table A.5. For all prices, the coefficient on squared inflation now turns negative and rises in magnitude, suggesting that the true data-generating process is different from Equation (1.11). For regular prices, however, the results of this alternative specification are similar to those in the baseline specification.

Robustness to MA(12) Filter Tables A.6–A.8 reproduce results in Section 1.4.1 for the case when simulated data is not MA(12)-filtered. All results qualitatively remain the same.

Table A.6. Calvo Model vs. The Data without MA(12) Filtering

	Model			Data	
	Monetary (1)	TFP (2)	Both Shocks (3)	All Prices (4)	Regular Prices (5)
Lag Price Dispersion	0.902	0.900	0.902	0.545	0.527
Inflation Squared	$4.5 \cdot 10^{-5}$	$-4.5 \cdot 10^{-5}$	$-1.3 \cdot 10^{-5}$	0.002	−0.049
Inflation	0.070	0.072	0.071	−0.003	0.010

Notes: The table reproduces results in Table 1.5 for the case when simulated data is not MA(12)-filtered. See Section 1.4.1 and Section A.1 for details.

Table A.7. Price Dispersion and Inflation in the Calvo Model without MA(12) Filtering

	Model			Data	
	Monetary (1)	TFP (2)	Both Shocks (3)	All Prices (4)	Regular Prices (5)
Baseline	0.229	0.464	0.375	−0.029	0.034
Alternatives					
Response to Inflation $\varphi_\pi = 10$ (4)	0.214	0.458	0.302		
Persistence of TFP Shock $\varphi_A = 0.4$ (0.95)	0.229	0.091	0.229		
Persistence of M Shock $\varphi_M = 0.8$ (0)	0.290	0.464	0.298		
Trend Inflation $\bar{\pi} = 0$ (4.4%)	0.115	0.200	0.155		
Probability of Price Change $\bar{\lambda} = 0.5$ (0.1)	0.029	0.034	0.029		

Notes: The table reproduces results in Table 1.6 for the case when simulated data is not MA(12)-filtered. See Section 1.4.1 and Section A.1 for details.

Table A.8. Price Dispersion and Inflation in the SSDP Model without MA(12) Filtering

	Model			Data	
	Monetary (1)	TFP (2)	Both Shocks (3)	All Prices (4)	Regular Prices (5)
Taylor Rule Setup	0.106	0.144	0.117	−0.029	0.034
Money Growth Setup	0.128	0.115	0.122		
Alternatives (Taylor Rule)					
Response to Inflation $\varphi_\pi = 10$ (4)	0.099	0.138	0.105		
Persistence of TFP Shock $\varphi_A = 0.4$ (0.95)	0.106	0.061	0.106		
Persistence of M Shock $\varphi_M = 0.8$ (0)	0.124	0.144	0.124		
Trend Inflation $\bar{\pi} = 0$ (4.4%)	0.079	0.103	0.085		

Notes: The table reproduces results in Table 1.8 for the case when simulated data is not MA(12)-filtered. See Section 1.4.1 and Section A.1 for details.

A.2 Details on the Search Model

The model extends Head et al. (2012) to the stochastic money growth case. There are two markets: one is conventional referred to as the Arrow-Debreu (AD) market, the other one is a search market as in Burdett and Judd (1983) referred to as the BD market. Household preferences are described by

$$\sum_{t=0}^{\infty} \beta^t \left[u\left(q_t\right) + \upsilon\left(x_t\right) - h_t \right] \tag{A.1}$$

with $u(\cdot)$ and $\upsilon(\cdot)$ being utility functions over goods consumed in the BJ (q_t) and AD (x_t) markets, respectively, and h_t be the hours supplied to the labor market. Let c be the marginal cost of BJ goods in terms of AD goods. Consumers shop sequentially on the BJ and AD markets. Let $V_t\left(m_t\right)$ and $W_t\left(m_t\right)$ be the corresponding value functions of the household with m_t dollars.

The AD Market The household problem can be written as

$$W_t\left(m_t\right) = \max_{h_t, x_t, \hat{m}_t} \left\{ \upsilon_t\left(x_t\right) - h_t + \beta V_{t+1}\left(\hat{m}_t\right) \right\} \tag{A.2}$$

$$\text{s. th. } x_t = h_t + \frac{m_t - \hat{m}_t + D_t + T_t}{P_t} \tag{A.3}$$

where $\hat{m}_t$ is the money left after shopping in the AD market, D_t is the dividend payments, T_t is total transfers, and P_t is the price level.

The first-order conditions (FOC) can be written as

$$\upsilon'\left(x_t\right) = \frac{\beta V'_{t+1}\left(\hat{m}_t\right)}{P_t} = 1 \tag{A.4}$$

The BJ Market The household optimization problem is

$$U_t\left(p, m_t\right) = \max_{q_t} \left\{ u\left(q_t\right) + W_t\left(m_t - p q_t\right) \right\} \tag{A.5}$$

$$\text{s. th. } p q_t \leq m_t \tag{A.6}$$

where p is the price drawn at the search market. The solution is then

$$q_t\left(p, m_t\right) = \begin{cases} m_t/p & \text{if } p \leq \hat{p}_t \\ \left(p/P_t\right)^{-\frac{1}{\gamma}} & \text{if } p > \hat{p}_t \end{cases}, \quad \hat{p}_t = \left(\frac{m_t^{\gamma}}{P_t}\right)^{\frac{1}{\gamma-1}} \tag{A.7}$$

where γ is the inverse intertemporal elasticity of substitution. This is because consumers have to choose how much money to carry over from AD into the next period's BJ market before they know they price drawn in the search market. If the price is low enough, they will choose to spend all the money left on the good in the search market (constrained demand), while they shop according to the unconstrained demand function otherwise.

Denote $\alpha_i,\ i=\{0,1,2\}$ the probability of obtaining i price quotes in the BJ market. Hence, the value function in the BJ market can be written as

$$\begin{aligned} V_t\left(m_t\right) = \alpha_0 W_t\left(m_t\right) + \alpha_1 \int U_t\left(p, m_t\right) dF_t\left(p\right) + \\ + \alpha_2 \int U_t\left(p, m_t\right) d\left\{1 - \left[1 - F_t\left(p\right)\right]^2\right\} \end{aligned} \tag{A.8}$$

where $F_t\left(p\right)$ is the equilibrium distribution of prices.

Firms The firm's total profit can be written as

$$\Pi_t\left(p\right) = \left[\alpha_1 + 2\alpha_2\left(1 - F_t\left(p\right)\right)\right] R_t\left(p\right) \tag{A.9}$$

where $R_t\left(p\right)$ is the total revenue.

$$R_t\left(p\right) = q_t\left(p, m_t\right)\left(\frac{p}{P_t} - c\right) \tag{A.10}$$

The first term in Equation (A.9) comes from consumers that drew only one price quote, while the remainder represents consumers who drew two price quotes and decided to buy from the given firm as their price is smaller.

In the unconstrained case, the profit-maximizing monopoly price (i.e., a price if every consumer only gets one price quote) is

$$p_t^m = \frac{cP_t}{1-\gamma} \tag{A.11}$$

which together with accounting for the constraint gives the monopoly price

$$p_t^M = \max\left\{p_t^m, \hat{p}\right\} \tag{A.12}$$

It is never optimal for a firm to charge a price above the monopoly one. However, if non-zero mass of consumers draw two price quotes, it can be optimal to charge a price below. The equilibrium price distribution is shown by Head et al. (2012) to be

$$F_t\left(p\right) = \frac{\alpha_1 + 2\alpha_2}{2\alpha_2} - \frac{\alpha_1}{2\alpha_2}\frac{R_t\left(p_t^M\right)}{R_t\left(p\right)} \tag{A.13}$$

with support $\mathscr{F}_t = \left[\underline{p}_t, p_t^M\right]$, s. th. $F_t\left(\underline{p}_t\right) = 0$.

Equilibrium The markets clear by the optimal value of money carried into the next period BJ market $\hat{m}_t^*$ that satisfies Equations (A.4), (A.8), and (A.13), i.e. for a given price distribution in the search market, AD and BJ markets clear by the optimal allocation of money between the two, and for the given allocation between the markets, price distribution in the search market is optimal. Combining these three conditions gives the following condition.

$$P_{t+1} = \beta P_t \left\{ 1 + \int_0^{\hat{p}_{t+1}} \left[\alpha_1 + 2\alpha_2 \left(1 - F_{t+1}\left(p\right)\right)\right] \left[\frac{P_{t+1}}{p} \left(\frac{\hat{m}_t^*}{p} \right)^{-\gamma} - 1 \right] dF_{t+1}\left(p\right) \right\} \tag{A.14}$$

Shocks and Unexpected Inflation The money supply is given by the process $M_{t+1} = \mu_{t+1} M_t$. If money supply growth is deterministic, then inflation is equal to μ_{t+1}. If it is stochastic instead, $E\mu_{t+1}$ determines $\hat{m}_t^*$ according to Equation (A.14), which in turn together with the actual realization of inflation μ_{t+1} determines $F_{t+1}\left(p\right)$.[1] Money growth follows the same process as in Equation (1.33).

[1]This is true to a first-order approximation only. In the second-order approximation inflation uncertainty will also have an effect, which is disregarded as in much of the previous work on the subject.

Appendix B

Appendix to Chapter 3

B.1 Additional Results

TABLE B.1. LIST OF COUNTRIES

LDC, 1950-80				UN, 1978-96						SIPRI/NATO, 1985-97	
Country	#	cont'd		Country	#	cont'd		cont'd		Country	#
Argentina	23	Peru	10	Argentina	4	Jordan	2	Togo	1	Belgium	13
Bangladesh	5	Philippines	26	Australia	15	Latvia	3	Turkey	12	Canada	13
Bolivia	3	Saudi Arabia	15	Austria	16	Lebanon	1	UK	14	Denmark	13
Botswana	12	Sierra Leone	16	Barbados	4	Luxembourg	8	USA	11	Germany	6
Brazil	9	Singapore	11	Belgium	13	Madagascar	1			Greece	13
Chile	30	SriLanka	26	Brazil	2	Malaysia	2			Italy	13
Colombia	24	Sudan	13	Burkina Faso	1	Malta	5			Luxembourg	13
Fiji	8	Tanzania	15	Canada	17	Mexico	4			Netherlands	13
Ghana	21	Thailand	8	Chile	10	Namibia	1			Norway	13
Guatemala	18	Trinidad & Tobago	18	Colombia	3	Netherlands	16			Portugal	13
Guyana	14	Uganda	7	Cyprus	3	New Zealand	15			Spain	11
Honduras	14	Venezuela	11	Czech Republic	2	Niger	3			Turkey	13
India	29			Denmark	13	Norway	16			UK	13
Iran	13			Ecuador	1	Panama	1			USA	13
Jamaica	17			El Salvador	1	Peru	3				
Jordan	10			Finland	15	Philippines	1				
Liberia	19			France	9	Poland	1				
Malagasy Rep.	19			Germany	9	Portugal	8				
Malaysia	15			Germany, Fed. Rep.	2	Romania	6				
Mauritius	8			Greece	9	Senegal	1				
Morocco	20			Hungary	6	Slovakia	2				
Nicaragua	21			Indonesia	3	Slovenia	2				
Nigeria	20			Ireland	7	Spain	9				
Pakistan	29			Israel	4	Suriname	1				
Panama	22			Italy	14	Sweden	14				
Papua New Guinea	5			Japan	13	Thailand	5				

Table B.2. Descriptive Statistics, by dataset

	LDC, 1950-80							UN, 1978-96							SIPRI/NATO, 1985-97						
Variable	Mean	Std. Dev. overall	Std. Dev. between	Std. Dev. within	N	n	$\bar{T}$	Mean	Std. Dev. overall	Std. Dev. between	Std. Dev. within	N	n	$\bar{T}$	Mean	Std. Dev. overall	Std. Dev. between	Std. Dev. within	N	n	$\bar{T}$
$\frac{\Delta^t y_{i,t}}{y_{i,t-1}}$	.053	.077	.040	.071	498	36	14	.027	.029	.027	.023	257	37	7	.031	.025	.011	.022	159	14	11
$\frac{\Delta^t g_{i,t}}{y_{i,t-1}}$	.013	.107	.081	.087	440	35	13	.004	.032	.007	.031	257	37	7	.001	.003	.001	.002	159	14	11
$\frac{\Delta^t g^d_{i,t}}{y_{i,t-1}}$	.002	.025	.012	.023	440	35	13	.001	.011	.003	.011	257	37	7	.000	.001	.000	.001	159	14	11
$\frac{\Delta^t g^n_{i,t}}{y_{i,t-1}}$	.011	.093	.069	.076	440	35	13	.003	.021	.005	.021	257	37	7	.000	.002	.001	.002	159	14	11
$\phi_{i,t} \equiv \frac{g^d_{i,t}}{g_{i,t}}$	.121	.155	.113	.108	541	37	15	.259	.143	.191	.048	365	55	7	.210	.074	.067	.032	173	14	12
$\Delta^t \phi_{i,t}$	.001	.116	.084	.110	477	37	13	.001	.048	.049	.041	261	40	7	.000	.029	.006	.028	159	14	11

Table B.3. Descriptive Statistics, UN sample

	UN, whole sample							UN, IMF advanced economies							UN, LDC sample						
Variable	Mean	Std. Dev. overall	Std. Dev. between	Std. Dev. within	N	n	$\bar{T}$	Mean	Std. Dev. overall	Std. Dev. between	Std. Dev. within	N	n	$\bar{T}$	Mean	Std. Dev. overall	Std. Dev. between	Std. Dev. within	N	n	$\bar{T}$
$\frac{\Delta^t y_{i,t}}{y_{i,t-1}}$	.027	.029	.027	.023	257	37	7	.025	.023	.017	.020	218	25	9	.033	.053	.045	.035	35	10	4
$\frac{\Delta^t g_{i,t}}{y_{i,t-1}}$	.004	.032	.007	.031	257	37	7	.004	.034	.008	.033	218	25	9	.001	.006	.002	.005	35	10	4
$\frac{\Delta^t g^d_{i,t}}{y_{i,t-1}}$	.001	.011	.003	.011	257	37	7	.001	.012	.003	.012	218	25	9	.000	.002	.001	.001	35	10	4
$\frac{\Delta^t g^n_{i,t}}{y_{i,t-1}}$	.003	.021	.005	.021	257	37	7	.003	.023	.006	.022	218	25	9	.000	.005	.001	.005	35	10	4
$\phi_{i,t} \equiv \frac{g^d_{i,t}}{g_{i,t}}$	.259	.143	.191	.048	365	55	7	.281	.117	.161	.042	281	27	10	.197	.200	.213	.066	76	24	3
$\Delta^t \phi_{i,t}$	.001	.048	.049	.041	261	40	7	.001	.037	.041	.033	220	27	8	.007	.089	.066	.074	37	11	3

Table B.4. Pairwise Correlations

Variable	LDC						SIPRI/NATO						UN, LDC					
	Pooled						UN						UN, advanced					
$\frac{\Delta^t y_{i,\ t}}{y_{i,\ t-1}}$	-	-.02	.01	-.03	.02	.02	-	.20$^{\bigstar}$	.13^{+}	.17*	.05	.09	-	.28^{+}	.31^{+}	.20	.16	.25
$\frac{\Delta^t g_{i,\ t}}{y_{i,\ t-1}}$	-.01	-	.64$^{\bigstar}$	.98$^{\bigstar}$	.03	.00	-.04	-	.53$^{\bigstar}$	.92$^{\bigstar}$	-.06	-.07	-.06	-	.45$^{\bigstar}$	.95$^{\bigstar}$	.19	.22
$\frac{\Delta^t g^d_{i,\ t}}{y_{i,\ t-1}}$	.01	.66$^{\bigstar}$	-	.47$^{\bigstar}$	.11*	.12$^{\bigstar}$	-.04	.95$^{\bigstar}$	-	.16*	.17*	.72$^{\bigstar}$	-.07	.95$^{\bigstar}$	-	.16	.49$^{\bigstar}$	.83$^{\bigstar}$
$\frac{\Delta^t g^n_{i,\ t}}{y_{i,\ t-1}}$	-.01	.98$^{\bigstar}$	.49$^{\bigstar}$	-	.00	-.03	-.03	.99$^{\bigstar}$	.88$^{\bigstar}$	-	-.14^{+}	-.42$^{\bigstar}$	-.06	.99$^{\bigstar}$	.89$^{\bigstar}$	-	.04	-.04
$\phi_{i,\ t} \equiv \frac{g^d_{i,\ t}}{g_{i,\ t}}$	-.09$^{\bigstar}$	.00	.08*	-.03	-	.36$^{\bigstar}$	.04	.03	.08	.00	-	.22$^{\bigstar}$	.02	.02	.07	-.02	-	.38$^{\bigstar}$
$\Delta^t \phi_{i,\ t}$	.03	.00	.12$^{\bigstar}$	-.04	.30$^{\bigstar}$	-	.16$^{\bigstar}$	.01	.11^{+}	-.05	.23$^{\bigstar}$	-	.09	-.01	.10	-.06	.12^{+}	-

Significance level: $^{\bigstar}$ – 1% * – 5% $^{+}$ – 10%

Figure B.1. Share of Durables in Total Military Expenditure, LDC dataset

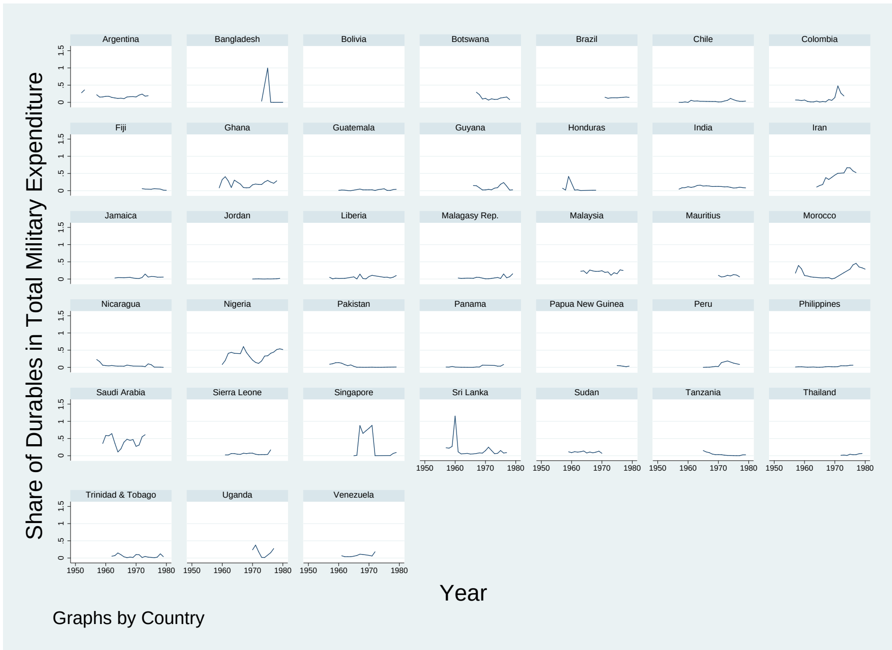


Figure B.2. Share of Durables in Total Military Expenditure, UN dataset

Figure B.3. Real GDP Growth vs Spending on Durables and Nondurables-Services: "between countries"

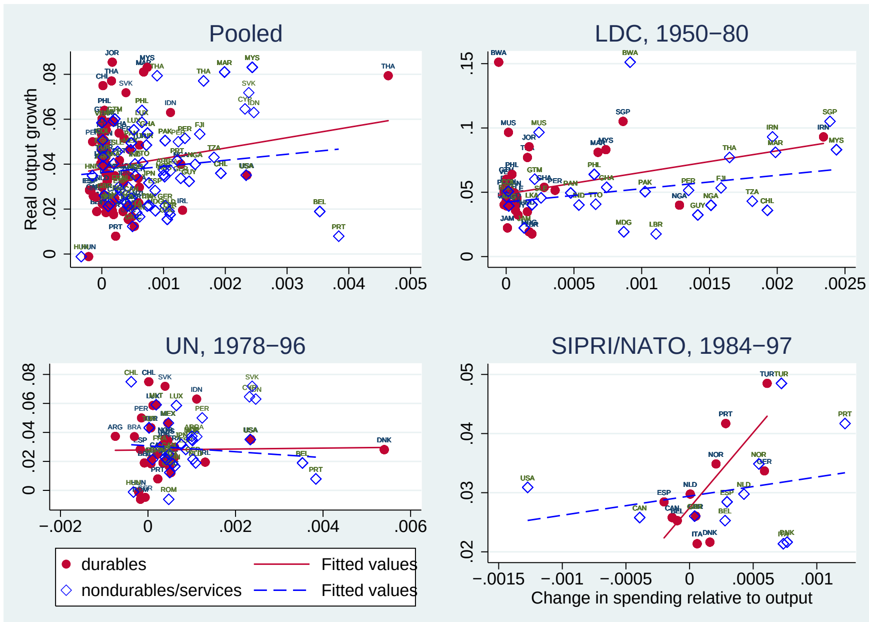


Figure B.4. Real GDP Growth vs Spending on Durables and Nondurables-Services: "between years"

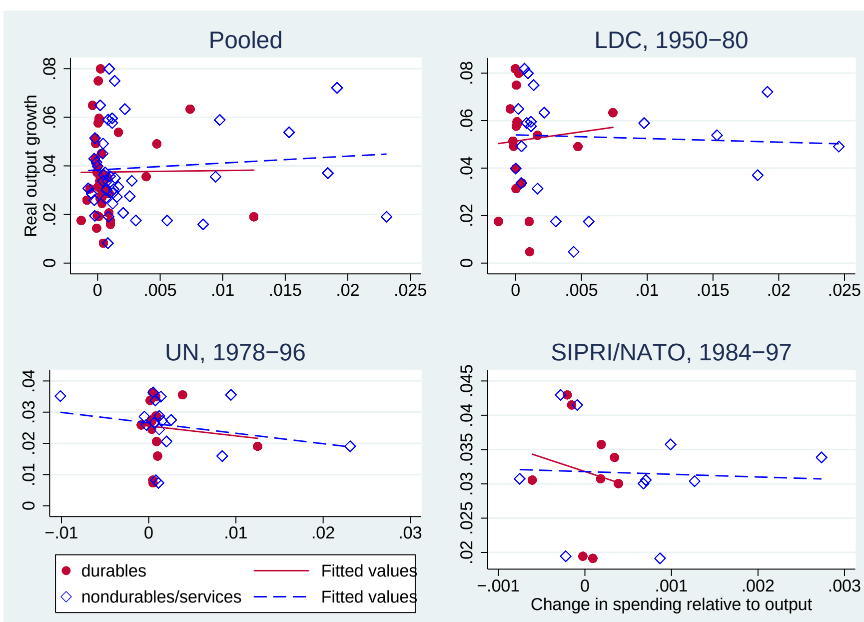


Figure B.5. Real GDP Growth vs Spending on Durables and Nondurables-Services: "within years"

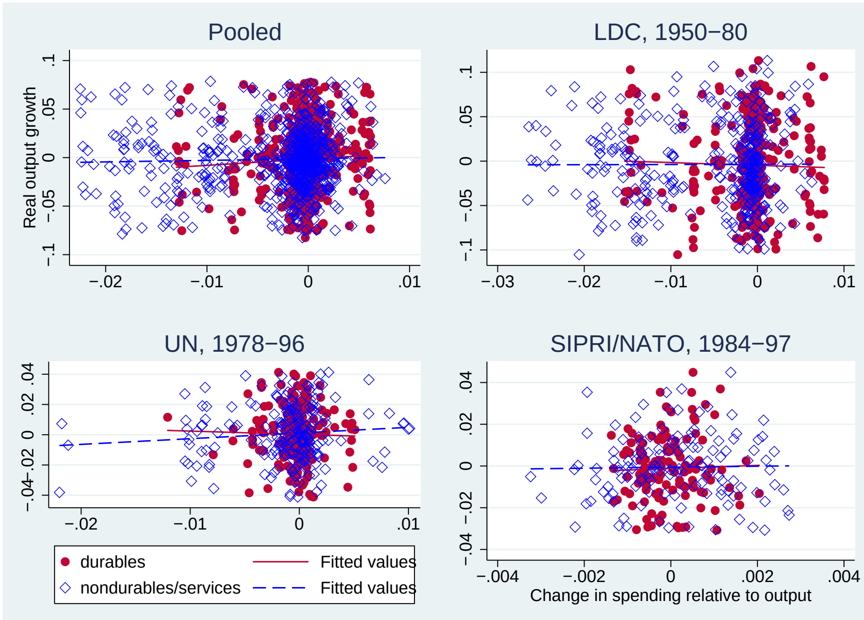


Figure B.6. Real GDP Growth vs Spending Composition: "within countries" variation, UN subsamples

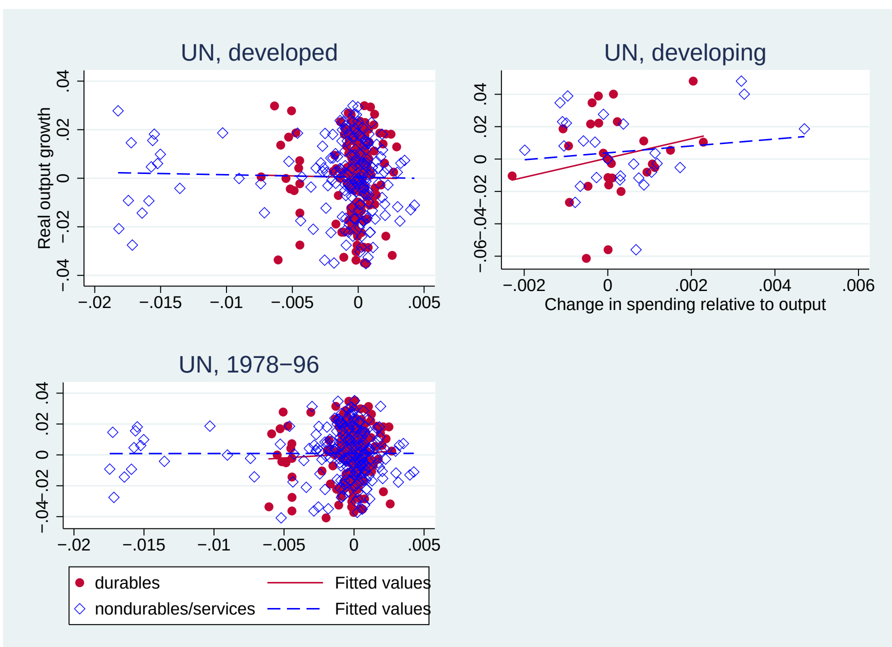


Figure B.7. Real GDP Growth vs Partialled-Out Spending on Durables: "between countries"

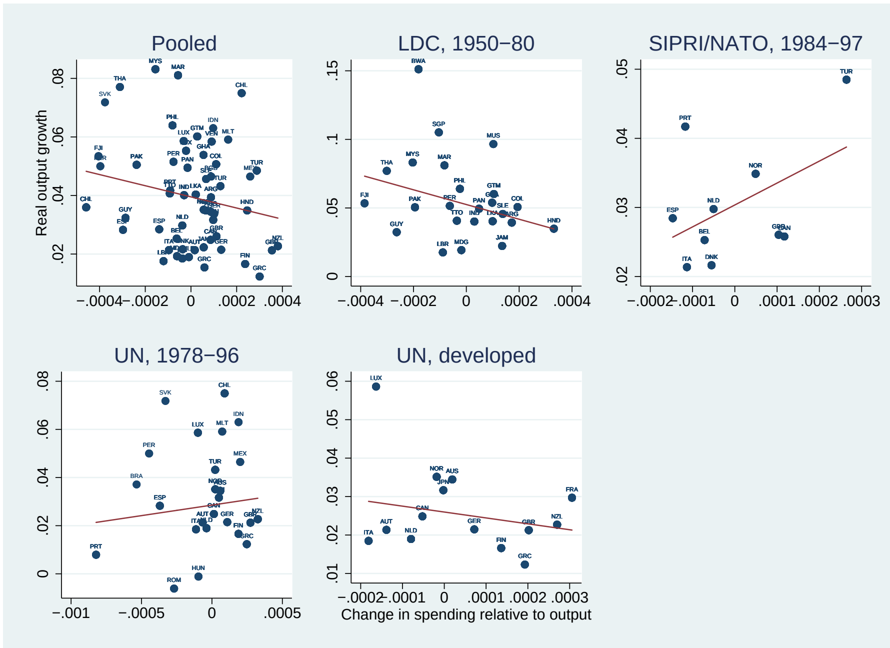


Figure B.8. Real GDP Growth vs Partialled-Out Spending on Durables: "within years"

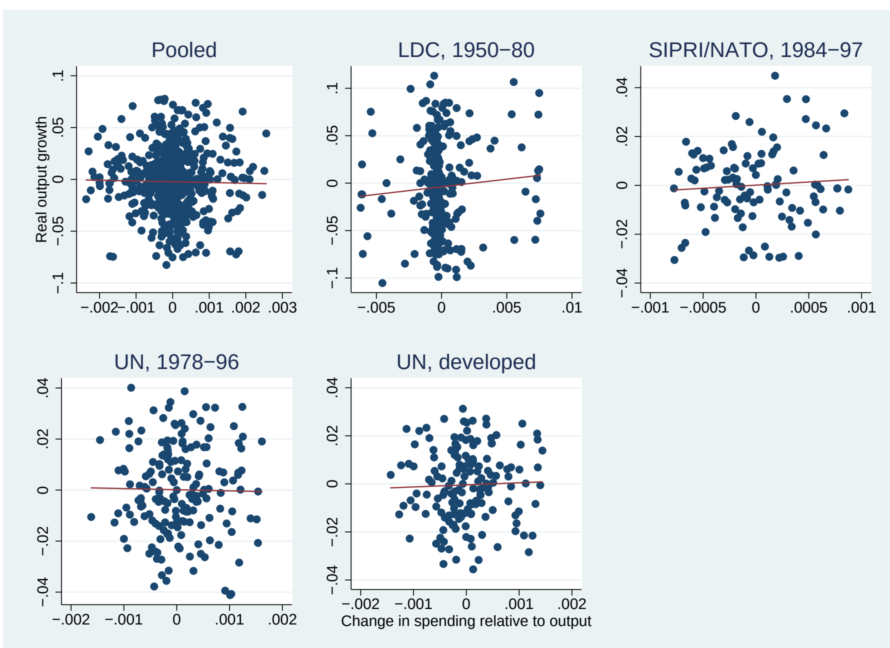


Figure B.9. Real GDP Growth vs Total Spending: "within years" variation