Price Setting Under Uncertainty About Inflation *

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Abstract

We analyze the manipulation of inflation statistics that occurred in Argentina starting in 2007 to test the relevance of informational frictions in price setting. We estimate that the manipulation of statistics had associated a higher degree of price dispersion. This effect is analyzed in the context of a quantitative general equilibrium model in which firms use information about the inflation rate to set prices. Not reporting accurate measures of the CPI entails significant welfare losses, especially in economies with volatile monetary policy.

Keywords: Price setting, informational frictions, social value of public information.

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1 Introduction

When setting prices firms use various sources of information, some of which are publicly-provided economic statistics. The accuracy of firms' pricing decisions depends on the amount and quality of information that they receive. A natural question is: how relevant is public information about the macroeconomic state for price setting decisions? Following early work by Phelps (1970) and Lucas (1972), a large strand of research developed positive theories that argue that lack of information when setting prices can have effects on the real economy. One challenge this body of work faces is that it is hard to test its predictions in the data, due to difficulties in identifying settings with variations in the availability of information. In this paper, we empirically analyze the relevance of information frictions in price setting and quantify the welfare effects of changing the availability of public information about the macroeconomic state.

Our paper focuses on the effects of the provision of public information about inflation on firms' pricing decisions and the macroeconomy. We develop a model of price setting with information frictions in which firms use public information about inflation to set prices. In the model, price dispersion increases when there is less precise information about inflation, as firms rely more on idiosyncratic information to set prices. We then exploit an episode in Argentina during which the quality of inflation statistics was undermined, and estimate an increase in price dispersion. Finally, we calibrate the model to match the empirical evidence, and find that there are welfare costs associated with less precise information about inflation and that the magnitude of these costs depends on the degree of predictability of monetary policy. In economies where monetary policy is less predictable, there are significant welfare gains associated with providing accurate inflation statistics.

In the model, monopolistically competitive firms make use of a noisy publicly-available signal of the aggregate price level, together with idiosyncratic information about their own revenues and costs to set prices. Given their information set, firms cannot perfectly tell apart the nature of all the shocks in the economy and perform Bayesian updating when setting prices. The model predicts that price dispersion increases in response to a decrease in the precision of the aggregate price signal. A less precise signal of the aggregate price makes firms increase the weight attached to their idiosyncratic signals and their prior, and reduce the weight attached to the aggregate signal. This increases price dispersion since idiosyncratic signals contain cross-sectional dispersion and the aggregate signal does not.

In the empirical analysis, we exploit a particular event in which policy makers tampered with the quality of public information about inflation. The episode of analysis is the misreporting of official inflation statistics conducted by the Argentinean government starting in January 2007. As a consequence of this misreporting, official inflation statistics stopped providing valuable information regarding the actual rate of inflation. We consider this event as an episode in which agents lost access to accurate aggregate information about the inflation rate. Simultaneously, after 2007 Argentina also experienced an increase in the volatility of inflation. We use this event to analyze the effect of this regime change on price dispersion by exploiting two sources of variation. The first analysis consists of a difference-in-difference estimation, in which Uruguay serves the purpose of the control group.[1] Second, we take advantage of the additional variation that arises from the fact that the pricing decisions of different goods might rely more or less on the aggregate inflation rate. Therefore, if higher uncertainty about inflation is associated with higher price dispersion, one should expect this relationship to be stronger for goods whose prices rely more on information about the inflation rate.

The empirical analysis is carried out with data on prices from the largest e-trade platform in Latin America. We have data on more than 140 million listings of goods available for sale. Using data on posted prices of each listing and the categorization of the product provided by the platform, we compute series of price dispersion for all categories of goods, and for both countries, on a quarterly basis during the period 2003-2012. Controlling for observed

[1]The choice of the control country is driven by their similar economic characteristics, similar exposure to external macroeconomic shocks, and the high synchronization of their business cycles.

inflation and other macroeconomic variables that can affect price dispersion, we then use a difference-in-difference approach to estimate how price dispersion was affected by the changes that occurred after 2007. The analysis shows that the manipulation of inflation statistics and higher inflation volatility had associated a statistically significant increase in the coefficient of variation of prices of 9.5% with respect to its median. When exploiting the heterogeneous sensitivity of different goods to inflation, we find that higher uncertainty about inflation is associated with higher price dispersion for goods that rely more on information about inflation at the price-setting stage.

We carry out additional analysis to demonstrate that the results are robust to the way we measure price dispersion, the way we control for changes in inflation rates, alternative specifications, and different sub-samples. Importantly, we estimate a specification that allows for a flexible effect over time and find a positive increase in price dispersion starting from the first semester of 2007, when the manipulation of statistics began. Additionally, in order to isolate variations in measured price dispersion coming from anomalous prices and from product differentiation, we re-estimate the analysis using transacted data and using a subset of goods that are narrowly identified in the platform, reaching similar results.

The empirical strategy estimates the effect of the regime change on price dispersion, which can be due to less accurate information about inflation and/or the increase in monetary volatility. We use a model-based inference to disentangle the effect of each of the two policies. In particular, we use the estimated increase in price dispersion and the observed increase in inflation volatility to calibrate the implicit increase in the variance of the noise of the signal of aggregate prices and the change in the volatility of the money supply shock. While both policy changes give rise to an increase in price dispersion in the model, the response of inflation volatility is qualitatively different. Therefore, including the change in inflation volatility provides a useful source of identification. The calibration exercise shows that both targets cannot be matched with changes in monetary policy only.

By analyzing each policy change one at a time, we find that 17% of the cumulative increase in price dispersion is due to the sole increase in the variance of the noise of the signal of aggregate prices, 13% is due to the sole increase in the volatility of the money supply shock and 70% is due to the interaction of both effects. The interaction term is important because a noisier signal of aggregate prices leads to higher price dispersion, especially so in volatile economies in which such information is more valuable.

Finally, we use the model to compute the welfare effects of not providing an accurate measure of aggregate prices. We find that these effects are negative and large, equivalent to a permanent decrease in consumption of 0.7%. With less accurate information, firms can predict their idiosyncratic demand for goods and the idiosyncratic labor costs in a less precise way. This leads to a less precise price setting, which in turn causes a poor allocation of labor and consumption across goods. The presence of such high welfare costs is related to the fact that the Argentinean economy is highly volatile. We illustrate this point by computing the same welfare exercise for a different parameterization of the model calibrated to match the US economy. The welfare cost of the same increase in the variance of the noise of the aggregate price signal in the US economy is equivalent to a permanent drop in consumption of only 0.16%. The main reason behind the difference in welfare costs is the fact that monetary policy is stable in the US, which allows agents to predict reasonably well the rate of inflation just with their prior beliefs about the money supply process. Thus, reducing the accuracy of the signal of aggregate prices does not significantly undermine the prediction capacity of firms and affect the efficiency of the allocation of resources.

Our paper provides a quantitative contribution to the literature that studies general equilibrium models of firms' price-setting behavior in the presence of informational frictions. In order to replicate the episode of analysis, we model informational frictions via the presence of incomplete and noisy information. A similar approach is used in other papers, including Woodford (2003), Angeletos and La'O (2009), Hellwig and Venkateswaran (2009), Baley and Blanco (2019) and Angeletos and Huo (2018). We contribute to this literature by making use of an event in which the quality of information available was significantly altered to empirically study its effect on price setting.

The paper is also related to a theoretical literature that studies the social value of releasing public information. The approach of this literature has been to identify circumstances under which the positive effects of providing public information can be overturned. Initial studies have analyzed general settings (e.g. Morris and Shin, 2002; Angeletos and Pavan, 2004, 2007) and showed that welfare can decrease with the provision of public information if the economy features payoff externalities and strategic complementarities. More recent papers have studied similar questions in the context of micro-founded macroeconomic models (e.g. Hellwig, 2005; Lorenzoni, 2010; Amador and Weill, 2010; Angeletos et al., 2016). We contribute to this literature by being the first paper that quantifies the welfare effects of better public information and showing that they are positive and large for volatile economies.

The paper is organized as follows. Section 2 presents a general equilibrium model of price setting. Section 3 documents the episode of analysis and describes the microdata. Section 4 discusses the empirical strategy, presents the main results and robustness exercises. A quantitative analysis of the model implications for price dispersion is carried out in Section 5. Welfare results are presented in section 6. Finally, Section 7 concludes.

2 A Model of Price Setting with Information Frictions

In this section, we formulate a price-setting general equilibrium model with monopolistically competitive firms that have access to incomplete and dispersed information. The model is based on Woodford (2003) and Hellwig and Venkateswaran (2009), enhanced with the availability of a public signal of the price level to place focus on the role of public information on firms' pricing decisions. The goal of the model is twofold: i) to analyze the effect that the precision of the public signal has on price dispersion, ii) to provide a framework with which to disentangle the effects of the misreporting of inflation statistics in a context of higher aggregate volatility in Argentina and to quantify its welfare effects.

2.1 Households

There is a continuum of identical infinitely-lived households whose preferences are defined over a continuum of varieties of goods C_{it}, a continuum of variety-specific labor supply L_{it} and real money balances $\frac{M_t}{P_t}$. The expected lifetime utility of households is given by

$$\mathbb{E}\left(\sum_{t=0}^{\infty}\beta^t\left[\frac{C_t^{1-\gamma}}{1-\gamma}-\int_0^1\Phi_{it}L_{it}\,\mathrm{d}i+\ln\left(\frac{M_t}{P_t}\right)\right]\right), \tag{1}$$

where C_t is the Dixit-Stiglitz composite of individual goods with elasticity of substitution θ

$$C_t=\left[\int_0^1\Psi_{it}^{1/\theta}C_{it}^{(\theta-1)/\theta}\,\mathrm{d}i\right]^{\theta/(\theta-1)}. \tag{2}$$

Consumption preferences for good i are affected by the preference shock Ψ_{it} and preferences over labor supply are influenced by a shock to the disutility of labor of type i, Φ_{it}, both of which are known to the household at time t. The log of these shocks is assumed to follow independent AR(1) processes

$$\ln\Psi_{it}=\rho_\Psi\ln\Psi_{it-1}+\sigma_\Psi\varepsilon_{it}^\Psi \qquad \varepsilon_{it}^\Psi\sim N(0,1),$$
$$\ln\Phi_{it}=\rho_\Phi\ln\Phi_{it-1}+\sigma_\Phi\varepsilon_{it}^\Phi \qquad \varepsilon_{it}^\Phi\sim N(0,1).$$

Households have access to riskless one-period bonds B_t in addition to money for saving purposes. The problem of the household involves choosing a sequence $\{C_{it},L_{it},M_t,B_t\}_{t=0}^{\infty}$ to maximize (1) subject to the budget constraint

$$M_t+\frac{B_t}{1+i_t}+\int_0^1P_{it}C_{it}\,\mathrm{d}i=M_{t-1}+B_{t-1}+\int_0^1W_{it}L_{it}\,\mathrm{d}i+\Pi_t+T_t,$$

where Π_t represents the aggregate profits from the ownership of firms, T_t are lump sum transfers of money from the central bank, i_t denotes the risk-free nominal interest rate, W_{it} is the wage paid by the firm that produces variety i and P_{it} is the price of the good of variety

i. The solution to the household's problem is characterized by a set of first order conditions, which we outline in Online Appendix A.

We assume that money supply follows the following stochastic process

$$\log(M_{t+1}) = \log(M_t) + \mu + \sigma_{mt}\varepsilon^m_{t+1} \qquad \varepsilon^m_{t+1} \sim N(0,1).$$

Since we are interested in analyzing the effects of a one-time change in the variance of the innovations of money supply, σ_{mt}, we allow this parameter to depend on time in a deterministic way. Combining the household's first order conditions and the fact that the log of money supply follows a random walk generates a nominal interest rate given by

$$(1+i_t) = \frac{1}{\beta}\left(E_t\left(\frac{M_t}{M_{t+1}}\right)\right)^{-1} = \frac{1}{\beta}\exp\left(\mu - \frac{\sigma^2_{mt}}{2}\right).$$

Given the linearity of preferences with respect to labor supply, we obtain the following equation for wages

$$W_{it} = \kappa_t \Phi_{it} M_t, \tag{3}$$

where $\kappa_t \equiv \frac{i_t}{1+i_t}$. Thus, nominal wages paid for variety i are proportional to the idiosyncratic marginal disutility of labor and aggregate money supply.[2] The demand for each variety is given by

$$C_{it} = \Psi_{it}\left(\frac{P_{it}}{P_t}\right)^{-\theta}\left(\frac{\kappa_t M_t}{P_t}\right)^{1/\gamma}, \tag{4}$$

where $P_t = \left(\int_0^1 \Psi_{it} P_{it}^{1-\theta} \mathrm{d}i\right)^{1/(1-\theta)}$ is the ideal price index.

[2]In the absence of the idiosyncratic disturbances Φ_{it}, firms would be able to perfectly infer the aggregate state of the economy (i.e. money supply) from the wages paid to its employees. If we want information about past values of the CPI to provide useful information to the firm, we must prevent this learning process via paid wages. We achieve this by including the idiosyncratic shocks to the disutility of variety-specific labor supply.

2.2 Firm's Problem

There is a continuum of firms, each of which sells one variety of the consumption good indexed by i. Firms are monopolistically competitive and face the demand derived from the household's problem given by equation (4). The production function of the firm is given by

$$Y_{it} = L_{it}^{\alpha} \qquad \text{with} \qquad \alpha < 1.$$

The firm's problem is to maximize expected profits (discounted by the appropriate pricing kernel, $\lambda_t = \beta^t \Phi_{it}/W_{it}$)

$$\max_{P_{it}} \mathbb{E}_t \left[\lambda_t \left(P_{it} C_{it} - W_{it} L_{it} \right) \middle| \mathcal{I}_{it} \right],$$

where $\mathbb{E}_t \left[\cdot | \mathcal{I}_{it} \right]$ denotes the expectation operator at period t conditional on the firm-specific information set $\mathcal{I}_{it}$ (which is defined below). The optimal price, expressed in logs,[3] is

$$p_{it} = const_{1t} + \frac{1}{1+\theta\left(\frac{1}{\alpha}-1\right)} \mathbb{E}_{it}\left[\left(\frac{1}{\alpha} - 1 \right) \psi_{it} + \phi_{it} \right] + \mathbb{E}_{it}\left[m_t\right] + \frac{\left(\theta - \frac{1}{\gamma}\right)\left(\frac{1}{\alpha}-1\right)}{1+\theta\left(\frac{1}{\alpha}-1\right)} \mathbb{E}_{it}\left[p_t - m_t\right], \tag{5}$$

where $const_{1t}$ is a constant that depends on time only to the extent that σ_{mt} is time-dependent. To simplify notation, we write $\mathbb{E}_{it}[\cdot]$ to refer to $\mathbb{E}_t \left[\cdot | \mathcal{I}_{it} \right]$. We provide a derivation of the optimal price along with expressions of all the constants in Online Appendix A. Equation (5) shows that the firm's optimal price is increasing in the conditional expectation of both idiosyncratic shocks and the conditional expectation of money. However, the quantitative reaction to these different shocks is different. Hence, the firm would find it valuable to know the nature of the shocks it faces. Additionally, as long as $\theta > \gamma^{-1}$, the model exhibits pricing complementarities, i.e., the optimal idiosyncratic price is increasing in the conditional expectation of the aggregate price.

[3] The natural logarithm of capital letters is denoted by small letters: $x = \log X$.

Similarly, we take logs to the equation defining the ideal price index to obtain

$$p_t = \log\left(\left(\int_0^1 \Psi_{it} P_{it}^{1-\theta}\, \mathrm{d}i\right)^{\frac{1}{1-\theta}}\right) = const_{2t} + \int_0^1 p_{it}\, \mathrm{d}i. \tag{6}$$

2.3 Firm's Information Structure

In each period, firms have access to idiosyncratic and aggregate signals. In the first place, each firm observes its total revenues $P_{it}C_{it}$ and the total wage bill $W_{it}L_{it}$ paid to its employees. This is equivalent to observing a demand signal s_{it}^d and a wage bill signal s_{it}^w:

$$s_{it}^d = \psi_{it} + \frac{1}{\gamma}m_t + \left(\theta - \frac{1}{\gamma}\right)p_t \quad \text{and} \quad s_{it}^w = \phi_{it} + m_t. \tag{7}$$

Firms also have access to a noisy public signal of the aggregate price level s_t^p,

$$s_t^p = p_t + \sigma_{pt}\varepsilon_t^p \qquad \varepsilon_t^p \sim N(0,1). \tag{8}$$

The noise associated with this signal can be interpreted as pure measurement error. We also allow for the variance of the innovations to the aggregate price signal σ_{pt} to depend on time in a deterministic way, since we are interested in analyzing the effects of a one-time change in this parameter partially reflecting what happened in Argentina after 2007.

In order to have information frictions in the model, we make the assumption that contemporaneous signals become available after firms choose their prices. If a firm observed the contemporaneous signals before choosing the price, it would be able to set the full-information price, which can be rewritten as a function of contemporaneous signals:

$$p_{it} = const_{1t} + \frac{\left(\frac{1}{\alpha} - 1\right)}{1 + \theta\left(\frac{1}{\alpha} - 1\right)} s_{it}^d + \frac{1}{1 + \theta\left(\frac{1}{\alpha} - 1\right)} s_{it}^w.$$

Thus, the firm's information set at the beginning of period t is characterized by the filtration $\mathcal{I}_{it} = \left\{s_{it-s}^d, s_{it-s}^w, s_{t-s}^p\right\}_{s=1}^{\infty}$. Given this information set, firms face a signal-extraction problem in which they are not able to perfectly disentangle the realization of all aggregate and idiosyncratic shocks. The reason is that the number of signals observed per period (three) is lower than the number of aggregate and idiosyncratic shocks (four). To summarize, firms face incomplete information due to two reasons. First, they are unable to tell apart the realization of the previous shocks with their information set. Second, regardless of their information set, they need to set prices before contemporaneous shocks are realized.

2.4 Solution

In order to find the equilibrium of the model, we follow the solution method proposed by Hellwig (2008), which provides an approximate solution by assuming that the aggregate state of the economy becomes common knowledge after T periods (which is allowed to be arbitrarily large, but finite).[4] Then, the filtration $\mathcal{I}_{it}$ is replaced by $\hat{\mathcal{I}}_{it} = \big\{ s^d_{it-s}, s^w_{it-s}, s^p_{t-s}\,,$ $\varepsilon^{\Phi}_{it-T-s}, \varepsilon^{\Psi}_{it-T-s}, \varepsilon^{m}_{t-T-s}, \varepsilon^{p}_{t-T-s} \big\}_{s=1}^{\infty}$. With this filtration, the dimensionality of the signal extraction problem is reduced to a finite number of shocks. In order to find the solution of the model, we conjecture that the equilibrium aggregate price level follows

$$p_t = \hat{p}_t + k_t^m diag(\boldsymbol{\sigma}_{mt})\boldsymbol{\varepsilon}_t^m + k_t^p diag(\boldsymbol{\sigma}_{pt})\boldsymbol{\varepsilon}_t^p,$$

where $\boldsymbol{\varepsilon}_t^x = \left(\varepsilon^x_{t-1}, \varepsilon^x_{t-2}, ..., \varepsilon^x_{t-T}\right)$, $k_t^x = (k^x_{t1}, k^x_{t2}, ..., k^x_{tT})$ for $x = \{m, p\}$, and $\hat{p}_t$ denotes the common knowledge component of the aggregate price. The matrices $diag(\boldsymbol{\sigma}_{xt})$ for $x = \{m, p\}$ denote the diagonal matrices with the elements $(\sigma_{xt-1}, \ldots, \sigma_{xt-T})$ in the main diagonal. This conjectured solution implies that aggregate prices fully reflect the common knowledge component, and that they react to innovations to the supply of money and to the noise of the aggregate price signal according to k_t^m and k_t^p, respectively. The vectors k_t^m and k_t^p have a time subscript because the standard deviations of the money process σ_{mt} and the standard deviation of the noise of the aggregate price signal σ_{pt} are time dependent. The model is then solved by aggregating individual prices according to equation (6), verifying the

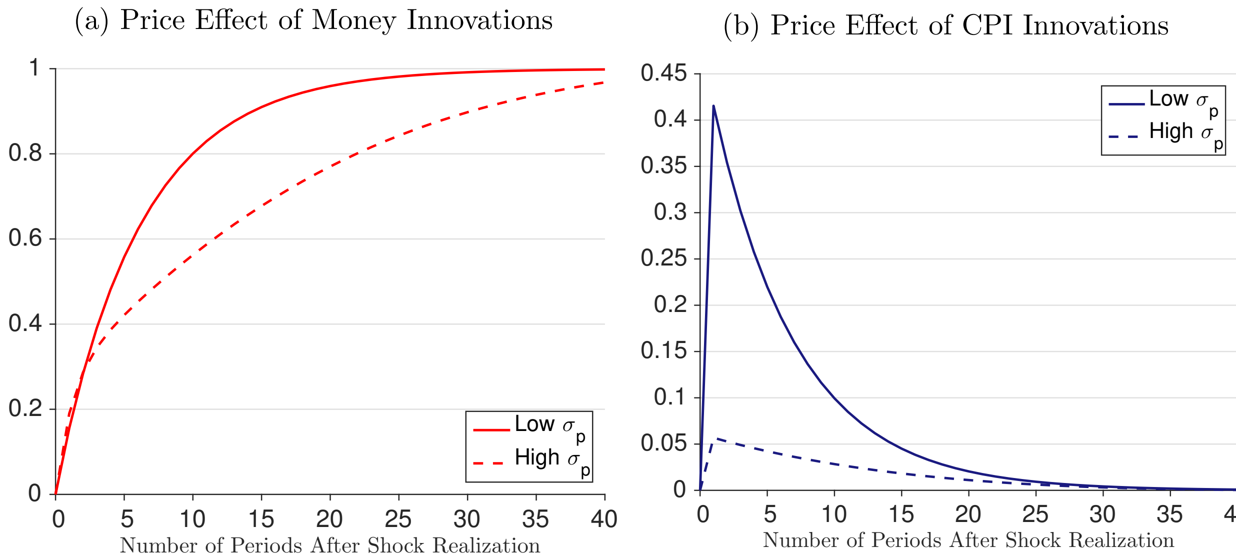
[4] In the quantitative analysis we choose T to be equal to 50 quarters.

conjecture and solving numerically for the unknown coefficients k_t^m and k_t^p. Further details on the computation of the expectations and the solution of the model are provided in Online Appendix A.

2.5 Optimal Price Setting Under Uncertainty About Inflation

We begin analyzing the predictions of the model by showing how aggregate shocks affect the dynamics of aggregate prices in an economy with constant σ_m and σ_p. Given the assumption about the process that governs money supply, an innovation in money supply produces a permanent effect on prices, as depicted by the impulse response function in Figure 1. The adjustment of prices is gradual, though, which reflects money non-neutrality. Since firms cannot tell apart the nature of the shock, they assign a positive probability to the shock being idiosyncratic. The optimal reaction to an idiosyncratic shock is different from the optimal reaction to a money shock given that idiosyncratic shocks die out and money shocks are permanent (how much will the optimal reaction differ depends on the persistence parameters of idiosyncratic shocks, ρ_ϕ and ρ_ψ). Therefore, the optimal reaction of firms is to adjust prices to somewhere in between. As time goes by, firms eventually learn the nature of the shock and increase prices until they reach full adjustment. This result is the principal mechanism behind Lucas (1972). Figure 1 also shows that the response of prices is more sluggish in an economy with high σ_p. This occurs because firms needs more time to learn about the shock in an economy with a less precise signal about inflation.

Figure 1: IRF on Aggregate Prices



Notes: The first graph shows the response over time of aggregate prices to a unitary innovation to money supply at period zero. The second graph shows the response over time of aggregate prices to a unitary noise shock associated to the signal of prices. These responses are given by the vectors k_t^m and k_t^p. The parametrization corresponds to the baseline calibration pre- and post- policy change.

We then analyze the effects of innovations to the signal of the aggregate price. Figure 1 shows the effect of a positive shock on aggregate prices. Immediately after the shock occurs, firms cannot determine the exact nature of it: a high aggregate price signal can either be due to a money supply shock or to noise in the signal. The optimal reaction of the firm is to adjust prices after they observe a high aggregate price signal. If in subsequent periods firms observe low reports of the price signal, they gradually infer that the original innovation was a noise shock to the public signal. In an economy with high σ_p, the original increase in aggregate prices is lower since firms assign a larger probability that the high signal is mostly due to a noise shock.

2.6 Price Dispersion and Inflation Volatility

Next, we analyze the effects of changes in the variance of the noise of the aggregate price signal σ_{pt} on price dispersion and inflation volatility. We also analyze the effects of changes in monetary volatility σ_{mt} on the same variables. As it will become clearer later, the latter is useful to recreate the episode of analysis in the model.

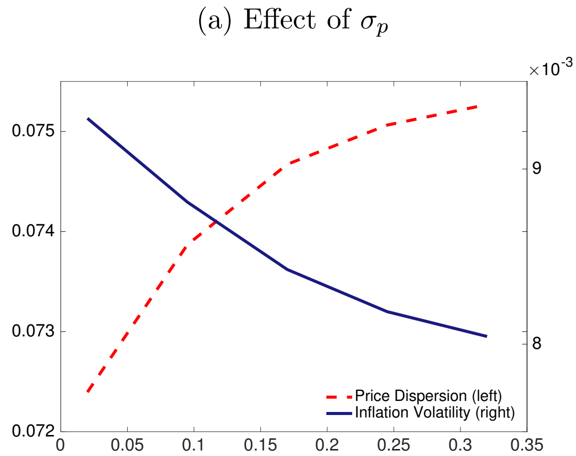
We first analyze the effect of an increase in σ_{pt}. The model predicts that price dispersion is increasing in σ_{pt} and that inflation volatility is decreasing in σ_{pt} (see Figure 2a). Faced with a noisier signal of aggregate prices, firms optimally perform Bayesian updates on the weights of each signal to set their prices. Since the aggregate signal of prices is noisier, firms reduce the weight attached to the aggregate signal and increase the weights attached to their idiosyncratic signals of demand and wages and to their common prior, as shown in Figure C.2 in Online Appendix A. Price dispersion increases because firms shift weight from a signal that is common to all firms (the aggregate price signal) to signals that contain cross-sectional dispersion (the idiosyncratic signals).[5] Inflation volatility is decreasing in σ_{pt} because, in addition to putting more weight in their idiosyncratic signals, firms also shift weight from an aggregate signal that responds to aggregate shocks to their common prior that does not. This implies that prices respond less to aggregate shocks, which in turn reduces the volatility of inflation.

We now analyze the effect of an increase in σ_{mt}. In this case, the model predicts that both price dispersion and inflation volatility are increasing in σ_{mt} (see Figure 2b). The firms' prior becomes less informative in the presence of more volatile monetary shocks. In response to an increase in the volatility of monetary policy, firms optimally increase the weights attached to all the three signals since these are more informative about monetary shocks than their prior (see Figure C.2). Price dispersion increases because firms shift weight from their prior (which is common to all firms) to their signals, some of which contain cross-sectional dispersion (the idiosyncratic signals). Inflation volatility also increases because prices react more to aggregate shocks as firms put more weight into their signals that react to shocks and less weight into their prior which does not.

Figure 2 is parametrized with the calibrated values described below. The fact that the

[5] As σ_{pt} increases, the associated increase in price dispersion is smaller. In fact, as $\sigma_{pt} \to \infty$ the signal of aggregate prices becomes completely uninformative and price dispersion converges to a level in which firms only use their idiosyncratic signals and their priors to set prices.

Figure 2: Price Dispersion and Inflation Volatility: Comparative Statics



Notes: The figure on the left plots price dispersion (measured as the coefficient of variation of prices) and the volatility of inflation (measured as the standard deviation of inflation) as a function of σ_p. The figure on the right plots price dispersion and volatility of inflation as a function of σ_m. The parametrization corresponds to the baseline calibration.

reaction of inflation volatility is different in response to changes in σ_{pt} and σ_{mt} provides a source of identification that allows us disentangle the effect of each policy by studying the joint reaction of price dispersion and inflation volatility.[6]

3 The Episode of Analysis and Data Description

In the previous section, we derived the implications of a model with information frictions. Here, we analyze a particular case study and provide a set of facts that are informative about the effects of changes in the availability of public information about inflation.

3.1 The Episode of Analysis

In 2007, the Argentinean government started manipulating official statistics of inflation presumably to prevent figures from reflecting accelerating inflation and save fiscal resources from

[6]While our model assumes a specific information structure, we argue that the predictions of the model are more general. In Online Appendix D we develop a stylized version of the model based on Hellwig (2005), that admits a closed-from solution and qualitatively corroborates the quantitative predictions obtained in the full model. We also analytically prove that this model-based identification strategy is globally valid under an alternative information structure that consists of a public and an idiosyncratic signal of the aggregate state.

being paid for CPI-linked government debt. The manipulation lasted for nine years and was reverted in 2017. The manipulation began and came to light to the public in January 2007 with the government's intervention of the National Statistics and Census Institute (INDEC). During the intervention, the main authorities in charge of computing and publishing the CPI were removed and replaced by members pinpointed by the government. After that episode, the official CPI statistics were manipulated, consistently under-reporting the level of inflation.[7] Since then, and only until recently, official inflation statistics were discredited by local and international media, international institutions and academic circles.[8]

In the absence of a trustworthy official measure of inflation, private and independent institutions, and provincial governments gradually started monitoring the evolution of prices and reporting alternative measures of inflation. As illustrated in Figure 3a, during the 2007-12 period, the average official annual inflation rate was 9%, less than half of the 21% average reported by the alternative measures of inflation. By the end of 2006 (right before the intervention), the few alternative measures that were available were in line with the official measure, and only after the manipulation they begin to deviate from the official inflation statistics.

Alternative measures of inflation provided a useful yet imperfect estimate of the actual inflation rate. Their coverage is significantly smaller and less representative than the official inflation measure.[9] One symptom of this is the high dispersion observed among these measures. The difference between the highest and lowest inflation measures averaged five

[7]It is believed that the manipulation was made through several ways, which included the reduction of the CPI weight of high-inflation goods and the collection of government-controlled prices for goods that were not available for sale at the stores where the data was collected.

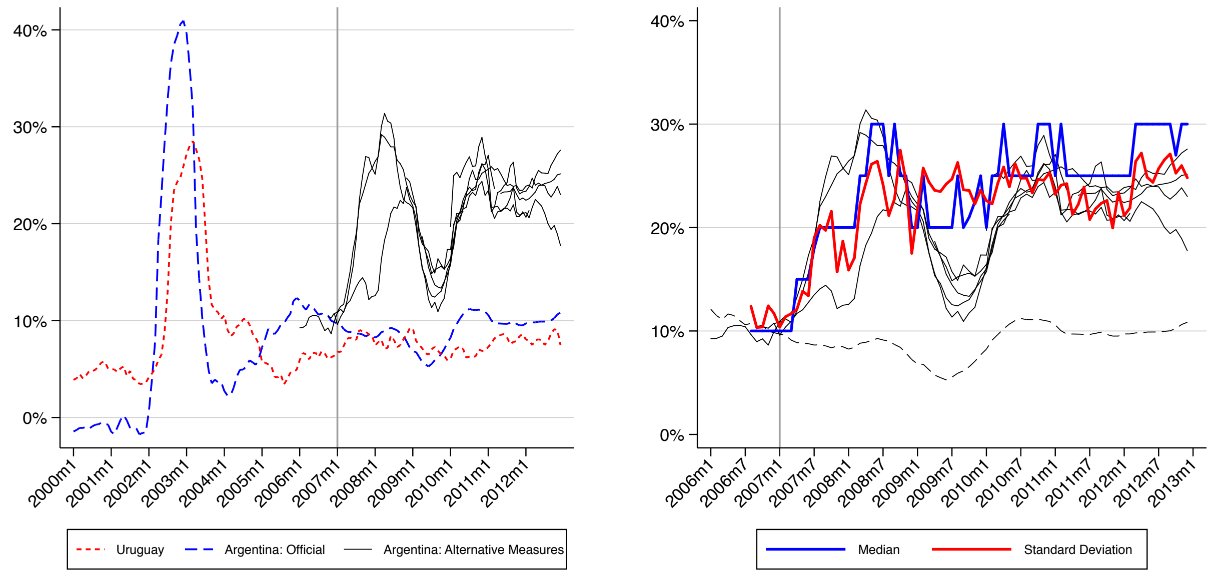
[8]See, *La Nacion*, February 10, 2007, *The Economist*, April 20, 2011 and IMF (2008), for examples on how the media and institutions discredited official inflation statistics. In 2012, the IMF censured Argentina for not providing adequate data on inflation. The official inflation statistics only regained reliability months after the launch of a new CPI index (requested by a new government) in December 2016. For example, *The Economist* incorporated the new official index to their statistics in May 2017.

[9]For example, three alternative measures correspond to measures of the CPI in small provinces, geographically distant from the denser areas in Argentina, with populations that do not exceed 10% of the total population. Another example is the FIEL measure (reported by an independent, private think tank) that covered only the city of Buenos Aires and measured 12,000 prices, compared to 230,000 in the official measure. Finally, PriceStats, another alternative measure, covered only online prices.

Figure 3: Inflation in Argentina Before and After Manipulation of Statistics

(a) Measures of Inflation

(b) Inflation Expectations



Notes: The figure on the left shows annual inflation rates for Uruguay and Argentina during the 2000-2012 period. Alternative measures of inflation for Argentina start around 2007 when the manipulation of official statistics begins (depicted by the vertical line). These alternative measures come from provincial statistical agencies (Santa Fe and San Luis), think tanks (FIEL), private companies (PriceStats and BACITY) and the National Congress. The figure on the right shows the median and the cross-sectional standard deviation of expected future annual inflation for Argentina during the 2006-2012 period. The thin solid lines are the alternative measures of inflation and the thin dotted line is the official inflation. The source of the data on inflation expectations is the Survey of Inflation Expectations developed by the Universidad Torcuato Di Tella.

percentage points during the 2007-12 period (see Figure 3a). In addition, there was lack of consensus among economic agents concerning which of these alternative measures provided the best estimate of inflation.[10]

Figure 3a also shows that concomitant with the manipulation of inflation statistics there was an increase in the level of inflation. The annual inflation rate - measured by the simple average of the alternative measures of inflation for the period after the manipulation - was higher during 2007-12 (21% on average) than the inflation rate during 2003-2006 (10% on

[10]For example, the IMF did not report any of the alternative measures of inflation, The Economist reported the measure of inflation computed by PriceStats and the Argentinean Congress reported an average of private measures of inflation estimated by local independent economists.

average). Furthermore, the 2007-2012 period was also characterized by a higher volatility of inflation relative to the 2003-2006 period (the standard deviation of quarterly inflation increased from 0.9% to 1.3%, a statistically significant difference).

The claim that Argentina entered a new period of less precise inflation statistics and more volatile inflation is supported by data on inflation expectations. Figure 3b shows the median inflation expectation in Argentina that comes from a national household survey that started being conducted in 2006.[11] At the end of 2006, the median expected inflation was close to the official inflation rate. After the manipulation, the median expected inflation starts to increase, remaining on the upper contour of the different measures of inflation that emerged after 2007. This evidence rules out the possibility that economic agents were deceived by official inflation statistics. Figure 3b additionally shows the cross-sectional standard deviation of inflation expectations, which increased significantly after the manipulation. The increase in the disagreement regarding inflation is consistent with a context of less precise public information about the level of inflation and more volatile inflation.

All in all, it can be argued that, during the past decade, Argentina has experienced two different regimes concerning the access to public information about the level of inflation and the level of inflation volatility.[12] From 2003 to 2006 the government provided a unique and credible official measure of inflation and inflation volatility was low in relative terms. On the other hand, from 2007 onwards official inflation statistics were discredited and there was overall uncertainty about the true level of inflation despite the presence of alternative noisier measures of inflation. Additionally, the economy experienced a higher degree of inflation volatility. These two differences across periods will be taken into account when disentangling the effect on price setting that can be attributed to information frictions.

[11] The data comes from the Survey of Inflation Expectations developed by the Universidad Torcuato Di Tella. This survey is conducted on a monthly basis and includes on average 1,100 participating households answering the following question: "Comparing current prices with those in the next year, by which percentage do you expect prices to increase on average in the next twelve months?".

[12] In Online Appendix B we discuss the broader economic context during this episode. We argue that no other major changes in key macroeconomic variables and other government policies were observed until the beginning 2009, two years after the beginning of the manipulation of inflation statistics.

3.2 Data Description

The data used for the analysis of price dispersion comes from MercadoLibre, the largest e-trade platform in Latin America that started its activities in 1999 and currently operates in 18 countries with more than 190 million users. The online site serves as a platform through which multiple retailers operate their online sales. Thus, we view the platform as a window to price and quantity information from multiple retailers.[13] The range of goods offered for sale and transacted on this platform is very wide and tilted towards durable goods.

We obtained data for all the listings and transactions made in Argentina and Uruguay during the 2003-12 period. The data on listings contain all the information available at the moment the seller listed the good on the platform. Some of the observed characteristics of a listing are: a description of the good, the good's category, the type of good (new or with previous use), the posted price along with its currency of denomination, the quantities available for sale, a seller identifier, and the start and end date of the listing. The data regarding transactions contain information related to each transaction associated with a listing. For each transaction, we have data on the date of the purchase, buyer and seller identifiers and the transacted price and quantity. In Online Appendix B, we provide further details of the online platform, the dataset, and on how we clean the data to make it suitable for the analysis. For an assessment of the representativeness of the goods traded in the platform see Drenik and Perez (2019).

An important variable in the empirical analysis is the category of the good. The platform offers the possibility to the seller to categorize the good being sold according to a pre-specified set of choices. Each good is placed within a category tree that has five levels, which go from a broader to a more specific classification. Given the relevance of price dispersion in the empirical analysis, in Online Appendix B we analyze the levels of price dispersion observed in the data from the platform and compare it with those from prior studies. Once we focus

[13] This view is supported by the conclusion in Cavallo (2017), that online prices provide a good representation of prices in conventional stores.

on those categories of goods that identify the good in a precise way, the median standard deviation is 53% and the median coefficient of variation is 31%, which is slightly above the upper estimates of prior studies that measure price dispersion for narrowly identified goods.[14]

4 Empirical Analysis

4.1 Estimation framework

We are interested in estimating the relationship between higher uncertainty about the rate of inflation and observed price dispersion. To pursue this, we exploit the regime switch in the access to information about the level of inflation in Argentina due to the manipulation of official statistics. In order to provide a better set of controls for any systemic macroeconomic shock and changes to the online platform, we include Uruguay as a control country and pursue a difference-in-difference analysis.[15]

To obtain a measure of price dispersion, we compute the coefficient of variation of prices originally posted when the listing was created, for each category-country pair and each quarter in the sample period.[16] Following this procedure gives us a panel of (at most) 36 observations for each category-country pair. The baseline estimations are conducted using a dependent variable computed with goods categorized at the level 3 (see Table B3 for examples). This category level provides a sufficiently detailed level of good specification, while preserving 92% of all the observed listings of new goods. However, we also conduct

[14] Kaplan and Menzio (2015) report that the average standard deviation of prices is 19% for goods with the same UPC, and 36% when goods are aggregated across different brands and sizes. Our measures of price dispersion of narrowly defined goods is similar to the measures in Gorodnichenko et al. (2018), who use data from an online-shopping/price-comparison platform in the US and UK and find a coefficient of variation of prices of uniquely identified goods of 20%.

[15] The choice of Uruguay as the control country is based on two reasons. First, it is a country with similar exposure to external macroeconomic shocks and similar socioeconomic characteristics to Argentina: income per capita in 2012 in Uruguay was $16,037 compared to $12,034 in Argentina, and the correlation of their annual growth rates (measured on a quarterly basis) is 47%. Second, throughout the period of analysis, the Uruguayan government has always credibly reported official statistics on inflation.

[16] Alternative measures of price dispersion such as the standard deviation of the log of prices and inter-quartile ranges are also considered. In the baseline analysis, we compute price dispersion using data on listings' posted prices. In addition, we corroborate the robustness of the results by computing measures of price dispersion based on transacted prices. All variables are constructed at a quarterly frequency, however results are robust to measuring price dispersion at a monthly frequency.

estimations using data with more detailed category levels and focusing only on categories of narrowly-defined goods, and find similar results.

As part of the control variables in the baseline estimations, we include measures of observed inflation, output gap, devaluation rate and exchange rate volatility. The reason for including these macroeconomic variables is that the previous literature has identified potential theories as well as empirical relationships between these variables and the level of price dispersion.[17] The inclusion of inflation as a control variable is particularly relevant as inflation increased in Argentina at the time of the manipulation of official statistics. By including observed inflation as a regressor, we are estimating an underlying relationship between inflation and price dispersion that help us determine how much of the variation in price dispersion in both regimes is associated with an increase in inflation. We also include quarterly time fixed effects to control for any aggregate shock in the evolution of price dispersion that affected both countries alike as well as for common trends in the online platform, and category-country fixed effects to control for time-invariant characteristics. Thus, the baseline estimations are based on the following empirical model:

$$PriceDispersion_{cit} = \delta \mathbb{1}\{Arg\}_c \times \mathbb{1}\{Post\}_t + \beta X_{ct} + \alpha_t + \alpha_{ci} + \varepsilon_{cit}, \tag{9}$$

where the dependent variable $PriceDispersion_{cit}$ is the coefficient of variation of prices of all listings in a given quarter t, category i and country c. The coefficient of interest is δ, which is associated with the interaction between the indicator variable that equals 1 for quarters in years 2007 or after (post-manipulation of inflation statistics) and the indicator variable that equals 1 for listings made in Argentina. We include a vector of controls X_{ct}: the annual inflation rate (for Argentina we use the official inflation measure until 2006 and the simple

[17] Workhorse New-Keynesian models with price stickiness à la Calvo (1983) predict a positive relationship between inflation and price dispersion. See Alvarez et al. (2018), Nakamura et al. (2018) and Sheremirov (Forthcoming) for empirical evidence on this relationship. The literature on varying uncertainty during the business cycle (e.g. Bloom, 2009) finds a negative correlation between measures of the business cycle and cross-sectional dispersion of macroeconomic variables like prices. The literature that studies varying degrees of pass-through (e.g. Gopinath et al., 2010) predicts an effect of exchange rate movements on price dispersion. We further discuss the role of controls in explaining price dispersion in Online Appendix B.3.

average of the available alternative measures after 2007), the cyclical component of GDP (measured as log deviations from HP-filtered real GDP), the standard deviation of the log monthly average exchange rate over a rolling window of 3 years and the quarterly devaluation rate, for quarter t and country c. We include time fixed effects α_t and category-country fixed effects α_{ci}. We cluster standard errors at the category-country level in all specifications.

We also take advantage of the additional variation that arises from the fact that the pricing decisions of different goods might rely more or less on the aggregate inflation rate. Therefore, if higher uncertainty about inflation is associated with higher price dispersion, one should expect this relationship to be stronger for goods whose prices rely more on information about the inflation rate. To test this, we obtain measures of price sensitivity to inflation at the category-country level by regressing the good-specific inflation rate on aggregate inflation throughout the entire sample,[18] and estimate the following extended specification:

$$\begin{aligned} PriceDispersion_{cit} = {} & \delta_0 \mathbb{1}\{Arg\}_c \times \mathbb{1}\{Post\}_t + \delta_1 \mathbb{1}\{Post\}_t \times Inf.Sens._{ci} \\ & + \delta_2 \mathbb{1}\{Arg\}_c \times \mathbb{1}\{Post\}_t \times Inf.Sens._{ci} + \beta_0 \pi_{ct} \times Inf.Sens._{ci} + \beta_1 X_{ct} + \alpha_t + \alpha_{ci} + \varepsilon_{cit}, \end{aligned} \tag{10}$$

where $Inf.Sens._{ci}$ is the estimated sensitivity to aggregate inflation for each category-country pair. In this specification, we extend the way we control for the effect of inflation on price dispersion, by allowing for differential effects of aggregate inflation on price dispersion according to the sensitivity of inflation of each category-country pair (captured by the interaction $\pi_{ct} \times Inf.Sens._{ci}$). The coefficient of interest is δ_2. Finally, this additional source of variation allows us to estimate equation (10) using data from Argentina only, and show that results are robust to the exclusion of Uruguay as a control country.

[18] In order to avoid noisy measures of sensitivity to aggregate inflation, we exclude goods with less than 12 quarters of data and drop goods with estimated sensitivity to inflation below (above) the 10th (90th) percentile.

4.2 Results

Table 1 reports the baseline regression estimates. The coefficient reported in Column (1) associated with the interaction between the indicator variable for Argentina and the indicator variable for the post-2007 period is positive, large in economic terms and significant. The coefficient of 0.095 indicates that the price dispersion of goods listed in Argentina is 9.5% higher than its median after the manipulation of inflation statistics. Column (2) presents the results obtained when using transaction-level data.[19] The point estimate of 0.081 implies an increase of 9.4% relative to the median. In column (3) we present the estimation results of equation (10), which includes the interaction term between the inflation rate and the sensitivity to inflation of each good. The results show that price dispersion increased in Argentina after 2007, more so for goods with prices that are more sensitive to aggregate inflation. In other words, higher uncertainty about inflation is associated with higher price dispersion for goods that rely more on information about inflation at the price-setting stage. This interaction effect is quantitatively important: a good with an average sensitivity to inflation experienced an increase in price dispersion of 0.08, while a good with a sensitivity to inflation that is one standard deviation higher observed an increase of 0.14.

In the last two columns of Table 1, we exploit the variation in the data coming from the heterogeneous sensitivity to inflation across goods to estimate equation (10) using data from Argentina only. In column (4), the point estimate of the interacted effect is highly significant and similar in magnitude, indicating that the results are robust to excluding Uruguay as a control country. One potential concern is that the categorization at level 3 provided by the online platform does not allow us to uniquely identify goods. To alleviate this concern, we fully browsed through the more than 30,000 categories provided by the platform in order to select those that uniquely identify goods based on the description of the category (see Online Appendix B.2 for a description of the procedure and examples of the identified goods). In the

[19]These data isolate variations in price dispersion due to goods with abnormal prices that are never sold (the median coefficient of variation falls by 13% due to this restriction).

last column, we restrict the estimation sample to those narrow categories, and find that the point estimate of the interaction remains statistically significant and similar in magnitude to previous specifications.

Table 1: Uncertainty About Inflation and Price Dispersion

	(1) Coef. Var.	(2) Coef. Var.	(3) Coef. Var.	(4) Coef. Var.	(5) Coef. Var.
$\mathbb{1}\{Arg\}_c \times \mathbb{1}\{Post\}_t$	0.095***	0.081***	0.051	0.082***	-0.025
	(0.028)	(0.028)	(0.032)	(0.017)	(0.032)
$\mathbb{1}\{Arg\}_c \times \mathbb{1}\{Post\}_t \times \text{Inf. Sens.}_{cit}$			0.023***	0.020***	0.022**
			(0.007)	(0.007)	(0.010)
N	74110	68887	52386	40483	2586
Median Arg.	0.996	0.864	0.984	0.984	0.335
Median Uru.	0.889	0.783	.851	-	-
Time FE	Yes	Yes	Yes	No	No
Categ.-Country FE	Yes	Yes	Yes	Yes	Yes
Specification	Baseline	Transacted	High Sens.	Arg. only	Arg. only (Fine)

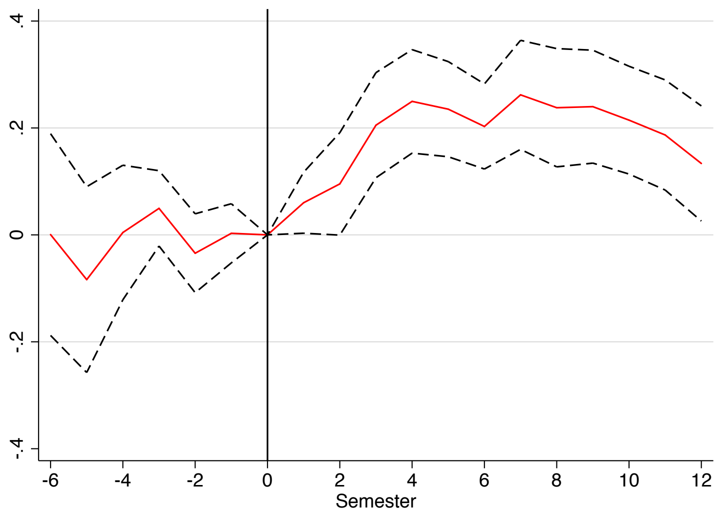
Notes: The dependent variable in all columns is the coefficient of variation of prices within quarter t, category i and country c. The set of control variables include measures of inflation, output gap, exchange rate devaluation rate and exchange rate volatility. Column (1) is the baseline specification based on data on posted prices. Column (2) shows the results using data on transacted prices. The remaining columns use data on posted prices. Column (3) estimates equation (10). Column (4) shows the estimates of equation (10) using data from Argentina only. Column (5) is similar to Column (4), but focuses on categories that narrowly identify goods (see Table B4 and the corresponding description). The estimation method used in all columns is OLS. Standard errors (in parentheses) are clustered at the Category-Country level. The median values correspond to the entire sample period by country. "Time FE" are quarter-year dummy variables. "Category-Country FE" are dummy variables specific to each category of goods at level 3 and country. $*$, $**$, and $***$ represent statistical significance at the 10%, 5%, and 1% level, respectively.

To provide evidence regarding the timing and dynamics of the estimated effect, we include semester-specific dummy variables and their interactions with the indicator variable for Argentina in the baseline specification.[20] The benefit of this specification is that it allows us to detect when the effect starts being significantly different from zero, while using all the data available to inform the relationship between price dispersion and the other control variables. As depicted in Figure 4, the time-varying coefficients are not statistically different from zero during the pre-2007 period (a more formal test of the null hypothesis of parallel trends) and start being positive and statistically significant in the first semester of 2007, remaining positive and significant thereon. The figure also reveals that the effect on price

[20] A visual inspection of the behavior of price dispersion in both countries over time is already informative of the effects of the regime-change. Figure B.9 in Online Appendix B plots the evolution of the mean price dispersion across categories in a given quarter and country. The difference between price dispersion in Argentina and Uruguay increases at the same time the manipulation of inflation statistics took place in Argentina.

dispersion was cumulative over time and increasing at a decaying rate. Importantly, we see that the effect attains its peak by the end of 2008, which is before the government started implementing changes in other policies.

Figure 4: The Effect of Inflation Uncertainty over Time



Notes: This figure shows the estimated coefficients for the interaction between semester-specific dummy variables and the indicator of Argentina for the period 2003-2012 (the coefficient for the first semester of 2003 is omitted, due to large standard errors). The omitted semester (depicted as semester "0") corresponds to the second semester of 2006, the semester previous to the beginning of the manipulation of inflation statistics in Argentina. The error bounds are the 90% confidence intervals ($\pm 1.65 \times SE$). The estimation method used is OLS. Standard errors are clustered at the Category-Country level. The regression includes as controls inflation and inflation squared (allowing the coefficients to differ across countries), the remaining set of macroeconomic variables, and Time and Category-Country fixed effects.

Online Appendix B includes an extensive set of robustness checks. We present robustness checks that dwell with three aspects of the analysis: the role of inflation as a control, the estimation strategy and the choice of the dependent variable. We first report and discuss the coefficients associated with the control variables, and particularly, the relationship between inflation and price dispersion. Given the importance of controlling for inflation, we show that the estimation results are robust to the way inflation is included in the specification (we allow for higher degree polynomials of inflation, country-specific coefficients of inflation, and measures of good-specific inflation rates computed from the micro-data). We also include inflation volatility as an additional control and find a smaller yet significant effect, which provides complementary supporting evidence of the role of the manipulation of inflation statistics on price dispersion.

Regarding the robustness of the results to the estimation strategy, we first pursue a complementary empirical strategy, in which we approximate the level of uncertainty about inflation using two continuous variables obtained from the survey of inflation expectations. We find that both proxies of uncertainty are positively associated with higher price dispersion. Second, we estimate level 1 category-specific coefficients and find that the estimated effects are positive in almost all categories. Finally, we designed a placebo test that consists of estimating the baseline regression for the 2003-2006 sub-period, considering the year 2006 as the treatment period for Argentina, and find no effect.

In order to assess the robustness to the choice of the dependent variable, we consider alternative measures of price dispersion: a weighted version of the coefficient of variation (where the weights are given by the quantity available for sale in each listing), the standard deviation of log prices, the 75-25 interquartile range and the 90-10 percentile range. The coefficient of interest remains positive and significant in all of the specifications. A related source of concern could be that specific goods are not perfectly identified in the online platform. We address this by estimating the baseline model for multiple subsamples: goods grouped according to category levels from 1 to 5, and categories with average price dispersion below certain thresholds used in the literature. In all cases, we find a significant increase in price dispersion.

To sum up, we interpret our results in the following way. As previously discussed in Section 3.1, the estimated higher price dispersion could be capturing the effect of information frictions due to the manipulation of inflation statistics, but also the effect of higher uncertainty about monetary policy that is manifested in higher inflation volatility. In the next section, we use these empirical findings to quantitatively discipline the model and assess the quantitative relevance of information frictions.

5 Quantitative Analysis

5.1 Calibration and Estimation

The model is calibrated to a quarterly frequency and is parametrized by preference parameters (β, γ, θ), productivity parameter α, four parameters that govern the idiosyncratic processes $(\rho_\Psi, \sigma_\Psi, \rho_\Phi, \sigma_\Phi)$, the growth rate of money supply μ, and the time-dependent volatility of the money process σ_{mt} and variance of the noisy signal of the aggregate price level σ_{pt}. We calibrate the model to the Argentinean economy for the period 2003-2012. This period includes the episode of analysis, which we replicate in the model as an unexpected and permanent change in both σ_{pt} and σ_{mt}.[21]

The set of parameters can be categorized into three groups: 1) those obtained from the previous literature $(\beta, \gamma, \theta, \alpha)$, 2) those estimated using external sources of data (ρ_Φ, σ_Φ), and 3) those that are jointly calibrated to match moments from the data with moments from model-based simulated data $(\rho_\Psi, \sigma_\Psi, \mu, \sigma_{mt}, \sigma_{pt})$. In order to match an annual interest rate of 4%, we choose $\beta = 0.99$. The risk aversion parameter is set at $\gamma = 2$, which is a standard value used by previous literature. We fix $\theta = 7$, which is in the middle of the range of values considered by the literature and in line with Golosov and Lucas (2007), and explore the sensitivity of the results of the model to changes in this parameter. For the parameter governing the marginal productivity of labor we choose $\alpha = 0.5$, which is the average labor share in Argentina (Frankema (2010)). The remaining calibrated parameters are summarized in Table 2.

In order to estimate the process of idiosyncratic labor costs, we make use of the household's first order condition (equation (3)), which can be expressed (in logs) as

[21] In principle, we could allow for changes in μ to target the observed increase in the average inflation rate. However, as we show in Online Appendix A, such a change in the model would only affect the average inflation rate and not have an impact on price dispersion nor on inflation volatility. Since prices are flexible, a change in μ would only imply a generalized change in the deterministic growth rate of all prices of the economy.

Table 2: Calibrated Parameters

Parameter	Value	Comments
ρ_Φ	0.969	Estimated with wage data
σ_Φ	0.091	Estimated with wage data
ρ_Ψ	0.500	Estimated process for quantities
σ_Ψ	0.780	Estimated process for quantities
μ	0.033	Average inflation 2003-12
σ_m^{pre}	0.012	Standard deviation of inflation 2003-06
σ_m^{post}	0.036	Standard deviation of inflation 2007-12
σ_p^{pre}	0.020	Lowest value with numerical stability
σ_p^{post}	0.320	Estimated increase in price dispersion

$$w_{it} = \log(\kappa_t) + \phi_{it} + m_t. \tag{11}$$

This equation links the process that governs the disutility of labor (and the aggregate shock) to idiosyncratic wages. We use data on a panel of wages to estimate an autoregressive process for idiosyncratic wages following the approach in Floden and Lindé (2001), and back out the underlying parameters that govern the process of the disutility of labor. We discuss this process in more detail in Online Appendix C. The estimated values of the autoregressive coefficient and the standard deviation for the innovations are 0.969 and 0.091, respectively.[22]

The parameters governing the demand shock are calibrated to deliver a consumption process for each variety that matches the process estimated using data on quantities sold in the online platform. In order to estimate a process for quantities, we use the data on quantities and prices transacted. We construct time series of the number of quantities sold by a given seller in a given category-quarter. Then, we estimate an AR(1) process for the log of quantities that includes time fixed effects and seller-category fixed effects. Similarly, we estimate the same regression with simulated data from the model that includes time and variety fixed effects. Finally, we set the autocorrelation and standard deviation of the demand shock so that the output of the regression with simulated data matches the output

[22] We tried re-estimating these parameters by splitting the micro-data into two subsamples: 2003-2006 and 2007-2012. Since we cannot reject the null hypothesis that the parameters are stable across subsamples, we keep them fixed across the entire 2003-2012 period.

of the regression with the main dataset. The resulting values of ρ_Ψ and σ_Ψ are 0.5 and 0.78, respectively.

The growth rate of the money supply process is chosen to match the Argentinean average quarterly inflation rate (3.3%) for the 2003-2012 period. We are left with the calibration of the volatility of monetary policy and the variance of the noise component of the aggregate price signal, each of which takes two values. The value σ_p^{pre}, which corresponds to the economy prior to the manipulation of the inflation statistics, is set to the lowest possible value for which numerical stability of the solution is preserved.[23] The value of σ_m^{pre} is set to match an observed standard deviation of inflation of 0.9% for the period 2003-06. Finally, the values of σ_p^{post} and σ_m^{post} are jointly set to match the observed increase in the standard deviation of inflation of 38% (from 0.9% in 2006-03 to 1.3% in 2007-12) and the increase in price dispersion of 9.5% that we estimated in Section 4.[24] The calibrated values are $\sigma_p^{post} = 0.32$ and $\sigma_m^{post} = 0.036$. Allowing for a change in σ_p is crucial for the success of the calibration. If we were to match the increase in price dispersion and inflation volatility with just a change in σ_m we would either fall short to replicate the increase in price dispersion or significantly over estimate the increase in inflation volatility. Table C2 in Online Appendix C reports the data moments and their model counterparts used in the joint calibration. All moments are accurately matched, with the exception of the autocorrelation of quantities sold which is well-approximated.

Before we analyze the predictions of the model, we discuss its merits by analyzing an over-identifying restriction imposed by the presence of information frictions. Coibion and Gorodnichenko (2012) showed that the presence of autocorrelated average forecast errors represents evidence against the null hypothesis of full information. Following their approach,

[23]For values of σ_{pt} that are close to zero the solutions to equations (19) and (20) in the Appendix become numerically unstable due to problems of invertibility of near singular matrices.

[24]Model-based moments are computed by simulating multiple samples of 40 quarters (same length as in the sample in the empirical analysis) of an economy that experiences an unanticipated and permanent change from σ_p^{pre} and σ_m^{pre} to σ_p^{post} and σ_m^{post} in the 17th quarter (same timing as in the episode of analysis). Thus, simulations incorporate the transitional dynamics associated with the policy changes and the simulated data is treated in the same way as the data used to calculate the targeted moments.

we use monthly data from the Survey of Inflation Expectations and estimate the persistence of the average forecast errors of future annual inflation. We regress the average forecast error on its lag and estimate a monthly autocorrelation of 0.90 with a Newey-West standard error of 0.052.[25] Then, we reproduce the same exercise in the model, and compute a quarterly autocorrelation of 0.677. If we roughly convert this autocorrelation to a monthly frequency, we obtain $0.677^{1/3} = 0.88$, which is quite similar to the estimated autocorrelation in the data and within the confidence interval. Given that this moment was not targeted during the calibration exercise, this exercise provides supporting evidence of the model with information frictions.

5.2 Disentangling the Increase in Price Dispersion

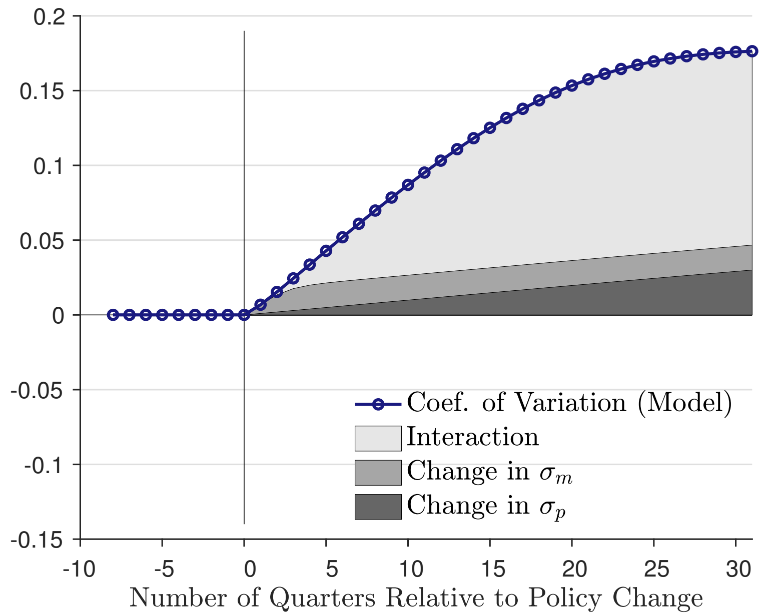
We use the calibrated model to compute the transitional dynamics of price dispersion and disentangle the effects of each policy. To do so, we compute the dynamics of price dispersion in two counterfactual economies: one that only experiences an increase in σ_p and another that only experiences an increase in σ_m. This allows us to compute the increase in price dispersion that is due to the change in the precision of the aggregate price signal and due to the increase in the volatility of monetary policy. We interpret the residual increase in price dispersion that exceeds the sum of the increase in price dispersion in these counterfactual economies as the effect of the interaction of both policies.

Figure 5 shows the transition dynamics of price dispersion in the model. The increase in price dispersion observed in the model is mostly due to the interaction of the increase in monetary volatility and the decrease in the precision of the aggregate price signal. Of the total cumulative increase in price dispersion up to 6 years after the policy changes, 17% is due to the sole increase in σ_p, 13% due to the sole increase in σ_m and 70% due to the interaction of both increases. The fact that the aggregate price signal becomes less accurate

[25]The average forecast error is given by $\pi_{t+h,t} - \bar{\mathbb{E}}_t[\pi_{t+h,t}]$, where $\pi_{t+h,t}$ is the inflation rate between periods t and $t+h$ and $\bar{\mathbb{E}}_t[\cdot]$ is the average forecast across firms. Since we are using the mean of alternative measures of inflation to construct the average forecast error, the estimated autocorrelation may contain an attenuation bias. However, this is not a major concern since we would be estimating a lower bound for this autocorrelation.

precisely in a moment in which monetary policy becomes more volatile makes firms shift weights from the aggregate signal and the common prior (that are common among firms) to the two idiosyncratic signals (that contain cross-sectional dispersion). This explains why the combination of both policy changes are important to explain the estimated increase in price dispersion.

Figure 5: Effect of Uncertainty About Inflation on Price Dispersion



Notes: The blue line shows the evolution of the coefficient of variation of prices after the policy change in σ_m and σ_p in the model. The shaded areas refer to how much of the increase in price dispersion is due to the sole change in σ_p (dark gray), the sole change in σ_m (medium gray) and the interaction of both changes (light gray).

Finally, notice that the increase in price dispersion is gradual even though the policy changes are discrete. This is consistent with the gradual increase estimated in the flexible specification shown in Figure 4. The reason for these dynamic effects in the model is that firms gradually shift their weight to their idiosyncratic signals in response to a less precise signal of the price level. The optimal short-term reaction of firms is not only to place more weight in their idiosyncratic signals but also to place more weight on past signals of the aggregate price level that were not contaminated by the high-variance noise (see Figure C.1 in Online Appendix C). As time goes by, the latter become less useful as predictors of current economic shocks and therefore firms shift their weights to current idiosyncratic shocks even further. Thus, price dispersion increases over time. According to the model, it takes approximately five years to reach the new steady state.

6 Welfare Effects of Uncertainty About Inflation

Next we analyze and quantify the welfare effects of providing less precise public information about the level of inflation. To do this, we focus on the effect of changing the variance of the noise associated with the aggregate price signal from σ_p^{pre} to σ_p^{post} in an economy that is parametrized according to the calibration presented in the previous section and in which the volatility of monetary policy σ_m is set at the average between σ_m^{pre} and σ_m^{post}. We measure the welfare effects as the percent change in the lifetime consumption stream required by a household living in an economy with an accurate signal of the aggregate price level (i.e., $\sigma_{pt} = \sigma_p^{pre}$) in order to be as well off as a household living in an economy in which at date zero the aggregate price signal becomes noisier (i.e., σ_{pt} increases to σ_p^{post} at $t = 0$).[26] The underlying assumption behind this exercise is that the change in the variance of the noise in the aggregate price signal is permanent.

Table 3 shows that not providing an accurate measure of the aggregate price level has associated significant welfare costs equivalent to a drop of 0.7% in permanent consumption. When faced with a less precise signal of aggregate prices firms reduce the weight they put in the aggregate signal from 43% to 13%. This shift in the weights brings about a long-run increase in price dispersion of 11%.

As noted by Hellwig (2005), a decrease in the precision of the public signal of the aggregate price level has two effects. First, it leads to a poorer allocation of consumption and labor

[26]Formally, the welfare effect λ^P is implicitly defined by

$$\mathbb{E}\left(\sum_{t=0}^{\infty}\beta^t\left[\frac{C_t^L(1+\lambda^P)^{1-\gamma}}{1-\gamma}-\int_0^1\Phi_{it}L_{it}^L\,\mathrm{d}i+\ln\left(\frac{M_t}{P_t^L}\right)\right]\right)=\mathbb{E}\left(\sum_{t=0}^{\infty}\beta^t\left[\frac{C_t^{H\,1-\gamma}}{1-\gamma}-\int_0^1\Phi_{it}L_{it}^H\,\mathrm{d}i+\ln\left(\frac{M_t}{P_t^H}\right)\right]\right),$$

where the superscripts L, H refer to allocations in economies with σ_p^{pre} and σ_p^{post}, respectively. For simplicity of the calculations (given the high dimensionality of the state space), we compute the initial state as the state in which the past T aggregate and idiosyncratic shocks are all at their unconditional mean of zero.

Table 3: Welfare Effects of an Increase in σ_p

	Baseline	$\theta = 4$	$\theta = 10$	Calib US
Weight CPI (σ_p^{pre})	43.3%	40.2%	44.2%	46.8%
Weight CPI (σ_p^{post})	12.5%	20.2%	7.0%	1.4%
Δ Price Dispersion	11.1%	7.1%	14.3%	24.9%
Δ Welfare	-0.70%	-0.27%	-1.18%	-0.16%

Notes: The first line indicates the cumulative weight attached to the aggregate price signal for a calibration with $\sigma_p = \sigma_p^{pre}$. The second line is the same variable but for a calibration in which $\sigma_p = \sigma_p^{post}$. The third line is the variation in the coefficient of variation of prices in the steady states of two different economies with $\sigma_p = \sigma_p^{pre}$ and $\sigma_p = \sigma_p^{post}$. The last line is the welfare cost of increasing σ_p measured in consumption equivalent changes. The first column corresponds to the baseline calibration in which σ_m is set at the average of σ_m^{pre} and σ_m^{post}. The second and third columns change the elasticity of substitution to 4 and 10, respectively. The last column corresponds to the calibration of the US economy.

across varieties (which is brought about by higher inefficient price dispersion), which is detrimental for welfare. More formally, we show the misallocation problem using the concept of wedges between the marginal rate of substitution and the marginal rate of transformation.[27] In the economy with a less precise aggregate price signal the histogram of wedges is more dispersed (see Figure C.3 in Online Appendix C). Second, a decrease in the precision of the public signal has a non-monotonic effect on output volatility. A lower precision of the public signal decreases the weight firms assign to it when setting prices. This reduces the effects of noise shocks on output but increases the effects of monetary shocks. The quantitative welfare results are in line with the findings in Hellwig (2005), who shows that the first effect dominates and welfare is increasing in the precision of the public signal of the monetary shock. In the model, this result cannot be shown analytically given the persistence of shocks and the presence of endogenous information through price signals. However, we show that

[27] Formally, we define the wedge as

$$wedge_{it} = \frac{U_{c_{it}}/U_{l_{it}}}{Y_{l_{it}}} = \frac{C_t^{1/\theta-\gamma}\Psi_{it}^{1/\theta}C_{it}^{-1/\theta}}{\Phi_{it}\frac{1}{\alpha}C_{it}^{1/\alpha-1}}.$$

Galí et al. (2007) show that, in the New Keynesian model, the utility function can be approximated by a decreasing function of the variance of these wedges.

the negative welfare costs of a decrease in the precision of the public signal quantitatively hold globally for a wide range of values of σ_p (see Figure C.4 in Online Appendix C).

We perform sensitivity analysis of our welfare calculations by changing the elasticity of substitution between goods of different varieties ($\theta = \{4, 10\}$). For higher values of the elasticity of substitution, firms face increasing competition and pay more attention to the prices set by other firms (which is summarized by the aggregate level of prices). In this context, precise information about the aggregate level of prices becomes more valuable for firms, which explains why the welfare costs are increasing in the value of θ. We also re-compute the welfare results by considering two alternative calibrations: one that targets moments computed with data until 2007-08, and another that matches the increase in the volatility of nominal output, instead of the change in the volatility of inflation.[28] We discuss the model fit and main results associated with the alternative calibrations in Online Appendix C.3. The welfare losses in both calibrations are similar to those estimated with the baseline calibration. In that Appendix, we also provide estimates of the welfare losses associated with the joint change in σ_p and σ_m in the baseline calibration.

6.1 The Value of Information and Economic Volatility

Finally, we investigate to what extent the value of providing public information about the aggregate level of prices depends on the underlying characteristics of the economy. For this, we compute the welfare effect of the same change from σ_p^{pre} to σ_p^{post} under a parametrization of the model calibrated to the US economy. For the US calibration, we leave the parameters $(\beta, \gamma, \theta, \alpha)$ at the same values as in the Argentinean calibration and change the parameters that govern the stochastic processes. The new calibrated parameters along with their values for the Argentinean calibration are shown in Table C5 in Online Appendix C. The most salient difference between Argentina and the US is the volatility of monetary policy, which

[28] The first alternative calibration abstracts from the potential effect of the recession and other macro policies put into place starting in 2009, by focusing on the estimated change in price dispersion and inflation volatility in 2007-08. The second calibration is aimed at capturing additional un-modeled effects of the regime shift that may have increased economic volatility by targeting the volatility of nominal output (which includes both nominal and real volatility), instead of inflation volatility.

is twice as large in the former than in the latter.

The results in the last column of Table 3 show that the same reduction in the precision of the public signal of aggregate prices has associated a welfare loss in the US that is equivalent to a permanent drop in consumption of 0.16%. The reason for the significantly lower welfare effect found for the US economy is the fact that the aggregate monetary shock is already well predicted with prior probabilities and without any Bayesian updating. Firms would not be losing much accuracy in their pricing decisions by expecting money to grow at a constant rate μ in every period.

7 Conclusion

Making use of an episode in which economic agents lost access to relevant public information about the rate of inflation, we estimate an increase in observed price dispersion. We use this estimate to calibrate a price-setting model with information frictions and find large welfare losses associated with that policy. Our results are indicative of a large value of providing precise information about inflation, particularly so in economies with more volatile monetary policy.

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ONLINE APPENDIX FOR

"Price Setting Under Uncertainty About Inflation"

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A Theoretical Appendix

A.1 Derivation of key equations

The first order conditions of the household's problem are given by

$$(C_{it}): \qquad \beta^t C_t^{1/\theta-\gamma} \Psi_{it}^{1/\theta} C_{it}^{-1/\theta} = \lambda_t P_{it} \tag{12}$$

$$(L_{it}): \qquad \beta^t \Phi_{it} = \lambda_t W_{it} \tag{13}$$

$$(B_{it}): \qquad -\frac{\lambda_t}{1+i_t} + \mathbb{E}_t \left[\lambda_{t+1}\right] = 0 \tag{14}$$

$$(M_t): \qquad \frac{\beta^t}{M_t} = \lambda_t - \mathbb{E}\left[\lambda_{t+1}\right], \tag{15}$$

where λ_t is the Lagrange multiplier corresponding to the budget constraint of period t.

The firm's problem is to maximize expected profits (discounted by the appropriate pricing kernel λ_t)

$$\max_{P_{it}} \mathbb{E}_t \left[\lambda_t \left(P_{it} C_{it} - W_{it} L_{it} \right) \middle| \mathcal{I}_{it} \right],$$

where $\mathbb{E}_t\left[\cdot|\mathcal{I}_{it}\right]$ denotes the expectation operator at period t conditional on the firm-specific information set $\mathcal{I}_{it}$. By replacing the expressions that define the firm's demand (equation (4)) and the nominal wage (equation (3)) into the firm's objective we can re-express the firm's optimization problem as

$$\max_{P_{it}} \mathbb{E}_t \left[\frac{\Phi_{it}}{W_{it}} \left(P_{it} \Psi_{it} \left(\frac{P_{it}}{P_t} \right)^{-\theta} \left(\frac{\kappa_t M_t}{P_t} \right)^{1/\gamma} - W_{it} \left(\Psi_{it} \left(\frac{P_{it}}{P_t} \right)^{-\theta} \left(\frac{\kappa_t M_t}{P_t} \right)^{1/\gamma} \right)^{1/\alpha} \right) \middle| \mathcal{I}_{it} \right]$$

The optimal price set by the firm is characterized by the following first order condition

$$P_{it} = \left(\frac{\theta \mathbb{E}_t \left(\Phi_{it} \left(\Psi_{it} (\kappa_t M_t)^{\frac{1}{\gamma}} P_t^{\theta - \frac{1}{\gamma}} \right)^{\frac{1}{\alpha}} \middle| \mathcal{I}_{it} \right)}{\alpha(\theta - 1) \mathbb{E}_t \left(\Psi_{it} (\kappa_t M_t)^{\frac{1}{\gamma} - 1} P_t^{\theta - \frac{1}{\gamma}} \middle| \mathcal{I}_{it} \right)} \right)^{\frac{1}{1 + \frac{\theta}{\alpha} - \theta}}. \tag{16}$$

In order to solve for the firm's optimal pricing strategy, we conjecture that

1. conditional on the firm's information set $\mathcal{I}_{it}$, $\Phi_{it}\left(\Psi_{it}(\kappa_t M_t)^{\frac{1}{\gamma}} P_t^{\theta-\frac{1}{\gamma}}\right)^{\frac{1}{\alpha}}$ and $\Psi_{it}(\kappa_t M_t)^{\frac{1}{\gamma}-1} P_t^{\theta-\frac{1}{\gamma}}$ are log-normally distributed, and
2. conditional on a realization of the aggregate shock, the cross-sectional distribution of prices across firms is also log-normally distributed.

The firm's i optimal (log) price is fully characterized by

$$
\begin{aligned}
p_{it} = & \frac{1}{1+\theta\left(\frac{1}{\alpha}-1\right)}\left\{\log\left(\frac{\theta}{\alpha\left(\theta-1\right)}\right)+\log(\kappa_t)\left(\frac{1}{\alpha\gamma}-\frac{1}{\gamma}+1\right)\right\} \\
& + \frac{1}{1+\theta\left(\frac{1}{\alpha}-1\right)}\left\{\frac{var\left(A_{it}|\mathcal{I}_{it}\right)}{2}-\frac{var\left(B_{it}|\mathcal{I}_{it}\right)}{2}\right\} \\
& + \frac{1}{1+\theta\left(\frac{1}{\alpha}-1\right)}\mathbb{E}_{it}\left[\left(\frac{1}{\alpha}-1\right)\psi_{it}+\phi_{it}\right]+\mathbb{E}_{it}\left[m_t\right]+\frac{\left(\theta-\frac{1}{\gamma}\right)\left(\frac{1}{\alpha}-1\right)}{1+\theta\left(\frac{1}{\alpha}-1\right)}\mathbb{E}_{it}\left[p_t-m_t\right],
\end{aligned}
$$

where

$$
A_{it} \equiv \phi_{it}+\frac{1}{\alpha}\left(\psi_{it}+\frac{1}{\gamma}\left(\log(\kappa_t)+m_t\right)+\left(\theta-\frac{1}{\gamma}\right)p_t\right)
$$

$$
B_{it} \equiv \psi_{it}+\left(\frac{1}{\gamma}-1\right)\left(\log(\kappa_t)+m_t\right)+\left(\theta-\frac{1}{\gamma}\right)p_t.
$$

Similarly, the complete definition of p_t is given by

$$
\begin{aligned}
p_t = \log P_t &= \frac{1}{1-\theta}\log\left(\int_0^1 \Psi_{it}P_{it}^{1-\theta}\,\mathrm{d}i\right) \\
&= \frac{1}{2(1-\theta)}\left(\frac{\sigma_\psi^2}{1-\rho_\psi^2}+(1-\theta)^2 var_t^i\left(p_{it}\right)+2(1-\theta)cov_t\left(\psi_{it},p_{it}\right)\right)+\int_0^1 p_{it}\,\mathrm{d}i,
\end{aligned}
$$

where

$$cov_t\left(\psi_{it},p_{it}\right)=cov\left(\rho_\psi^{T+1}\psi_{it-T-1}+\sigma_\psi\left(\sum_{s=0}^{T}\rho_\psi^s\varepsilon_{it-s}^{\psi}\right),p_{it}\right)$$
$$=\rho_\psi^{2(T+1)}\frac{1}{1+\theta\left(\frac{1}{\alpha}-1\right)}\left(\frac{1}{\alpha}-1\right)\left(\frac{\sigma_\psi^2}{1-\rho_\psi^2}\right)+\sigma_\psi\rho_\psi\left[\rho_\psi^0\dots\rho_\psi^{T-1}\right]\Delta_3'\Omega_t'$$

$$cov_t\left(\phi_{it},p_{it}\right)=cov\left(\rho_\phi^{T+1}\phi_{it-T-1}+\sigma_\phi\left(\sum_{s=0}^{T}\rho_\phi^s\varepsilon_{it-s}^{\phi}\right),p_{it}\right)$$
$$=\rho_\phi^{2(T+1)}\frac{1}{1+\theta\left(\frac{1}{\alpha}-1\right)}\left(\frac{\sigma_\phi^2}{1-\rho_\phi^2}\right)+\sigma_\phi\rho_\phi\left[\rho_\phi^0\dots\rho_\phi^{T-1}\right]\Delta_4'\Omega_t'.$$

The expressions for the common knowledge components of p_{it} and p_t are given by

$$\hat{p}_{it}=\frac{1}{1+\frac{1}{\gamma}\left(\frac{1}{\alpha}-1\right)}\left\{\log\left(\frac{\theta}{\alpha\left(\theta-1\right)}\right)+\log(\kappa_t)\left(\frac{1}{\alpha\gamma}-\frac{1}{\gamma}+1\right)\right\}$$
$$+\frac{1}{1+\frac{1}{\gamma}\left(\frac{1}{\alpha}-1\right)}\left\{\frac{var\left(A_{it}|\mathcal{I}_{it}\right)}{2}-\frac{var\left(B_{it}|\mathcal{I}_{it}\right)}{2}\right\}$$
$$+\frac{1}{2(1-\theta)}\left(\frac{\sigma_\psi^2}{1-\rho_\psi^2}+(1-\theta)^2var_t^i\left(p_{it}\right)+2(1-\theta)cov_t\left(\psi_{it},p_{it}\right)\right)\frac{\left(\theta-\frac{1}{\gamma}\right)\left(\frac{1}{\alpha}-1\right)}{1+\frac{1}{\gamma}\left(\frac{1}{\alpha}-1\right)}$$
$$+m_{t-T-1}+(T+1)\,\mu+\frac{1}{1+\theta\left(\frac{1}{\alpha}-1\right)}\left(\left(\frac{1}{\alpha}-1\right)\rho_\psi^{T+1}\psi_{it-T-1}+\rho_\phi^{T+1}\phi_{it-T-1}\right)$$

and

$$\hat{p}_{t}=\frac{1}{1+\frac{1}{\gamma}\left(\frac{1}{\alpha}-1\right)}\left\{\log\left(\frac{\theta}{\alpha\left(\theta-1\right)}\right)+\log(\kappa_t)\left(\frac{1}{\alpha\gamma}-\frac{1}{\gamma}+1\right)\right\}$$
$$+\frac{1}{1+\frac{1}{\gamma}\left(\frac{1}{\alpha}-1\right)}\left\{\int_0^1\frac{var\left(A_{it}|\mathcal{I}_{it}\right)}{2}-\frac{var\left(B_{it}|\mathcal{I}_{it}\right)}{2}\,\mathrm{di}\right\}$$
$$+\frac{1}{2(1-\theta)}\left(\frac{\sigma_\psi^2}{1-\rho_\psi^2}+(1-\theta)^2var_t^i\left(p_{it}\right)+2(1-\theta)cov_t\left(\psi_{it},p_{it}\right)\right)\left(\frac{\left(\theta-\frac{1}{\gamma}\right)\left(\frac{1}{\alpha}-1\right)}{1+\frac{1}{\gamma}\left(\frac{1}{\alpha}-1\right)}+1\right)$$
$$+m_{t-T-1}+(T+1)\,\mu,$$

respectively. Note that the two terms in the integral do not vary across firms. In particular the terms $var\left(A_{it}|\mathcal{I}_{it}\right)$ and $var\left(B_{it}|\mathcal{I}_{it}\right)$ are the same for all firms despite the fact that firms' filtrations may vary depending on the realizations of their own idiosyncratic signals. The reason is that idiosyncratic signals affect the conditional mean of shocks but *not* the conditional variance. However, we still compute these expressions because they will be used for welfare analysis. Then, using the fact that the variance of the common knowledge component conditional on the common knowledge component is zero, we get

$$\begin{aligned}
var\left(A_{it}|\mathcal{I}_{it}\right) = var & \left\{\sigma_\Phi \varepsilon^\phi_{it} + \sigma_\Phi\rho_\Phi \boldsymbol{\Upsilon_\Phi}\boldsymbol{\varepsilon^\phi_{it}} + \frac{1}{\alpha}\left(\sigma_\Psi\varepsilon^\psi_{it} + \sigma_\Psi\rho_\Psi\boldsymbol{\Upsilon_\Psi}\boldsymbol{\varepsilon^\psi_{it}}\right)\right. \\
& \left. + \frac{1}{\alpha}\left(\frac{1}{\gamma}diag(\boldsymbol{\sigma}_{mt})\boldsymbol{\varepsilon}^m_t + \frac{1}{\gamma}\sigma_{mt}\varepsilon^m_t + \left(\theta - \frac{1}{\gamma}\right)\left(k^m_t diag(\boldsymbol{\sigma}_{mt})\boldsymbol{\varepsilon}^m_t + k^p_t diag(\boldsymbol{\sigma}_{pt})\boldsymbol{\varepsilon}^p_t\right)\right)\right| \mathcal{I}_{it}\Bigg\} \\
& = \sigma^2_\Phi + \frac{\sigma^2_\Psi}{\alpha^2} + \frac{\sigma^2_{mt}}{\alpha^2\gamma^2} + \Delta^1_{\Sigma t} var\left(\left.\begin{bmatrix}\boldsymbol{\varepsilon}^m_t & \boldsymbol{\varepsilon}^p_t & \boldsymbol{\varepsilon}^\psi_{it} & \boldsymbol{\varepsilon}^\phi_{it}\end{bmatrix}'\right| \mathcal{I}_{it}\right)\Delta^{1\,\prime}_{\Sigma t},
\end{aligned}$$

where

$$\Delta^1_{\Sigma t} \equiv \begin{bmatrix}\frac{1}{\alpha}\left(\frac{1}{\gamma}\mathbf{1} + \left(\theta - \frac{1}{\gamma}\right)k^m_t\right)diag(\boldsymbol{\sigma}_{mt}) & \frac{1}{\alpha}\left(\theta - \frac{1}{\gamma}\right)k^p_t diag(\boldsymbol{\sigma}_{pt}) & \frac{\sigma_\Psi\rho_\Psi\boldsymbol{\Upsilon_\Psi}}{\alpha} & \sigma_\Phi\rho_\Phi\boldsymbol{\Upsilon_\Phi}\end{bmatrix}$$

and

$$\begin{aligned}
var\left(B_{it}|\mathcal{I}_{it}\right) = var & \left\{\sigma_\Psi\varepsilon^\psi_{it} + \sigma_\Psi\rho_\Psi\boldsymbol{\Upsilon_\Psi}\boldsymbol{\varepsilon^\psi_{it}} + \left(\frac{1}{\gamma} - 1\right)\left(diag(\boldsymbol{\sigma}_{mt})\boldsymbol{\varepsilon}^m_t + \sigma_{mt}\varepsilon^m_t\right)\right. \\
& \left. + \left(\theta - \frac{1}{\gamma}\right)\left(k^m_t diag(\boldsymbol{\sigma}_{mt})\boldsymbol{\varepsilon}^m_t + k^p_t diag(\boldsymbol{\sigma}_{pt})\boldsymbol{\varepsilon}^p_t\right)\right| \mathcal{I}_{it}\Bigg\} \\
& = \sigma^2_\Psi + \left(\frac{1}{\gamma} - 1\right)^2\sigma^2_{mt} + \Delta^2_{\Sigma t} var\left(\left.\begin{bmatrix}\boldsymbol{\varepsilon}^m_t & \boldsymbol{\varepsilon}^p_t & \boldsymbol{\varepsilon}^\psi_{it} & \boldsymbol{\varepsilon}^\phi_{it}\end{bmatrix}'\right| \mathcal{I}_{it}\right)\Delta^{2\,\prime}_{\Sigma t}
\end{aligned}$$

with

$$\Delta^2_{\Sigma t} \equiv \begin{bmatrix}\left(\left(\frac{1}{\gamma} - 1\right)\mathbf{1} + \left(\theta - \frac{1}{\gamma}\right)k^m_t\right)diag(\boldsymbol{\sigma}_{mt}) & \left(\theta - \frac{1}{\gamma}\right)k^p_t diag(\boldsymbol{\sigma}_{pt}) & \sigma_\Psi\rho_\Psi\boldsymbol{\Upsilon_\Psi} & \mathbf{0}\end{bmatrix}.$$

Finally,

$$var\left[\begin{array}{c|}\boldsymbol{\varepsilon}_{t}^{m}\\ \boldsymbol{\varepsilon}_{t}^{p}\\ \boldsymbol{\varepsilon}_{it}^{\psi}\\ \boldsymbol{\varepsilon}_{it}^{\phi}\end{array}\ \mathcal{I}_{it}\right]=\begin{bmatrix}I&0&0&0\\0&I&0&0\\0&0&I&0\\0&0&0&I\end{bmatrix}-\begin{bmatrix}\Delta_{1t}^{'}\\ \Delta_{2t}^{'}\\ \Delta_{3}^{'}\\ \Delta_{4}^{'}\end{bmatrix}\Delta_{t}^{-1}\begin{bmatrix}\Delta_{1t}&\Delta_{2t}&\Delta_{3}&\Delta_{4}\end{bmatrix}.$$

A.2 Conditional Expectations and Model Solution

In order to find the equilibrium of the model, we follow the solution method proposed by Hellwig (2008), which provides an approximate solution by assuming that the aggregate state of the economy becomes common knowledge after T periods (which is allowed to be arbitrarily large, but finite). In the quantitative analysis we choose T to be equal to 50 quarters. Then, the filtration $\mathcal{I}_{it}$ is replaced by $\hat{\mathcal{I}}_{it}=\left\{s_{it-s}^{d},s_{it-s}^{w},s_{t-s}^{p}\ ,\ \varepsilon_{it-T-s}^{\Phi},\varepsilon_{it-T-s}^{\Psi},\varepsilon_{t-T-s}^{m},\varepsilon_{t-T-s}^{p}\right\}_{s=1}^{\infty}$. With this filtration, the dimensionality of the signal extraction problem is reduced to a finite number of shocks. Before proceeding with the solution of the model we need to introduce some notation. Let $\boldsymbol{\varepsilon}_{it}^{x}$ denote the vector of innovations to the process x that have occurred but not been fully revealed as of time t:

$$\boldsymbol{\varepsilon}_{it}^{x}=\left(\varepsilon_{it-1}^{x},\varepsilon_{it-2}^{x},...,\varepsilon_{it-T}^{x}\right)$$

for $x=\{\Phi,\Psi,m,p\}$. It is useful to decompose the optimal pricing decision of the firm into a common knowledge component and a filtering component that depends on the unobserved innovations. Let $\boldsymbol{\Upsilon_{\Psi}}\equiv\left(1,\rho_{\Psi},\rho_{\psi}^{2},\ldots,\rho_{\psi}^{T-1}\right)$, $\boldsymbol{\Upsilon_{\Phi}}\equiv\left(1,\rho_{\Phi},\rho_{\phi}^{2},\ldots,\rho_{\phi}^{T-1}\right)$ and $\mathbf{1}=(1,\ldots,1)$. Then, we can write the firm's optimal price as

$$\begin{aligned}p_{it}=\hat{p}_{it}&+\frac{\left(\frac{1}{\alpha}-1\right)\sigma_{\Psi}\rho_{\Psi}}{1+\theta\left(\frac{1}{\alpha}-1\right)}\boldsymbol{\Upsilon_{\Psi}}\mathbb{E}_{it}\left[\varepsilon_{it}^{\Psi}\right]+\frac{\sigma_{\Phi}\rho_{\Phi}}{1+\theta\left(\frac{1}{\alpha}-1\right)}\boldsymbol{\Upsilon_{\Phi}}\mathbb{E}_{it}\left[\varepsilon_{it}^{\Phi}\right]\\&+\left(\frac{1+\frac{1}{\gamma}\left(\frac{1}{\alpha}-1\right)}{1+\theta\left(\frac{1}{\alpha}-1\right)}\right)\sigma_{mt}\mathbf{1}\mathbb{E}_{it}\left[\varepsilon_{t}^{m}\right]+\left(\frac{\left(\theta-\frac{1}{\gamma}\right)\left(\frac{1}{\alpha}-1\right)}{1+\theta\left(\frac{1}{\alpha}-1\right)}\right)\left(\mathbb{E}_{it}\left[p_{t}\right]-\hat{p}_{t}\right),\end{aligned}$$

where $\hat{p}_{it}$ denotes the common knowledge component of the firm's price and $\hat{p}_t$ denotes the common knowledge component of the aggregate price, shown below.

In order to find the solution of the model, we conjecture that the equilibrium aggregate price level follows

$$p_t = \hat{p}_t + k_t^m diag(\boldsymbol{\sigma}_{mt})\boldsymbol{\varepsilon}_t^m + k_t^p diag(\boldsymbol{\sigma}_{pt})\boldsymbol{\varepsilon}_t^p,$$

where $k_t^x = (k_{t1}^x, k_{t2}^x, ..., k_{tT}^x)$ for $x = \{m, p\}$ and the common knowledge component of the aggregate price, $\hat{p}_t$, is given by $\hat{p}_t = const_{3t} + m_{t-T-1}$. The matrices $diag(\boldsymbol{\sigma}_{xt})$ for $x = \{m, p\}$ denote the diagonal matrices with the elements $(\sigma_{xt-1}, \ldots, \sigma_{xt-T})$ in the main diagonal. This conjectured solution implies that aggregate prices fully reflect the common knowledge component, and that they react to innovations to the money supply and to the noise of the aggregate price signal according to k_t^m and k_t^p, respectively. The reason why the vectors k_t^m and k_t^p have a time subscript is that the standard deviations of the money process σ_{mt} and the standard deviation of the noise of the aggregate price signal σ_{pt} are time dependent and will change in the exercises we perform with the model. Using this conjecture, the optimal price set by the firm is given by

$$\begin{aligned} p_{it} = \hat{p}_{it} &+ \frac{\left(\frac{1}{\alpha}-1\right)\sigma_\Psi \rho_\Psi}{1+\theta\left(\frac{1}{\alpha}-1\right)} \boldsymbol{\Upsilon_\Psi} \mathbb{E}_{it}\left[\varepsilon_{it}^\Psi\right] + \frac{\sigma_\Phi \rho_\Phi}{1+\theta\left(\frac{1}{\alpha}-1\right)} \boldsymbol{\Upsilon_\Phi} \mathbb{E}_{it}\left[\varepsilon_{it}^\Phi\right] \\ &+ \left(\frac{1+\frac{1}{\gamma}\left(\frac{1}{\alpha}-1\right)}{1+\theta\left(\frac{1}{\alpha}-1\right)}\right)\sigma_{mt}\mathbf{1}\mathbb{E}_{it}\left[\varepsilon_t^m\right] \\ &+ \left(\frac{\left(\theta-\frac{1}{\gamma}\right)\left(\frac{1}{\alpha}-1\right)}{1+\theta\left(\frac{1}{\alpha}-1\right)}\right)\left(k_t^m diag(\boldsymbol{\sigma}_{mt})\mathbb{E}_{it}\left[\boldsymbol{\varepsilon}_t^m\right] + k_t^p diag(\boldsymbol{\sigma}_{pt})\mathbb{E}_{it}\left[\boldsymbol{\varepsilon}_t^p\right]\right). \end{aligned} \tag{17}$$

First, we obtain expressions for the expectation terms in equation (17). Let $\boldsymbol{s}_{it}^x = \left(s_{it-1}^x, s_{it-2}^x, ..., s_{it-T}^x\right)$ denote the vector of signals of type x. It is also useful to decompose the firm's signals into a common knowledge component and a filtering component

$$\begin{aligned}
\boldsymbol{s}_{it}^{d} &= \hat{\boldsymbol{s}}_{it}^{d} + \sigma_{\Psi}\mathcal{T}(\Upsilon_{\Psi})\boldsymbol{\varepsilon}_{it}^{\Psi} + \left(\frac{1}{\gamma}\mathcal{T}(\mathbf{1}) + \left(\theta - \frac{1}{\gamma}\right)\mathcal{T}\left(\tilde{k}_t^m\right)\right) diag(\boldsymbol{\sigma}_{mt})\boldsymbol{\varepsilon}_t^m \\
&\quad + \left(\theta - \frac{1}{\gamma}\right)\mathcal{T}\left(\tilde{k}_t^p\right) diag(\boldsymbol{\sigma}_{pt})\boldsymbol{\varepsilon}_t^p \\
\boldsymbol{s}_{it}^{w} &= \hat{\boldsymbol{s}}_{it}^{w} + \sigma_{\Phi}\mathcal{T}(\Upsilon_{\Phi})\boldsymbol{\varepsilon}_{it}^{\Phi} + \mathcal{T}(\mathbf{1}) diag(\boldsymbol{\sigma}_{mt})\boldsymbol{\varepsilon}_t^m \\
\boldsymbol{s}_{t}^{p} &= \hat{\boldsymbol{s}}_{t}^{p} + \mathcal{T}\left(\tilde{k}_t^m\right) diag(\boldsymbol{\sigma}_{mt})\boldsymbol{\varepsilon}_t^m + \left(\mathcal{T}\left(\tilde{k}_t^p\right) + I\right) diag(\boldsymbol{\sigma}_{pt})\boldsymbol{\varepsilon}_t^p,
\end{aligned}$$

where $\mathcal{T}(v_t)$ is an upper triangular matrix that includes the first components of the vector v, i.e.

$$\mathcal{T}(v_t) = \begin{bmatrix} v_{t-1,1} & v_{t-1,2} & \cdots & v_{t-1,T} \\ 0 & v_{t-2,1} & \cdots & v_{t-2,T-1} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & v_{t-T,1} \end{bmatrix},$$

$\tilde{k}_t^x$ denotes the lagged vector $(0, k_{t,1}^x, \ldots, k_{t,T-1}^x)$ for $x = \{m, p\}$ and $\hat{\boldsymbol{s}}_{it}^x$ denotes the common knowledge component of signals of type x. Given the distributional assumptions made about the idiosyncratic and aggregate processes, the vector $\left(\boldsymbol{\varepsilon}_t^m, \boldsymbol{\varepsilon}_t^p, \boldsymbol{\varepsilon}_{it}^{\psi}, \boldsymbol{\varepsilon}_{it}^{\phi}, \boldsymbol{s}_{it}^d, \boldsymbol{s}_{it}^w, \boldsymbol{s}_t^p\right)$ is jointly normally distributed and therefore we can use properties of the multivariate normal distribution to compute the conditional expectations. These expectations are summarized by the following lemma and corollary:

Lemma 1. *The expectation of the innovations conditional on the firm-specific information set is given by*

$$\mathbb{E}_{it}\left[\begin{array}{c|} \boldsymbol{\varepsilon}_t^m \\ \boldsymbol{\varepsilon}_t^p \\ \boldsymbol{\varepsilon}_{it}^{\psi} \\ \boldsymbol{\varepsilon}_{it}^{\phi} \end{array}\ \hat{\mathcal{I}}_{it}\right] = \begin{bmatrix} \Delta_{1t}' \\ \Delta_{2t}' \\ \Delta_{3}' \\ \Delta_{4}' \end{bmatrix} \Delta_t^{-1} \begin{bmatrix} \boldsymbol{s}_{it}^d - \hat{\boldsymbol{s}}_{it}^d \\ \boldsymbol{s}_{it}^w - \hat{\boldsymbol{s}}_{it}^w \\ \boldsymbol{s}_t^p - \hat{\boldsymbol{s}}_t^p \end{bmatrix}$$

where

$$\Delta_{1t} = \begin{bmatrix} \frac{1}{\gamma}\mathcal{T}(\mathbf{1}) + \left(\theta - \frac{1}{\gamma}\right)\mathcal{T}\left(\tilde{k}_t^m\right) diag(\boldsymbol{\sigma}_{mt}) \\ \mathcal{T}(\mathbf{1}) diag(\boldsymbol{\sigma}_{mt}) \\ \mathcal{T}\left(\tilde{k}_t^m\right) diag(\boldsymbol{\sigma}_{mt}) \end{bmatrix} \qquad \Delta_{2t} = \begin{bmatrix} \left(\theta - \frac{1}{\gamma}\right)\mathcal{T}\left(\tilde{k}_t^p\right) diag(\boldsymbol{\sigma}_{pt}) \\ 0 \\ \left[\mathcal{T}\left(\tilde{k}_t^p\right) + I\right] diag(\boldsymbol{\sigma}_{pt}) \end{bmatrix}$$

$$\Delta_3 = \sigma_\Psi \begin{bmatrix} \mathcal{T}(\Upsilon_\Psi) \\ 0 \\ 0 \end{bmatrix} \qquad \Delta_4 = \sigma_\Phi \begin{bmatrix} 0 \\ \mathcal{T}(\Upsilon_\Phi) \\ 0 \end{bmatrix}$$

and $\Delta_t = \Delta_{1t}\Delta_{1t}^{'} + \Delta_{2t}\Delta_{2t}^{'} + \Delta_3\Delta_3^{'} + \Delta_4\Delta_4^{'}$.

COROLLARY **1.**

$$\bar{\mathbb{E}}_t \left[\begin{array}{c|c} \boldsymbol{\varepsilon}_t^m & \\ \boldsymbol{\varepsilon}_t^p & \\ \boldsymbol{\varepsilon}_{it}^\psi & \hat{\mathcal{I}}_{it} \\ \boldsymbol{\varepsilon}_{it}^\phi & \end{array} \right] = \begin{bmatrix} \Delta_{1t}^{'} \\ \Delta_{2t}^{'} \\ \Delta_3^{'} \\ \Delta_4^{'} \end{bmatrix} \Delta_t^{-1}\left(\Delta_{1t}\boldsymbol{\varepsilon}_t^m + \Delta_{2t}\boldsymbol{\varepsilon}_t^p\right)$$

The corollary follows from the fact that $\int_0^1 \boldsymbol{\varepsilon}_{it}^\Psi \, \mathrm{d}i = \int_0^1 \boldsymbol{\varepsilon}_{it}^\Phi \, \mathrm{d}i = 0$.

The expression for the optimal price of the firm in equation (17) can be replaced in the definition of p_t (equation (6)) to get

$$\begin{aligned} k_t^m diag(\boldsymbol{\sigma}_{mt})\boldsymbol{\varepsilon}_t^m + k_t^p diag(\boldsymbol{\sigma}_{pt})\boldsymbol{\varepsilon}_t^p = & \\ & \frac{\left(\frac{1}{\alpha} - 1\right)\sigma_\Psi\rho_\Psi}{1 + \theta\left(\frac{1}{\alpha} - 1\right)} \boldsymbol{\Upsilon_\Psi}\bar{\mathbb{E}}_t\left[\varepsilon_{it}^\Psi\right] + \frac{\sigma_\Phi\rho_\Phi}{1 + \theta\left(\frac{1}{\alpha} - 1\right)} \boldsymbol{\Upsilon_\Phi}\bar{\mathbb{E}}_t\left[\varepsilon_{it}^\Phi\right] \\ & + \left(\left(\frac{1 + \frac{1}{\gamma}\left(\frac{1}{\alpha} - 1\right)}{1 + \theta\left(\frac{1}{\alpha} - 1\right)}\right)\mathbf{1} + \left(\frac{\left(\theta - \frac{1}{\gamma}\right)\left(\frac{1}{\alpha} - 1\right)}{1 + \theta\left(\frac{1}{\alpha} - 1\right)}\right) k_t^m\right) diag(\boldsymbol{\sigma}_{mt})\bar{\mathbb{E}}_t\left[\varepsilon_t^m\right] \\ & + \left(\frac{\left(\theta - \frac{1}{\gamma}\right)\left(\frac{1}{\alpha} - 1\right)}{1 + \theta\left(\frac{1}{\alpha} - 1\right)}\right) k_t^p diag(\boldsymbol{\sigma}_{pt})\bar{\mathbb{E}}_t\left[\boldsymbol{\varepsilon}_t^p\right], \end{aligned} \tag{18}$$

where we use the conjecture for equilibrium aggregate prices. After computing the conditional expectations, the right-hand side of (18) can be expressed as a linear function of $\boldsymbol{\varepsilon}_t^m$ and $\boldsymbol{\varepsilon}_t^p$. We then equate each term associated to $\boldsymbol{\varepsilon}_t^m$ and $\boldsymbol{\varepsilon}_t^p$ to solve for k_t^m and k_t^p. Thus, we obtain the following system of equations that form the fixed point that defines the equilibrium of the model:

$$
\begin{aligned}
k_t^m diag(\boldsymbol{\sigma}_{mt}) = {} & \frac{1}{\left(1+\theta\left(\frac{1}{\alpha}-1\right)\right)} \left\{ \left(\frac{1}{\alpha}-1\right) \sigma_\Psi \rho_\Psi \boldsymbol{\Upsilon}_{\boldsymbol{\Psi}} \Delta_3^{'} + \sigma_\Phi \rho_\Phi \boldsymbol{\Upsilon}_{\boldsymbol{\Phi}} \Delta_4^{'} \right. \\
& + \left(\theta - \frac{1}{\gamma}\right)\left(\frac{1}{\alpha}-1\right) k_t^p diag(\boldsymbol{\sigma}_{pt}) \Delta_{2t}^{'} \\
& \left. + \left(\left(1+\frac{1}{\gamma}\left(\frac{1}{\alpha}-1\right)\right) \mathbf{1} diag(\boldsymbol{\sigma}_{mt}) + \left(\theta - \frac{1}{\gamma}\right)\left(\frac{1}{\alpha}-1\right) k_t^m diag(\boldsymbol{\sigma}_{mt})\right) \Delta_{1t}^{'} \right\} \Delta_t^{-1} \Delta_{1t}
\end{aligned}
\tag{19}
$$

and

$$
\begin{aligned}
k_t^p diag(\boldsymbol{\sigma}_{pt}) = {} & \frac{1}{\left(1+\theta\left(\frac{1}{\alpha}-1\right)\right)} \left\{ \left(\frac{1}{\alpha}-1\right) \sigma_\Psi \rho_\Psi \boldsymbol{\Upsilon}_{\boldsymbol{\Psi}} \Delta_3^{'} + \sigma_\Phi \rho_\Phi \boldsymbol{\Upsilon}_{\boldsymbol{\Phi}} \Delta_4^{'} \right. \\
& + \left(\theta - \frac{1}{\gamma}\right)\left(\frac{1}{\alpha}-1\right) k_t^p diag(\boldsymbol{\sigma}_{pt}) \Delta_{2t}^{'} \\
& \left. + \left(\left(1+\frac{1}{\gamma}\left(\frac{1}{\alpha}-1\right)\right) \mathbf{1} diag(\boldsymbol{\sigma}_{mt}) + \left(\theta - \frac{1}{\gamma}\right)\left(\frac{1}{\alpha}-1\right) k_t^m diag(\boldsymbol{\sigma}_{mt})\right) \Delta_{1t}^{'} \right\} \Delta_t^{-1} \Delta_{2t}.
\end{aligned}
\tag{20}
$$

The solution of the model is closed by finding the vectors k_t^m and k_t^p that satisfy these equations. Since this system of equations is highly nonlinear in k_t^m and k_t^p, closed-form solutions are not available. Therefore, we solve the model numerically. We compute the transition dynamics of an economy that at period 0 is unexpectedly hit by a shock that increases σ_{pt} and σ_{mt} permanently. In this case, we solve for vectors k_t^m and k_t^p for each period t during the transition, taking the values of past vectors $(k_0^m, k_0^p, \ldots, k_{t-1}^m, k_{t-1}^p)$ as given.

Using Lemma 1 to solve for the conditional expectations in equation (17), we can express idiosyncratic prices as a linear combination of idiosyncratic and aggregate signals

$$
\begin{aligned}
p_{it} &= \hat{p}_{it} \\
&+ \left\{ \frac{\left(\frac{1}{\alpha}-1\right)\sigma_\Psi \rho_\Psi}{1+\theta\left(\frac{1}{\alpha}-1\right)} \boldsymbol{\Upsilon}_{\boldsymbol{\Psi}} \Delta_3^{'} + \frac{\sigma_\Phi \rho_\Phi}{1+\theta\left(\frac{1}{\alpha}-1\right)} \boldsymbol{\Upsilon}_{\boldsymbol{\Phi}} \Delta_4^{'} + \left(\frac{\left(\theta - \frac{1}{\gamma}\right)\left(\frac{1}{\alpha}-1\right)}{1+\theta\left(\frac{1}{\alpha}-1\right)} \right) k_t^p diag(\boldsymbol{\sigma}_{pt}) \Delta_{2t}^{'} \right. \\
&+ \left. \left(\left(\frac{1+\frac{1}{\gamma}\left(\frac{1}{\alpha}-1\right)}{1+\theta\left(\frac{1}{\alpha}-1\right)} \right) \mathbf{1} + \left(\frac{\left(\theta - \frac{1}{\gamma}\right)\left(\frac{1}{\alpha}-1\right)}{1+\theta\left(\frac{1}{\alpha}-1\right)} \right) k_t^m \right) diag(\boldsymbol{\sigma}_{mt}) \Delta_{1t}^{'} \right\} \Delta_t^{-1} \boldsymbol{s}_{it} \\
&\equiv \hat{p}_{it} + \Omega_t \boldsymbol{s}_{it},
\end{aligned} \tag{21}
$$

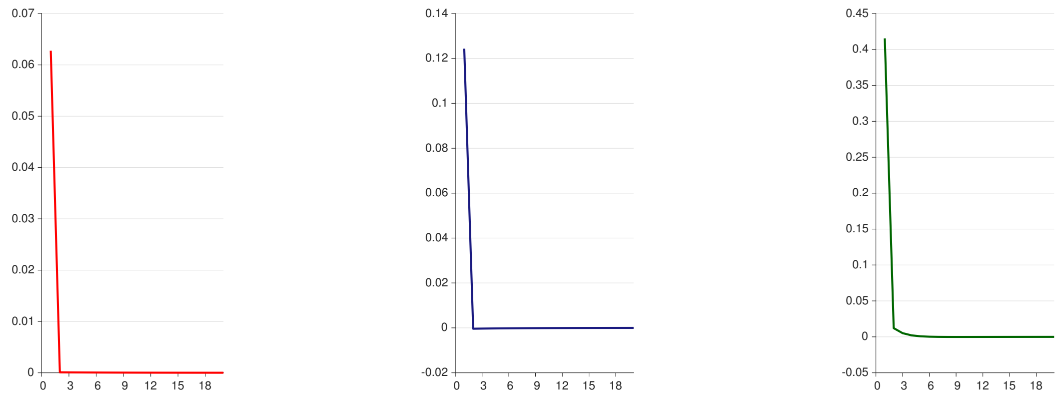
where

$$
\boldsymbol{s}_{it} \equiv \begin{bmatrix} \boldsymbol{s}_{it}^d - \hat{\boldsymbol{s}}_{it}^d \\ \boldsymbol{s}_{it}^w - \hat{\boldsymbol{s}}_{it}^w \\ \boldsymbol{s}_t^p - \hat{\boldsymbol{s}}_t^p \end{bmatrix}.
$$

Figure A.1 plots the weights associated to the three signals used to set idiosyncratic prices (those in the matrix Ω_t in equation (21)) as a function of the "vintage" of each signal. As it can be seen, most of the weight is placed on recent signals since these are better predictors of contemporaneous innovations. However, firms do place some positive weight in past signals. The reason is that, in order to set prices, firms not only need to form expectations about current aggregate and idiosyncratic shocks but also about past aggregate shocks since these affect current aggregate prices.

Figure A.1: Bayesian Weights on Signals

(a) Weight Attached to s^d_{it} (b) Weight Attached to s^w_{it} (c) Weight Attached to s^p_t



Notes: These graphs show the weights attached to each component of $\boldsymbol{s}_{it}$ as a function of the number of period since a signal was first observed. The parametrization corresponds to the baseline calibration with $\sigma_p = \sigma_p^{post}$ and $\sigma_m = \sigma_m^{post}$.

A.3 Price Dispersion and Inflation Volatility

This section derives expressions for the cross-sectional dispersion of prices and for inflation volatility.

The following proposition provides expressions for price dispersion and inflation volatility.

Proposition 1. *The cross-sectional dispersion of prices is characterized by the following expressions*

$$Coef\ Var^i_t(p_{it}) = \left(\exp\left(var^i_t(p_{it})\right) - 1\right)^{1/2},$$

where

$$var^i_t(p_{it}) = \left(\frac{1}{1+\theta\left(\frac{1}{\alpha}-1\right)}\right)^2 \left(\left(\frac{1}{\alpha}-1\right)^2 \left(\rho_\psi^{T+1}\right)^2 var^i\left(\psi_{it-T-1}\right) + \left(\rho_\phi^{T+1}\right)^2 var^i\left(\phi_{it-T-1}\right)\right)$$
$$+ \Omega_t \begin{bmatrix} \sigma_\Psi^2 \mathcal{T}\left(\Upsilon_\Psi\right)\mathcal{T}\left(\Upsilon_\Psi\right)' & 0 & 0 \\ 0 & \sigma_\Phi^2 \mathcal{T}\left(\Upsilon_\Phi\right)\mathcal{T}\left(\Upsilon_\Phi\right)' & 0 \\ 0 & 0 & 0 \end{bmatrix} \Omega_t'.$$

The standard deviation of inflation is characterized by the following expression

$$var(p_t - p_{t-1}) = \sigma_m^2 v_m I v_m' + \sigma_p^2 v_p I v_p',$$

where

$$v_m = \left(k_1^m, k_2^m - k_1^m, ..., k_T^m - k_{T-1}^m, 1 - k_T^m\right),$$
$$v_p = \left(k_1^p, k_2^p - k_1^p, ..., k_T^p - k_{T-1}^p, -k_T^p\right).$$

B Empirical Appendix

B.1 The Episode of Analysis: The Macroeconomic Context

This Appendix describes the macroeconomic context of the episode of analysis. We argue that the macroeconomic scenario and other government policies did not exhibit major changes until the beginning 2009, two years after the beginning of the manipulation of inflation statistics. Only during 2009, after the burst of the global financial crisis, did the government implement a devaluation and an expansionary fiscal policy.

Figure B.1 shows the observed and median expectation of the level of the exchange rate and the primary fiscal balance, as well as the cross-sectional standard deviation of these forecasts. Until 2009 there were no major changes in either the actual fiscal and exchange rate policies, nor in their market expectations. Figure B.2 shows the observed and median expectation of the stock of international reserves and the growth rate of bank deposits, as well as the cross-sectional dispersion of these forecasts. The dynamics of these variables suggest that there were no major changes in the external and financial outlook until 2009. Figure B.3 shows the sovereign spread of Argentina and the stock market volatility, which did not exhibit large changes until the onset of the global financial crisis. Figure B.4a presents the mean applied import tariffs. Similarly, tariffs were not significantly altered, with the exception of a temporary increase in 2009 which was reverted in the following year. Finally, Figure B.4b compares the official exchange rate with the exchange rate obtained in the unofficial market.[29] The government implemented capital controls in the foreign exchange market in 2011, which led to the emergence of an unofficial market in which the US dollar traded at a premium relative to the official exchange rate.

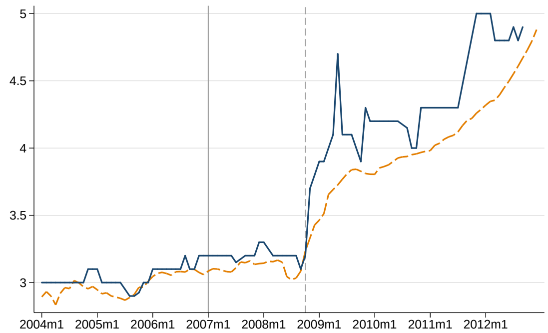
Due to the presence of these additional changes in policy after 2009, we carry out ro-

[29] Data on expectations come from a survey conducted by the Central Bank of Argentina and observed data come from the Ministry of Finance and the Central Bank. The unofficial exchange rate series are obtained from a national newspaper and data on applied tariffs are obtained from the World Bank. Sovereign spreads are taken from Bloomberg.

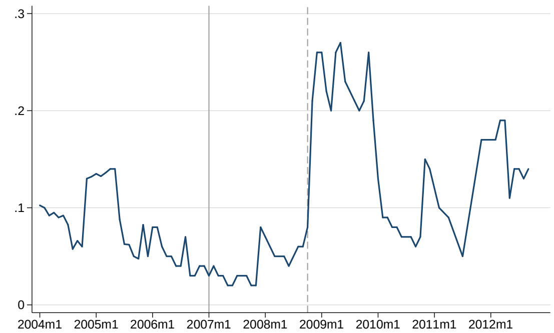
bustness analysis of all the main results of the paper (both in the empirical analysis and the quantitative analysis of the model) by restricting the sample to the 2003-2008 period.

Figure B.1: Observed and Expected Macroeconomic Policies in Argentina

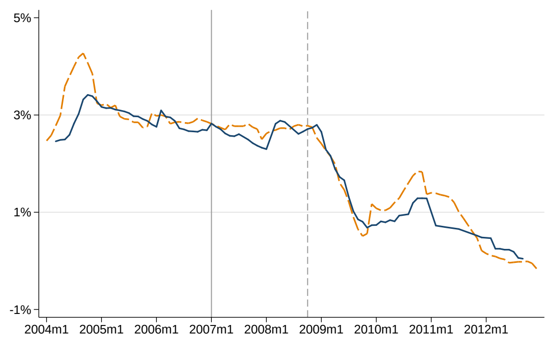
(a) Exchange Rate (Actual & Median Expectation)



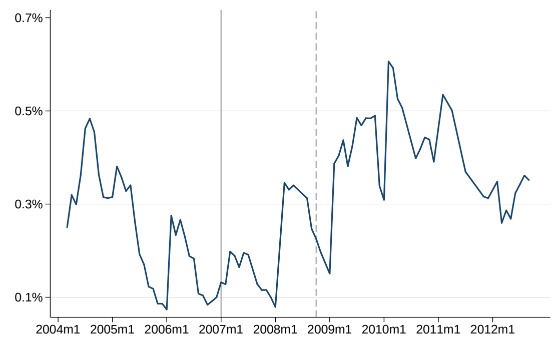
(b) Exchange Rate (Dispersion of Expectations)



(c) Fiscal Balance (Actual & Median Expectation)



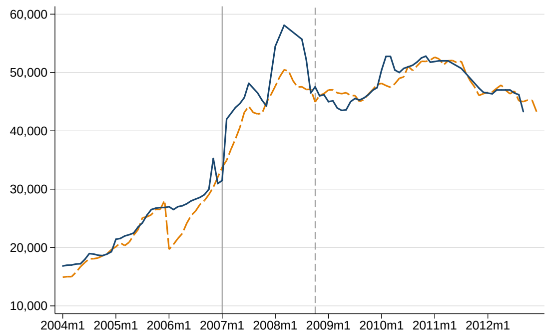
(d) Fiscal Balance (Dispersion of Expectations)



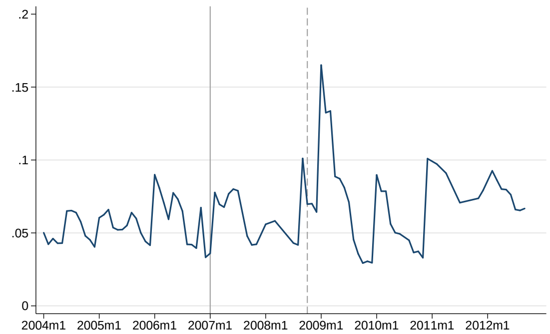
Notes: Panel (A) shows the observed exchange rate (dashed line) and the median expectation of the exchange rate at the end of calendar year (solid line). Panel (B) shows the cross-sectional standard deviation of expectations of the level of the exchange rate. Panel (C) shows the observed primary fiscal balance of the last 12 months in % of GDP (dashed line) and the median expectation of the primary fiscal balance in % of GDP at the end of calendar year (solid line). Panel (D) shows the cross-sectional standard deviations of expectations of the primary fiscal balance in % of GDP. Sources: Expectations survey from central bank and observed data from ministry of finance.

Figure B.2: Observed and Expected External and Financial Outlook in Argentina

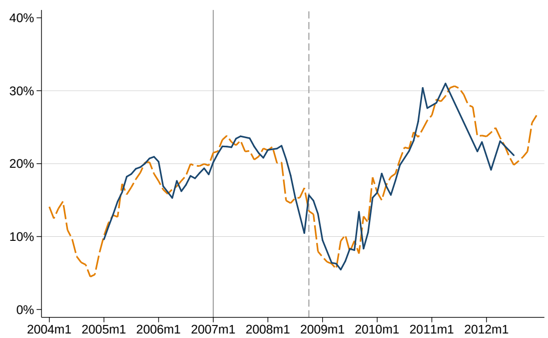
(a) Intl. Reserves (Actual & Median Expectation)



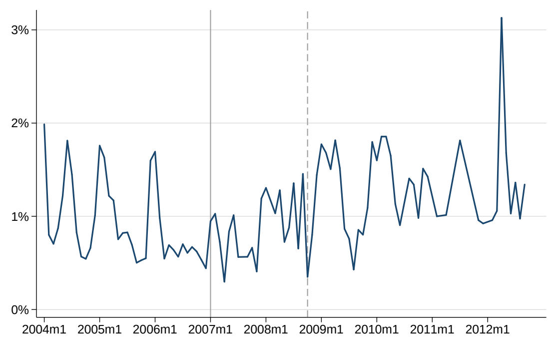
(b) Intl. Reserves (Dispersion of Expectations)



(c) Bank Deposits (Actual & Median Expectation)



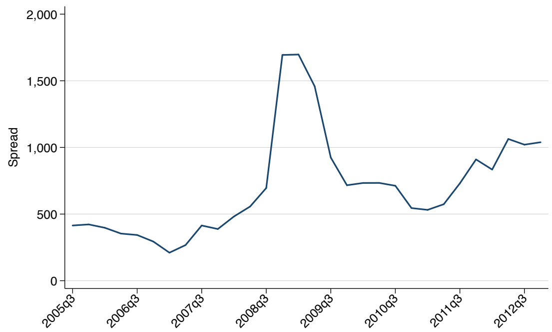
(d) Bank Deposits (Dispersion of Expectations)



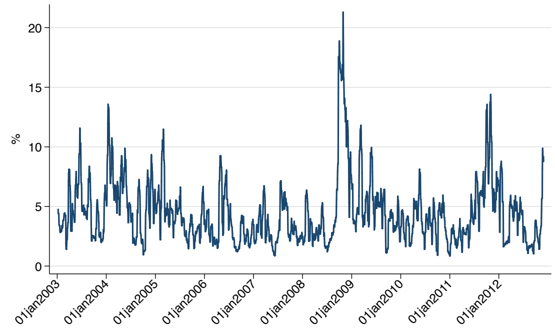
Notes: Panel (A) shows the observed stock of international reserves (dashed line) and the median expectation of the same variable at the end of calendar year (solid line). Both variables are measured in millions of dollars. Panel (B) shows the cross-sectional coefficient of variation of expectations of the stock of international reserves. Panel (C) shows the observed (dashed line) and median expectation (solid line) of the annual growth rate of bank deposits from the private sector in %. Panel (D) shows the cross-sectional coefficient of variation of expected bank deposits from the private sector. Sources: central bank.

Figure B.3: Financial Outlook in Argentina

(a) Default Risk



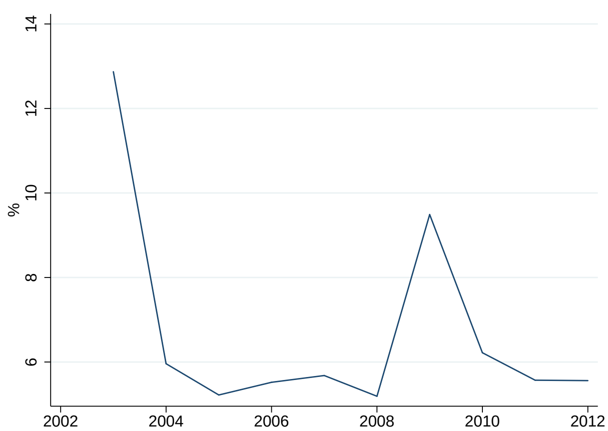
(b) Stock Market Volatility



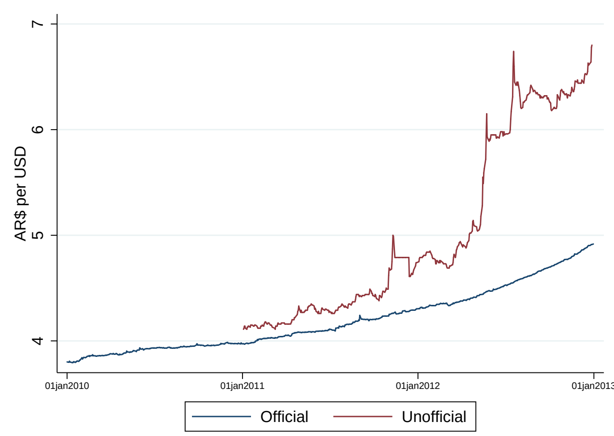
Notes: The first figure shows the EMBI spread for Argentina measured in basis points. It is computed as the average spreads of a synthetic basket of Argentinean bonds in foreign currency. The spread of a bond is its yield minus the yield of the US Treasuries of similar maturities. The second figure shows the volatility of the main stock market index in Argentina (MERVAL). It is computed as the rolling 30-day standard deviation of monthly returns.

Figure B.4: Additional Policies Implemented in Argentina

(a) Average Applied Tariff Rates



(b) Capital Controls in the FX Market



Notes: Panel (A) shows the average of effectively applied rates weighted by the product import shares corresponding to each partner country by year in Argentina. The data was obtained from the *World Bank*. Panel (B) compares the monthly official exchange rate (peso per dollar) with the unofficial exchange rate obtained in the informal foreign exchange market. The source of the data for the unofficial exchange rate is *La Nacion Data* (the data portal of a national newspaper).

B.2 Data

B.2.1 The Online Platform

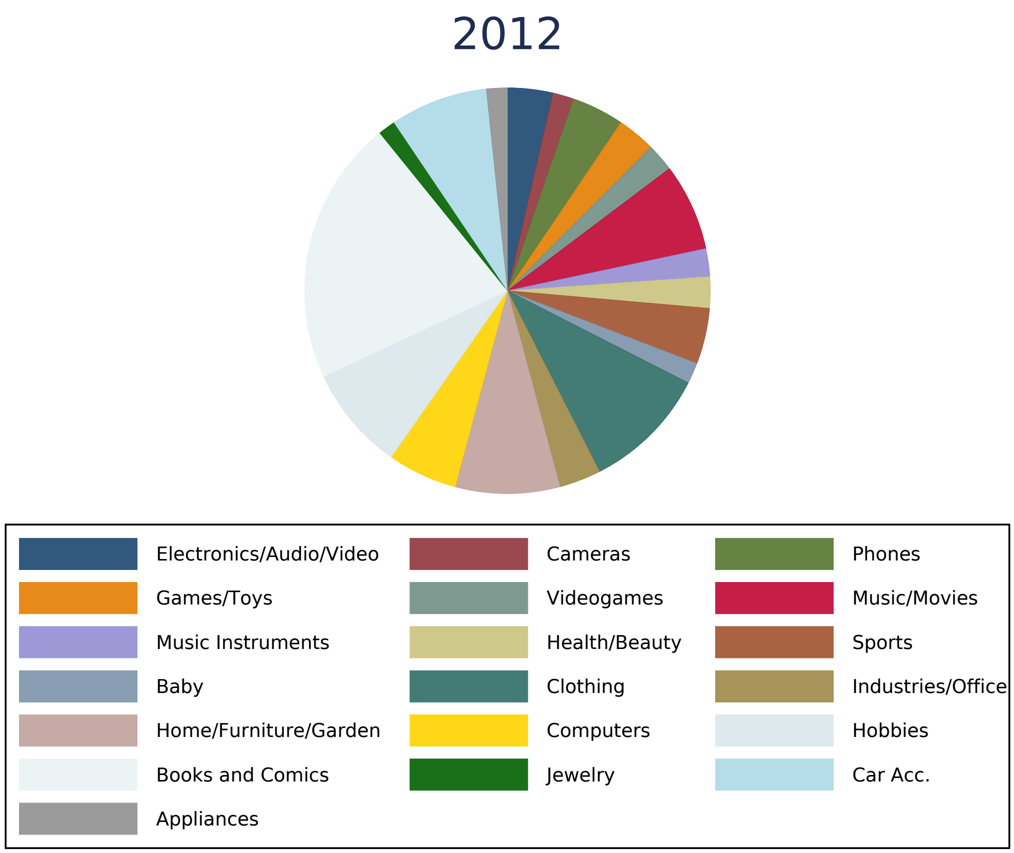
Here, we describe how the online platform works and present summary statistics. In order to list goods in this platform, sellers generate a listing, which includes a title describing the good, a picture and a more detailed description of the good, the selling price, and other characteristics of the good. On the other hand, buyers can find goods by either searching the good by name or by navigating a tree that categorizes goods in different groups. Once the buyer locates a good of interest, she can click on the listing and decide to make the purchase. Although the platform allows sellers to sell via auctions, almost all of the listings are of the posted-price type.

The range of goods offered for sale and transacted on this platform is very wide and tilted toward durable goods (see Figure B.5 for a snapshot of the basket of products in 2012). In Drenik and Perez (2019), we analyze the relevance of goods that are available for sale on the platform in the representative consumption basket of Uruguayan households. We find that the online platform has a broad and relevant coverage. Goods that are traded on the platform account for 31% of the total consumption basket with a heavy concentration in certain categories of the consumption basket such as apparel, furniture, and home appliances.

The platform has grown rapidly during the period of analysis. Figure B.6 shows the evolution of the number of listings over time. On an average quarter there are 65,000 new sellers, 158,000 new buyers and 2.3 million goods sold in Argentina. The corresponding numbers for Uruguay are 12,000 new sellers, 17,000 new buyers and 235,000 goods sold per quarter (this is consistent with the fact that the Argentinean economy is ten times as large as the Uruguayan economy).

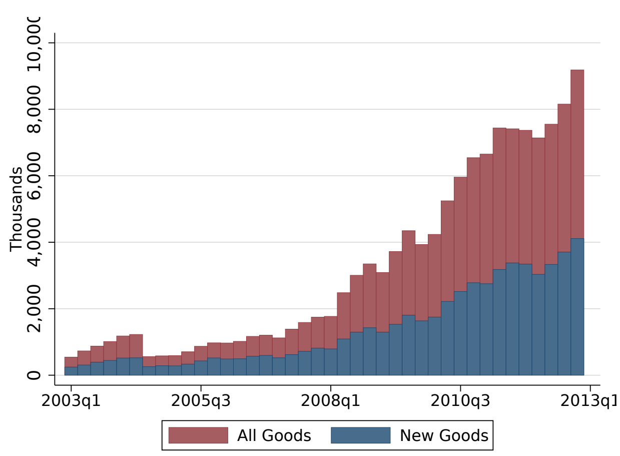
Tables (B1) and (B2) present summary statistics of the entire platform in Argentina and Uruguay, and by groups of goods categorized at level 1. The average posted price of a product in the sample is US$94 (US$80 and US$105 in Argentina and Uruguay, respectively).

Figure B.5: Composition of Goods Sold



Notes: This figure shows the composition of goods available for sale in 2012. Goods are categorized according to the broadest level of categorization in the category tree.

Figure B.6: Number of Listings over Time (in Thousands)



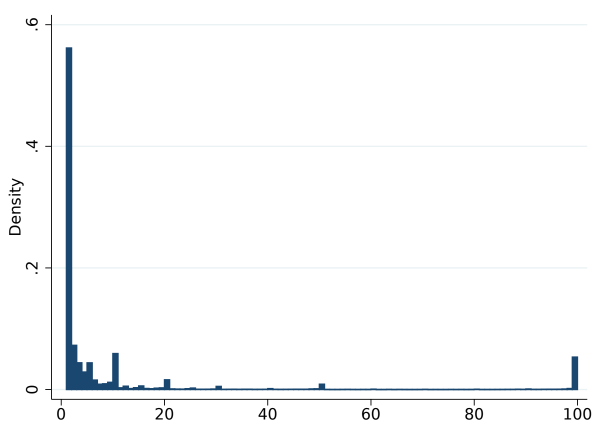
Notes: This figure shows the number of total listings made in the platform by quarter.

On average, the most expensive goods are "music and instruments", "industry and office" and "electronics, audio and video". Most of the prices are posted in domestic currency, and the remaining are posted in US dollars (8% and 34% of goods in Argentina and Uruguay, respectively). The average listing lasts for 26 and 21 days in Argentina and Uruguay, respectively, and between 12% and 21% of all listings experience a sale in the platform in each quarter.

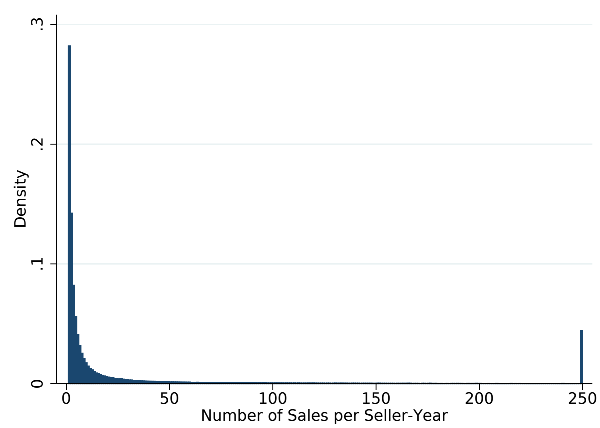
The data show substantial heterogeneity in the type of sellers that make use of this online platform. While the median number of units of new products available for sale by listing is 1, the average quantity offered per listing is 10.8 (see Figure B.7a for a histogram of the quantities available for sale by listing). The median number of sales made by a seller of new products in 2012 is 8 and the distribution exhibits fat tails, suggesting that a significant fraction of the users recurrently make use of this platform (see Figure B.7b).

Figure B.7: Histograms of Goods per Listing and Sales per Sellers

(a) Histograms of Goods Offered by Listing



(b) Histogram of Number of Sales per Seller



Notes: Panel A shows the histogram of quantities of new goods available for sale by listing. We winsorize the number of units at 100. Panel B shows the histogram of the number of sales of new goods by seller in 2012. We winsorize the number of listings at 250.

Table B1: Summary Statistics

Category	Avg. price		Std. price		% Foreign curr.		% New		Duration (days)	
	Arg.	Uru.	Arg.	Uru.	Arg.	Uru.	Arg.	Uru.	Arg.	Uru.
All goods	84.3	108.7	264.9	237.6	8	35	45	47	26	21
Electronics, audio and video	199.6	168.4	423.1	304.3	20	51	52	52	25	20
Cameras and accesories	180.4	191.0	317.3	230.4	26	64	52	57	25	21
Cellphones and phones	112.0	118.6	177.5	148.1	7	35	46	50	19	20
Games and toys	41.8	57.8	153.9	162.6	2	16	64	46	23	21
Videogames	82.8	81.5	141.5	128.4	9	34	37	37	19	20
Music and movies	13.9	19.7	23.5	54.9	4	13	36	37	31	25
Music instruments	357.2	262.9	535.5	422.9	18	52	37	22	24	20
Health and beauty	57.0	50.3	266.6	142.3	2	9	75	68	24	24
Sports and fitness	78.8	88.2	164.0	210.5	6	22	56	42	25	22
Babies	41.1	36.1	66.8	44.5	0	5	45	36	21	21
Clothing	25.6	28.2	54.3	81.6	1	6	53	45	22	20
Industries, office	298.8	272.4	831.0	691.7	4	24	52	44	26	23
Home, furniture, garden	87.2	95.5	175.8	203.1	1	8	55	42	25	23
Computers	142.1	150.7	316.9	276.9	24	59	48	58	23	20
Hobbies	21.3	33.8	51.7	95.8	2	16	43	25	25	24
Books and magazines	10.4	20.1	21.4	53.3	1	6	18	29	36	27
Jewelry	123.5	169.4	323.5	296.8	21	38	53	44	26	24
Car accesories	93.7	99.4	219.5	208.5	3	26	52	43	28	24
Appliances	166.1	101.6	302.0	165.8	1	14	36	30	20	20

Notes: This table shows summary statistics of all the goods published in the platform (in Argentina and Uruguay separately) and by groups of goods categorized at level 1. The first two columns show the mean and standard deviation of prices in US dollars (prices set in local currency were converted using the daily spot exchange rate). The next columns show the average over time of the quarterly share of goods with prices set in foreign currency and the share of goods that are new (as opposed to previously used). The last set of columns show the average time (in days) during which the listing is online.

Table B2: Summary Statistics (continued)

Category	# Posts (1,000's)		# Sellers (1,000's)		# Buyers (1,000's)		# Sales (1,000's)		% Sold	
	Arg.	Uru.	Arg.	Uru.	Arg.	Uru.	Arg.	Uru.	Arg.	Uru.
All goods	2639.3	576.1	61.3	11.0	149.8	16.3	1105.6	106.5	22	12
Electronics, audio and video	105.4	28.5	11.1	2.0	40.8	3.3	105.6	7.0	32	13
Cameras and accesories	49.4	13.2	5.3	1.1	21.8	1.6	46.6	2.8	31	10
Cellphones and phones	119.9	42.0	15.4	3.5	39.5	5.1	107.1	13.8	35	18
Games and toys	82.5	13.0	3.5	0.7	17.4	1.4	38.7	2.4	22	12
Videogames	49.3	19.4	6.7	1.4	15.8	1.8	38.0	4.4	31	15
Music and movies	191.0	15.2	2.7	0.4	6.5	0.6	18.0	1.2	11	9
Music instruments	60.9	7.9	5.3	0.9	8.4	0.8	17.2	1.5	21	15
Health and beauty	65.9	10.2	3.7	0.6	18.8	1.5	40.2	2.7	27	11
Sports and fitness	127.0	28.3	10.0	2.2	36.3	3.7	83.0	7.4	30	14
Babies	38.4	8.2	3.1	0.6	8.2	0.8	16.8	1.5	25	14
Clothing	265.4	86.2	9.1	2.0	27.9	3.3	87.7	10.4	21	10
Industries, office	83.3	12.4	6.6	0.8	22.9	1.7	52.6	3.0	26	10
Home, furniture, garden	190.9	61.3	11.4	2.6	35.0	4.8	108.0	13.9	24	12
Computers	202.1	72.2	14.5	3.0	38.0	5.0	155.5	17.8	31	13
Hobbies	247.3	37.8	3.1	0.5	9.8	0.9	33.2	2.2	14	6
Books and magazines	490.1	53.1	3.1	0.5	14.3	1.0	41.1	2.0	9	5
Jewelry	45.9	10.4	2.1	0.4	6.5	0.6	13.2	1.1	20	7
Car accesories	185.3	43.2	9.2	1.8	28.0	3.3	76.9	8.0	21	12
Appliances	39.3	13.5	6.7	1.6	14.3	1.9	26.1	3.4	33	16

Notes: This table shows summary statistics of all the goods published in the platform (in Argentina and Uruguay separately) and by groups of goods categorized at level 1. The first two columns show the average number of new listings made per quarter (in thousands). The following two sets of columns show the average number of new sellers and buyers that enter the platform or a specific category per quarter (in thousands). Next we present the average number of sales made per quarter (in thousands) and the average fraction of all published goods that end up being sold per quarter.

B.2.2 Data Cleaning and Comparison with other Data

To make the data suitable for analysis, we implement a series of procedures to clean the micro-data. First, we remove outliers by dropping the top 1% and the bottom 1% of prices in each category-country-year triplet. We also remove all prices that are above US$10,000. To make prices comparable across countries, we convert all prices to domestic currency using the spot nominal exchange rate on the day the listing was posted online. Second, since we are interested in the price dispersion associated with comparable goods, we drop all observations coming from listings of "divisible" goods. In order to implement this filter, we make use of the description of the good that sellers include in the listing and the description of the category provided by the platform to isolate two types of listings: (1) those with sales in bulk, and (2) those with "divisible" goods. More specifically, we delete all listings that contained any of the following texts (in Spanish): promotion, batch, kilo (and variations), gram (and variations), liter (and variations), meter (and variations), centimeter (and variations), kilometer (and variations), pack, units, "2 for 1". Based on this, we are able to identify the categories of goods in which these words appeared more often and dropped them completely (virgin CDs/DVDs, food, cigars/cigarettes, batteries, diapers, hobbies (bills/coins/stamps)). Once cleaned, the entire dataset contains more than 128 million listings and around 48 million transactions in both countries during the 2003-2012 period. The main analysis focuses on listings of new goods. By "new" goods we refer to goods without prior usage (and not new models/vintages).

An important variable in the empirical analysis is the category of the good, which we use to compute measures of price dispersion for goods of similar characteristics. The platform offers the possibility to the seller to categorize the good being sold according to a pre-specified set of choices. Each good is placed within a category tree that has five levels, which go from a broader to a more specific classification. The first level of categories contains broad good types such as computers, books, and health/beauty. On the other extreme, the fifth level contains very detailed goods such as a Sony Vaio notebook with Intel Core i7 processor.

In Table B3, we show different examples of categories for different levels. In some cases, a detailed specification of the good is obtained even before the last category level. For example, an iPhone 5 with 16 GB of capacity (which precisely defines a unique good) can be identified with the categorization level 4. As one considers higher levels of category specification, the number of listings that are categorized under that level decreases. In particular, 92% of the total number of listings of new goods are categorized in level 3 or higher.

Table B3: New Product Listings According to Maximum Category Level

Category Level	Observations	% of Total Obs.	Examples
1	63,121,213	100%	1. Computers
			2. Consoles & Videogames
			3. Cellphones & Phones
2	63,121,055	100%	1. Notebooks & Accessories
			2. Xbox 360
			3. Cellphones
3	58,318,807	92%	1. Notebooks
			2. Consoles
			3. Apple iPhone
4	40,349,384	64%	1. Sony Vaio
			2. Xbox 360 4GB
			3. Apple iPhone 5 16GB
5	17,844,041	28%	1. Intel Core i7
			2. -
			3. -

Notes: This table shows the composition of listings of new products according to the maximum level of categorization available. The first (second) column shows the number (percentage) of total listings of new goods that have information on each level of categorization. For example, 92% of the sample has information about the level 3 of categorization (i.e., only 8% of the sample has missing information about level 3). The last column gives an example of the type of categorization available for a given product.

In order to assess the external validity of the data we perform two exercises. First, we compare the levels of price dispersion in the data from the platform with those from prior studies. We compute several measures of price dispersion for different levels of aggregation of products. First, we aggregate products according to good categories at levels 3 and 5. Both levels of aggregation group goods with similar characteristics that can be differentiated along certain dimensions. In order to isolate sources of price dispersion coming from product differentiation, we also compute measures of price dispersion for those categories with products that can be narrowly identified according to their brand and model. We identified around 600 good categories that narrowly identified goods.[30] Some examples of these closely identified goods are listed in Table B4. Identifying this specific goods also allows us to draw comparisons of the dispersion measures observed in this data with those reported in previous studies.

Table B4: Examples of Fine Good Categories

GPS Garmin Nuvi 1450	Palm Treo 360
Apple iPad 2 Wi-Fi	Xbox 360
Nokia 5600	PlayStation 2
Samsung Galaxy 3 5800	Windows Vista
Apple iPhone 5 16GB	Microsoft Office 2010

Table B5 reports four different measures of price dispersion: the median coefficient of variation, the median standard deviation of log prices, the median gap between the prices in the 75th and 25th percentile (expressed relative to the average price), the median gap between the 90th and 10th percentiles (expressed relative to the average price). When goods are categorized at level 3, the median coefficient of variation is 99% for posted prices and 86% for transacted prices in Argentina. The fact that price dispersion is lower when we consider transacted prices is consistent with the fact that goods with prices at the tail of the price distribution rarely get sold. Once we group goods according to categories at level 5, the coefficient of variation of posted prices drops to 53%. Finally, when we focus on those categories that narrowly identify goods, the coefficient of variation drops to 31%, and the standard deviation to 50%. These figures are slightly above the upper estimates of price dispersion in previous studies. For example, Kaplan and Menzio (2015), report an average standard deviation of prices of 36% when goods are aggregated across different brands and sizes, whereas Gorodnichenko and Talavera (Forthcoming) report a standard deviation of log prices of 24% for narrowly identified products (at the UPC level) using data from US

[30] Given that the category tree for Uruguay is not as disaggregated as the one for Argentina, we cannot identify these categories in Uruguay.

online markets.[31] Our measures of price dispersion of narrowly defined goods is similar to the measures in Gorodnichenko et al. (2018), who use data from an online-shopping/price-comparison platform in the US and UK and find a coefficient of variation of prices of uniquely identified goods of 20%.

Table B5: Price Dispersion Statistics

Measures of Price Dispersion	Category Level 3 Posted	Category Level 3 Transacted	Category Level 5 Posted	Fine Categories Posted
Panel A: Argentina				
Coef. Var.	0.99	0.86	0.53	0.31
SD Log(P)	1.00	0.87	0.59	0.50
IQ75-25	0.79	0.73	0.50	0.30
ID90-10	1.84	1.62	1.07	0.67
Panel B: Uruguay				
Coef. Var.	0.88	0.78	0.47	-
SD Log(P)	1.00	0.83	0.52	-
IQ75-25	0.77	0.64	0.45	-
ID90-10	1.73	1.45	1.00	-

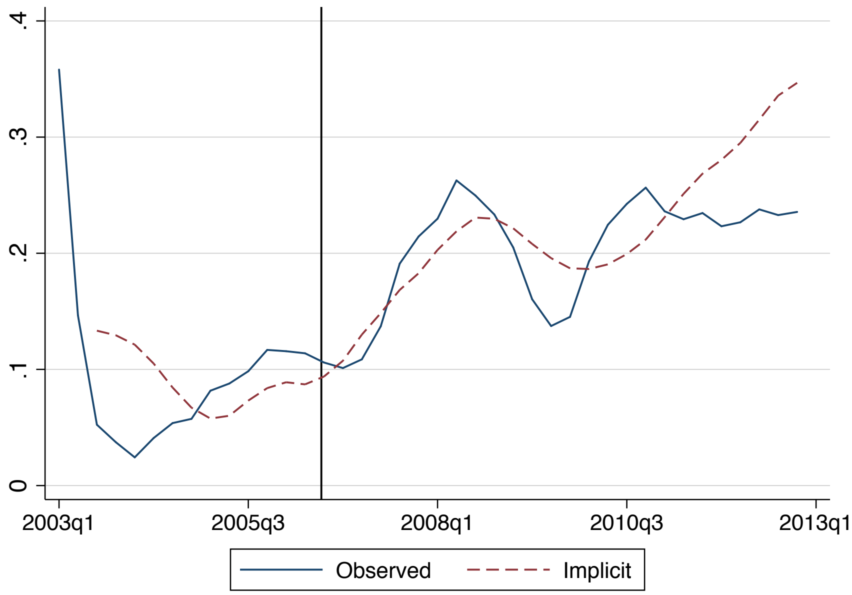
Notes: Each row refers to the median of the each statistic among all category-quarter pairs. Coef Var. refers to the coefficient of variation. SD Log(P) refers to the standard deviation of log prices. IQ75-25 (ID90-10) refers to ratio of the difference between the 75th and 25th percentile (90th and 10th percentile) prices to the average price.

Second, we compare the implicit inflation rate from our data set with the evolution of measured aggregate inflation in Argentina. As shown in Figure B.8, the implicit inflation closely follows the evolution of aggregate inflation (both in the co-movement and average levels), arguing in favor of the representativeness of the data set.[32] This confirms the conclusion in Cavallo (2017), that online prices provide a good representation of prices in conventional stores.

[31] A recent paper that tries to explain why price dispersion is widespread in online commerce, where the physical costs of search are much lower, is Dinerstein et al. (2018).

[32] Category-specific price indices were constructed using median prices, as opposed to average prices, to reduce the influence of outliers. Also, we drop category-specific inflation rates that are below the 5th and above the 95th percentile.

Figure B.8: Observed and Implicit Annual Inflation in Argentina



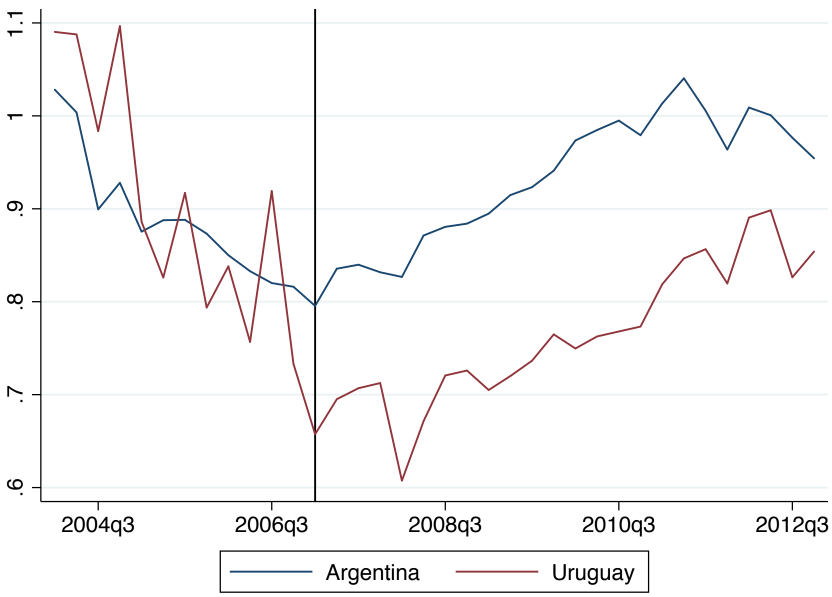
Notes: The observed inflation in Argentina is measured by official inflation statistics until 2006 and as the simple average of the alternative measures of inflation for 2007-12. The implicit inflation is computed as the average inflation rate across categories of level 3. We smoothed the series with a moving average.

B.3 Robustness Analysis

In this subsection, we present further analysis to assess the validity of the main results. First, a visual inspection of the behavior of price dispersion in both countries over time is already informative of the effects of the regime-change. Figure (B.9) plots the evolution of the mean price dispersion across categories in a given quarter and country. The difference between price dispersion in Argentina and Uruguay increases at the same time the manipulation of inflation statistics took place in Argentina.

Next, we present the estimation results of the baseline specification, including the coefficients of the control variables. Column (1) of Table B6 shows the results of the baseline estimation. The estimates indicate a small and negative, albeit not statistically significantly different from zero, relationship between inflation and price dispersion. This evidence is at odds with the prediction of workhorse New-Keynesian models with Calvo pricing, but is consistent with Alvarez et al. (2018), who find almost no relationship between inflation and

Figure B.9: Median Coefficient of Variation Across Categories by Country



Notes: This figure shows the mean coefficient of variation across categories of level 4 by quarter and country. The sample used in this figure is restricted to categories with data for at least 20 quarters. The vertical line represents the first quarter of 2007, when the treatment began in Argentina.

price dispersion in Argentina for low values of inflation (in line with those observed in the sample) and a positive elasticity for higher levels of inflation (larger than 30% per year). The estimates are also consistent with the results presented in a paper by Nakamura et al. (2018), which finds no evidence of a relationship between price dispersion and inflation during the late 1970's and early 1980's in the United States. Other previous studies have found positive and negative relationships between these two variables in the US (Sheremirov (Forthcoming) and Reinsdorf (1994), respectively).

We estimate a negative correlation between the output gap and price dispersion. This finding is consistent with theories of uncertainty-driven business cycles (see, for example, Bloom (2009) and Vavra (2014)), with theories that predict higher price 'experimentation' in recessions (Bachmann and Moscarini (2012)) and theories on unemployment and shopping behavior (Kaplan and Menzio (2016)). Finally, we find a statistically significant relationship between the exchange rate policy and price dispersion. A 10 pp devaluation of the exchange rate decreases the coefficient of variation of prices by 0.018 and an increase in the volatility of the exchange rate of 10 pp increases the dependent variable by 0.05. The latter effect could be explained by heterogeneous degrees of pass-through of the goods in the platform.

Next, we assess the robustness of our results to the way inflation is included as a control variable. For this, we estimate different specifications that vary in the functional form according to which inflation enters the regression equation. First, we re-estimate the baseline specification with a non-linear relationship between inflation and price dispersion, by including the square of inflation as an additional control variable. Results, shown in column (3) of Table B6, indicate that the point estimate of the difference-in-difference coefficient remains unchanged, positive and significant. Second, we estimate a version of the estimation equation in which we allow for country-specific coefficients associated with inflation. The difference-in-difference coefficient remains positive, significant and similar in magnitude for this specification as well, as indicated in column (4). Third, we also estimate the main specification including category-country-specific inflation rates from the platform as an alternative measure of inflation. For this, we compute time series of the average price for each category, country and quarter and compute growth rates. Column (5) shows the results. The point estimate of the coefficient remains unchanged and statistically significant. Finally, columns (6) and (7) control for the volatility of inflation (measured as the standard deviation of inflation over a rolling window of 36 months) and the lagged dependent variable, and the estimated coefficients drop from the baseline value 0.095 to 0.081 and 0.05, respectively, still positive and significant at the 1 percent level.

To isolate the potential effect of the other policies mentioned above, we exploit the time dimension of the introduction of these different policies and estimate the baseline specification for shorter sample periods that end before 2012. Specifically, we estimate the main regression for different subsamples that vary in the length of the "second regime" from 1 year (only 2007) to 2 years (2007-2008), 3 years (2007-2009), and so on. Results are shown in Table B7. The difference-in-difference coefficient is positive and increasing across subsamples. Although not

Table B6: Uncertainty About Inflation and Price Dispersion

	(1) Coef. Var.	(2) Coef. Var.	(3) Coef. Var.	(4) Coef. Var.	(5) Coef. Var.	(6) Coef. Var.	(7) Coef. Var.
$\mathbb{1}\{Arg\}_c \times \mathbb{1}\{Post\}_t$	0.095***		0.097***	0.089***	0.094***	0.081***	0.050***
	(0.028)		(0.028)	(0.028)	(0.029)	(0.028)	(0.019)
$\mathbb{1}\{Arg\}_c \times \mathbb{1}\{Post\}_t \times$ Inf. Sens.$_{cit}$		0.022**					
		(0.009)					
π_{ct}	-0.108	-0.212	-0.326			0.052	-0.034
	(0.132)	(0.267)	(0.486)			(0.134)	(0.107)
π_{ct}^2			0.605				
			(1.242)				
$\pi_{arg,t}$				-0.093			
				(0.133)			
$\pi_{uru,t}$				-0.534**			
				(0.257)			
π_{cit}					-0.000		
					(0.000)		
GDP Cycle$_{ct}$	-0.695**	0.567	-0.770**	-0.905**	-0.549	-0.399	-0.193
	(0.338)	(0.483)	(0.345)	(0.356)	(0.356)	(0.332)	(0.248)
Δ FX$_{ct}$	-0.177**	0.356	-0.171**	-0.098	-0.137*	-0.077	-0.038
	(0.071)	(0.236)	(0.073)	(0.075)	(0.075)	(0.075)	(0.067)
Volatility FX$_{ct}$	0.537***	0.485*	0.495***	0.375**	0.263	0.279**	0.002
	(0.129)	(0.290)	(0.137)	(0.155)	(0.178)	(0.124)	(0.094)
Volatility π_{ct}						2.390***	0.984***
						(0.394)	(0.278)
Coef. Var.$_{cit-1}$							0.420***
							(0.014)
N	74110	1225	74110	74110	60247	74110	69892
Median Arg.	0.996	0.335	0.996	0.996	0.996	0.996	0.996
Median Uru.	0.889	-	0.889	0.889	0.889	0.889	0.889
Time FE	Yes	No	Yes	Yes	Yes	Yes	Yes
Categ.-Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Specification	Baseline	Fine, 04-09	2nd Deg. Inf.	Country Inf.	Categ. Inf.	-	-

Notes: The dependent variable in all columns is the coefficient of variation of prices within quarter t, category i and country c. The set of control variables include measures of inflation, output gap, exchange rate devaluation rate and exchange rate volatility. Column (1) is the baseline specification. Column (2) estimates equation (10) focusing on categories that narrowly identify goods using data from 2004 to 2009. Column(3) includes inflation squared as an additional control. Column (4) allows the coefficient of inflation to be country-specific. Column (5) replaces the country-specific inflation rate by country-category-specific inflation rates computed using data from the platform. Columns (6) and (7) add the volatility of inflation and the lagged dependent variable as additional controls. The estimation method used in all columns is OLS. Standard errors (in parentheses) are clustered at the Category-Country level. The median values correspond to the entire sample period by country. "Time FE" are quarter-year dummy variables. "Category-Country FE" are dummy variables specific to each category of goods at level 3 and country. $*$, $**$, and $***$ represent statistical significance at the 10%, 5%, and 1% level, respectively.

significant in the first two columns, it is consistently significant from column (3) onwards. In addition, column (2) of Table B6 estimates equation (10) focusing on categories that narrowly identify goods using data from 2004 to 2009. The point estimate remains unchanged.

Next, we pursue an empirical strategy that complements the difference-in-difference approach. We approximate the level of uncertainty about inflation using two continuous variables, and assess its relationship with price dispersion. The first variable is the deviation of expected inflation from actual inflation, measured as the absolute value of the difference between average expected inflation and actual inflation. It is expected that agents are more

Table B7: Robustness Analysis: Alternative Window Lengths Post-2007

	(1) Coef. Var.	(2) Coef. Var.	(3) Coef. Var.	(4) Coef. Var.	(5) Coef. Var.	(6) Coef. Var.
$\mathbb{1}\{Arg\}_c \times \mathbb{1}\{Post\}_t$	0.041	0.045	0.059**	0.083***	0.084***	0.095***
	(0.033)	(0.029)	(0.029)	(0.029)	(0.028)	(0.028)
π_{ct}	-0.149	0.179	0.221	0.025	0.073	-0.108
	(0.191)	(0.160)	(0.155)	(0.133)	(0.135)	(0.132)
GDP Cycle$_{ct}$	0.649	-0.449	-1.030*	-1.853***	-1.799***	-0.695**
	(0.860)	(0.714)	(0.548)	(0.528)	(0.457)	(0.338)
Δ FX$_{ct}$	-0.393*	-0.337**	-0.287**	-0.238**	-0.142	-0.177**
	(0.222)	(0.143)	(0.111)	(0.097)	(0.089)	(0.071)
Volatility FX$_{ct}$	0.425**	0.479***	0.513***	0.463***	0.558***	0.537***
	(0.167)	(0.148)	(0.144)	(0.135)	(0.132)	(0.129)
N	23520	31292	40905	51498	62632	74110
Median Arg.	0.984	0.984	0.984	0.984	0.984	0.984
Median Uru.	0.851	0.851	0.851	0.851	0.851	0.851
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Categ.-Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Specification	2003-2007	2003-2008	2003-2009	2003-2010	2003-2011	2003-2012

Notes: The dependent variable in all columns is the coefficient of variation of prices within quarter t, category i and country c. The set of control variables include measures of inflation, output gap, exchange rate devaluation rate and exchange rate volatility. Each column estimates the baseline specification, but differs in the subsample used. In each column we extend the length of the post-2007 sample by one year at a time. The estimation method used in all columns is OLS. Standard errors (in parentheses) are clustered at the Category-Country level. The median values correspond to the entire sample period by country. "Time FE" are quarter-year dummy variables. "Category-Country FE" are dummy variables specific to each category of goods at level 3 and country. $*$, $**$, and $***$ represent statistical significance at the 10%, 5%, and 1% level, respectively.

likely to forecast inflation less precisely when uncertainty about inflation is higher. The second variable we consider is the cross-sectional standard deviation of inflation expectations. In times of higher uncertainty about the level of inflation, higher dispersion between inflation forecasts of different economic agents can be expected.

We assess the relationship between these measures of uncertainty about inflation on price dispersion by regressing the coefficient of variation of prices on the set of baseline controls and the corresponding proxy for uncertainty about inflation. Given that data on inflation expectations is available since 2006, the identification of this relationship does not come from the timing of the manipulation of statistics but rather from variation in the continuous proxies of uncertainty during the period after the manipulation. Results are shown in the first two columns of Table B8. The coefficient associated with deviations of expected inflation is positive and significant (column (1)), and the coefficient associated with the standard deviation of inflation forecasts is also positive and significant (column (2)). In the latter case, the point estimate of the coefficient indicates that an increase in the cross-sectional standard deviation of expected inflation by 10 pp has associated an increase in the coefficient of variation of prices of 5% with respect to its mean. It could also be argued that statistical significance should be somewhat expected given the large dimension of the dataset. In order to strengthen the validity of the identified effect we designed a placebo test that consists of estimating the baseline regression for the 2003-2006 sub-period, considering the year 2006 as the treatment period for Argentina. Results are shown in column (3) of Table B8. The difference-in-difference coefficient in this case is negative and not significantly different from zero, an expected result given that the policy was not in place during the year 2006.

In order to assess the robustness of the results to the choice of the dependent variable, we consider alternative measures of price dispersion: a weighted version of the coefficient of variation (where the weights are given by the quantity available for sale in each listing), the standard deviation of log prices, the 75-25 interquartile range and the 90-10 percentile range.[33] Results are shown in columns (4)-(7) of Table B8. The difference-in-difference coefficient remains positive and significant in all of the specifications with alternative dependent variables. The effect is of the order of 36% relative to the median of the dependent variable for the specification with the standard deviation of log prices, 26% for the specification with the weighted coefficient of variation, and 7.5% and 5% for the specifications of 75-25 and 90-10 percentile ranges.

In the main specification the dependent variable is computed by pooling prices set in local and foreign currency (converted at the spot exchange rate). One concern with this approach could be that the observed increase in price dispersion is coming from goods with prices set in a specific currency or due to changes in the fraction of prices set in foreign currency over time. Columns (8)-(11) in Table B8 deal with this concern. Columns (8) and (9) estimate the baseline specification in which the dependent variable is constructed using prices set

[33] The 75-25 interquartile range is defined as the difference between the price in the 75th percentile and the price in the 25th percentile normalized by the average price of goods in a given category to make units comparable. An analogous definition applies for the 90-10 percentile range.

Table B8: Robustness Analysis: Continuous Measures, Different Dependent Variables and Subsamples

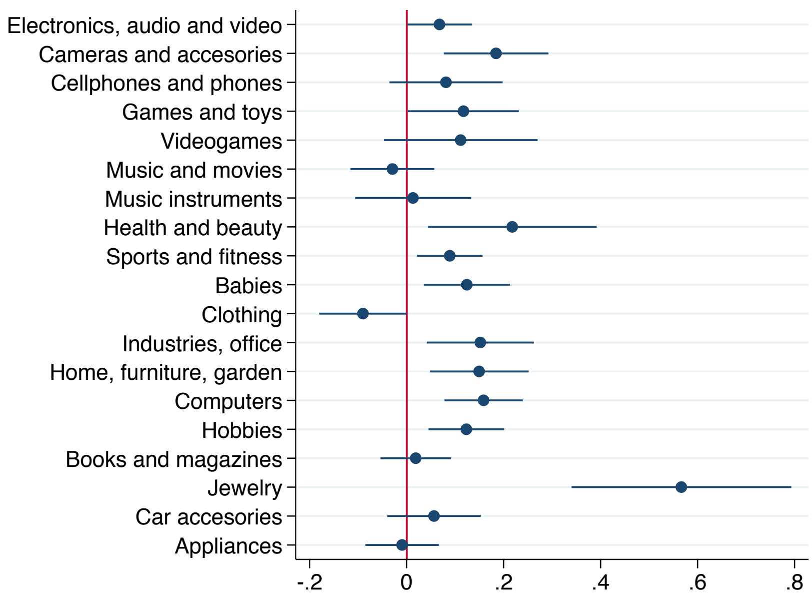
	(1) Coef. Var.	(2) Coef. Var.	(3) Coef. Var.	(4) Coef. Var. (w)	(5) SD Log(P)	(6) IQ75-25	(7) IQ90-10	(8) Coef. Var.	(9) Coef. Var.	(10) Coef. Var.	(11) Coef. Var.	(12) Coef. Var.
Gap Expectations$_{ct}$	0.797***											
	(0.128)											
SDev. Expectations$_{ct}$		0.501***										
		(0.162)										
$\mathbb{1}\{Arg\}_c \times \mathbb{1}\{Placebo\}_t$			-0.0624									
			(0.0416)									
$\mathbb{1}\{Arg\}_c \times \mathbb{1}\{Post\}_t$				0.267***	0.358***	0.0603***	0.0879**	0.119***	0.0787***	0.120***	0.0751**	0.120***
				(0.0426)	(0.0261)	(0.0217)	(0.0408)	(0.0286)	(0.0236)	(0.0276)	(0.0369)	(0.0293)
N	40642	40642	16999	74110	74109	75215	75215	73026	45430	74110	22919	75925
Median Arg.	0.996	0.996	0.996	0.999	1.000	0.799	1.848	0.984	0.640	0.996	0.962	1.082
Median Uru.	-	-	0.889	0.886	1.008	0.772	1.738	0.880	0.619	0.889	0.878	1.009
Time FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Categ.-Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Specification			Placebo					Local	Foreign	Add. controls	High foreign	All goods

Notes: The set of control variables included in all regressions are measures of observed annual inflation, output gap, the standard deviation of the log monthly average exchange rate and the quarterly devaluation rate. Column (1) includes the deviation of mean expected inflation from actual inflation (denoted "Gap Expectations") computed using data from the household survey of expectations. Column (2) includes the cross-sectional standard deviation of inflation expectations (denoted "SDev Expectations"). Column (3) reports the results of a Placebo test, in which the sample is restricted to the 2003-2006 period and the year 2006 is considered as the treatment period for Argentina. In column (4) each listing is weighted by the number of units available for sale before computing the coefficient of variation. The dependent variables in columns (5)-(7) are the standard deviation of log prices, the 75th-25th percentile range standardized by the mean price and the 90th-10th percentile range standardized by the mean price, respectively. Column (8) estimates the baseline specification with the coefficient of variation computed using data on goods with prices set in local currency only. Column (9) estimates the baseline specification with the coefficient of variation computed using data on goods with prices set in foreign currency only. Column (10) includes the following set of controls computed at the category-country-quarter level: share of listings with prices posted in foreign currency, total number of listings, total number of listings with prices set in local currency. Column (11) estimates the baseline specification using only data from categories with an average (over time) share of goods with prices set in foreign currency that is above the sample average (over time and category). Column (12) estimates the baseline specification with the coefficient of variation computed using data on all goods (new and also used). The estimation method used in all columns is OLS. Standard errors (in parentheses) are clustered at the Category-Country level. The median values correspond to the entire sample period by country. "Time FE" are quarter-year dummy variables. "Category-Country FE" are dummy variables specific to each category of goods at level 3 and country. $*$, $**$, and $***$ represent statistical significance at the 10%, 5%, and 1% level, respectively.

in local and foreign currency only, respectively. In both cases we estimate a positive and statistically significant increase in prices dispersion of 12% relative to the mean dispersion in each subgroup of goods. In column (10), we include as additional control variables the share of goods with prices set in dollars, the number of total listings and the number of listings with prices set in local currency (all computed within each category-country-quarter bin). The estimated coefficient of 0.12 is statistically significant and similar in magnitude to the effect estimated in the main specification. Finally, for each category-country bin, we compute the average share of goods with prices set in foreign currency (over time) and split the sample in two groups: those with a share above and below the average share across all categories. Column (11) presents the estimation results using the sample with categories of goods that are more "dollarized". The parameter of interest remain positive and significant. The corresponding estimate using the sample with categories of goods that are less dollarized than the average category is 0.12 and significant at the 1% level. In the last column of Table B8 we also include data on prices of used goods when computing the coefficient of variation of prices. As expected, the average coefficient of variation is higher when including used goods that incorporate additional heterogeneity (1.082 versus 0.996). However, we continue estimating a positive and significant increase in price dispersion of 11% relative to the mean. Finally, we also re-computed the same analysis by grouping data at monthly frequencies and using data on transacted prices -as opposed to posted prices-. In both cases, we obtain similar results (available upon request).

Another potential concern is related to changes in the composition of goods over time. Notice that in order to pose a threat to our analysis, this change in composition should affect Argentina differently than Uruguay and the timing of the change should have coincided with the beginning of the manipulation of inflation statistics. A way to address this concern is to estimate the effect on price dispersion allowing for differential effects across categories. More specifically, we estimate the main specification using data on prices at category level 3, but we interact the coefficient of interest $\mathbb{1}\{Arg\}_c \times \mathbb{1}\{Post\}_t$ with dummy variables that are equal to 1 if the observation belongs to a certain category at level 1 in Argentina. That is, instead of estimating the overall effect on price dispersion, we estimate 19 effects (each corresponding to a group of goods categorized at level 1). Figure B.10 presents the results. The estimated effect is positive for all but 3 categories (for these 3 categories, only 1 is barely significant at the 10% level). Of the remaining 16 positive effects, 11 are statistically significant.

Figure B.10: The Effect of Uncertainty by Categories



Notes: This figure shows the point estimates of a regression similar to the main specification using data on listings of goods categorized at category level 3, but allowing for differential effects by categories grouped at category level 1. The error bounds are the 90% confidence intervals ($\pm 1.65 \times SE$). The estimation method used is OLS. Standard errors are clustered at the Category-Country level. The regression includes the same set of controls as the main specification, and Time and Category-Country fixed effects.

Next, we assess whether the relationship between higher uncertainty about the levels of inflation and price dispersion depends on the level of substitutability of the products considered. To make this assessment, we exploit the different levels of product categories available in the sample. Our working assumption is that the elasticity of substitution is higher for higher levels of categories, as products are more similar to each other in these categories. We estimate the baseline specification for category levels 1 to 5. Results are shown in columns (1)-(5) of Table B9. The coefficient of interest is positive and significant for category levels 3 to 5. The estimated effects expressed as a fraction of the sample mean are increasing in the level of specificity of goods from 9.5% to 28%.[34] We interpret this result in the following way: for a given shock to the availability of precise information about inflation, the effect on price dispersion is higher, the higher the elasticity of substitution between products. Additionally, notice that in Table B3 we can identify examples of goods that are already fully identifiable with the categorization at level 4 (e.g., iPhone 5 16GB). The fact that we keep finding a positive and significant increase in price dispersion among goods categorized at level 4 and 5, alleviates the concern that changes in price dispersion are just reflecting changes in the composition of goods within categories. Another way to deal with such concern and the fact that we cannot fully identify all products sold in the platform is to restrict the sample of goods categorized at level 3 that have an average coefficient of variation below 0.75 and 0.5 through the sample period (this has been previously done in the literature; e.g., Kaplan and Menzio (2015) restrict the sample to goods with a coefficient of variation below 1). This procedure reduces the median coefficient of variation of the estimation sample to 0.6/0.57 and 0.41/0.36, for Argentina and Uruguay, respectively, indicating that the estimation sample includes categories with more similar goods. In both cases, we find a significant increase in price dispersion.

[34] The sample mean of the coefficient of variation is decreasing in the category level, which is consistent with the fact that products are more similar to each other in higher levels of categories.

Table B9: Robustness Analysis: Different Category Levels

	(1) Coef. Var.	(2) Coef. Var.	(3) Coef. Var.	(4) Coef. Var.	(5) Coef. Var.	(6) Coef. Var.	(7) Coef. Var.
$\mathbb{1}\{Arg\}_c \times \mathbb{1}\{Post\}_t$	0.0241	0.0774	0.0950***	0.167***	0.152**	0.133***	0.0933*
	(0.143)	(0.0485)	(0.0280)	(0.0445)	(0.0706)	(0.0335)	(0.0553)
N	1515	18045	74110	122221	110192	17454	3367
Median Arg.	2.061	1.304	0.996	0.736	0.536	0.609	0.412
Median Uru.	1.783	1.262	0.889	0.649	0.479	0.570	0.365
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Categ.-Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Specification	Cat. 1	Cat. 2	Cat. 3	Cat. 4	Cat. 5	< 0.75	< 0.5

Notes: Columns (1)-(5) run the baseline specification for the dependent variable computed by grouping goods at category level 1 to 5, respectively. The set of control variables included in all regressions are measures of observed annualized inflation, output gap, the standard deviation of the log monthly average exchange rate and the quarterly devaluation rate. In columns (6) and (7), we use measures of price dispersion computed at the category level 3, but keeping only categories with an average coefficient of variation (throughout the sample period) below 0.75 and 0.5, respectively. The estimation method used in all columns is OLS. Standard errors (in parentheses) are clustered at the Category-Country level. The median values correspond to the entire sample period by country. "Time FE" are quarter-year dummy variables. "Category-Country FE" are dummy variables specific to each category of goods at level 3 and country. $*$, $**$, and $***$ represent statistical significance at the 10%, 5%, and 1% level, respectively.

C Quantitative Appendix

C.1 Estimation of Idiosyncratic Wage Process

In order to calibrate the process for the idiosyncratic labor costs, we estimate a process for wages that allows for the presence of measurement error. Using the first order condition (11) and adding measurement error as well as individual controls we re-express the joint process for wages and disutility of labor shocks as

$$
\begin{aligned}
w_{it} =& \boldsymbol{\chi} \boldsymbol{X_{it}} + \phi_{it} + \sigma_v v_{it} \\
\phi_{it} =& \rho_\Phi \phi_{it-1} + \sigma_\Phi \varepsilon^\Phi_{it},
\end{aligned}
$$

where v_{it} is a measurement error component associated to wage measurement distributed *iid* with zero mean and variance one. The vector $\boldsymbol{X_{it}}$ includes a set of control variables at the individual level (age_{it}, age^2_{it}, $tenure_{it}$,$education_{it}$, etc.) and a set of aggregate time dummies (that capture the effect of the aggregate money shock in our model). This equation links the process that governs the disutility of labor (and the aggregate shock) to idiosyncratic wages.

We estimate this system of equations using data from the Argentinean Household Survey (*Encuesta Permanente de Hogares*), which is a rotating survey following workers. The estimation was done using data from 2003 to 2011 (we also computed estimations for the sample 2003 to 2006 to avoid including the effect that the policy might also have had on the wage setting process, and results yield very similar point estimates). The structure of the household survey is such that workers are surveyed in two consecutive quarters, then dropped from the sample for two quarters and finally interviewed again for two additional consecutive quarters. This allows us to apply the methodology presented in Floden and Lindé (2001) to estimate the (log) hourly wage process using observations from workers aged between 18 and 65 years old that were continuously employed during the sampling window.

The estimation procedure consists of two steps. In the first step we regress w_{it} on $\boldsymbol{X_{it}}$.

The estimation results are used to compute the net real hourly wage

$$\hat{w}_{it} = w_{it} - \hat{\boldsymbol{\chi}} \boldsymbol{X_{it}}$$

In the second step of the estimation, we use this residualized wage to estimate the idiosyncratic AR(1) component by GMM. In order to identify the persistence parameter ρ_Φ, the variance of idiosyncratic shocks σ_Φ and the variance of the measurement error component σ_v we use observations from workers that were continuously employed to construct the following moment conditions

$$\mathbb{E}\left[(\hat{w}_{it})^2\right] - \frac{{\sigma_\Phi}^2}{1 - {\rho_\Phi}^2} - {\sigma_v}^2 = 0$$

$$\mathbb{E}\left[\hat{w}_{it}\hat{w}_{it-l}\right] - {\rho_\Phi}^l \frac{{\sigma_\Phi}^2}{1 - {\rho_\Phi}^2} = 0$$

for lags $l = \{1, 4\}$.

The GMM estimates are presented in Table C1. The results show that idiosyncratic wages are highly persistent and that there is a large error associated to the measurement of wages.

Table C1: GMM Estimation of Idiosyncratic Wage Process

Parameter	Estimate	Std. Error
ρ_Φ	0.9696	(0.0052)
σ_Φ	0.0819	(0.0069)
σ_v	0.1168	(0.0014)

Notes: Estimation method is GMM. Block bootstrapped standard errors.

C.2 Model Fit

Table C2: Goodness of Fit of Targeted Moments

Target	Data	Model
ρ_c	0.24	0.19
σ_c	0.85	0.85
Avg. Inflation	0.03	0.03
SDev. Inflation Pre-Episode	0.009	0.009
SDev. Inflation Post-Episode	0.013	0.013
Δ CV	0.10	0.09

Notes: Data moments correspond to the sample 2003-2012. Model moments correspond to simulated data for 40 quarters for an economy that suffers a change in σ_p and σ_m in the 17th quarter. ρ_c and σ_c refer to the point estimates of estimating an AR(1) process for quantities. Δ CV refers to the percent change in the coefficient of variation of prices.

C.3 Alternative Calibrations and Welfare Exercises

This subsection reports the new calibrated parameters and the targeted moments in the data and model for two alternative calibrations. The first calibration, which we label *Alternative Calibration 1*, uses the target moments computed with data until 2007-08, before the recession and other macro policies that were put into place starting in 2009. The second calibration, which we label *Alternative Calibration 2*, matches the increase in the volatility of nominal output, instead of the change in the volatility of inflation. This calibration is aimed at capturing additional un-modeled effects of the regime shift that may have increased economic volatility by targeting the volatility of nominal output instead of the volatility of inflation. Table C3 reports the new parameters of each calibration, and the targeted moments along with its data counterparts. All moments are correctly matched. In both calibrations the calibrated increase in σ_p is lower than that in the baseline, and the increase in σ_m is larger than that in the baseline. In both calibrations the model is unable to jointly match the change in the volatility of inflation/nominal GDP and the increase in price dispersion, without relying on a deterioration of the precision of the public signal of inflation.

Table C3: Alternative Calibrations: New Parameters and Goodness of Fit

Alternative Calibration 1: 2007-08			Alternative Calibration 2: Nominal GDP		
Parameters			*Parameters*		
σ_m^{03-06}	0.012		σ_m^{03-06}	0.028	
σ_m^{07-08}	0.048		σ_m^{07-08}	0.049	
σ_p^{07-08}	0.200		σ_p^{07-08}	0.170	
Targeted Moments	Data	Model	*Targeted Moments*	Data	Model
SDev. Inflation Pre	0.009	0.009	SDev. Nom Output Pre	0.017	0.016
SDev. Inflation Post	0.013	0.014	SDev. Nom Output Post	0.026	0.027
Δ CV Pre-Post	0.05	0.05	Δ CV Pre-Post	0.10	0.10

Notes: The left panel of this table shows the new parameters, and model simulated moments (compared with their data counterparts) of the calibration that matches the increase in price dispersion and inflation volatility in 2007-08. The right panel is symmetric but shows the calibration that targets the increase in price dispersion and volatility of nominal output.

We then re-compute the welfare exercise of a change from σ_p^{pre} to σ_p^{post} in an economy with a volatility of monetary policy of the average between σ_m^{pre} and σ_m^{post}. Results, shown in the second and third column of Table C4, indicate that the welfare losses in both calibrations are similar to those estimated in the baseline calibration. In both alternative calibrations, we analyze the welfare effects of changes in σ_p of smaller magnitude than that in the baseline calibration, which would imply lower negative welfare effects. However, both alternative calibrations also involve higher σ_m. This, in turn, leads to larger welfare effects due to the complementarity between information frictions and volatility, explained in section 6.1. Both effects roughly offset each other in both calibrations, leading to similar welfare losses as in the baseline calibration.

Finally, the fourth column of Table C4 presents estimates of the welfare losses in an economy with monetary volatility set at σ_m^{pre}. The welfare losses of changing σ_p are 0.14% of permanent consumption, significantly lower than the baseline due to the complementarities of information and monetary volatility analyzed in section 6.1. In the last column, we analyze the welfare losses associated with the joint change in σ_p and σ_m in the baseline calibration, which would correspond to the welfare losses of the episode of analysis. The welfare loss is

Table C4: Welfare Results: Additional Calibrations and Exercises

	Baseline Change σ_p	Alt Calib 1 Change σ_p	Alt Calib 2 Change σ_p	$\sigma_{m0} = \sigma_m^{pre}$ Change σ_p	$\sigma_{m0} = \sigma_m^{pre}$ Change σ_p, σ_m
Weight CPI (pre)	43.3%	43.2%	43.1%	43.4%	43.4%
Weight CPI (post)	12.5%	21.0%	24.1%	11.1%	12.0%
Δ Price Dispersion	11.1%	9.9%	10.7%	4.0%	17.4%
Δ Welfare	−0.70%	−0.61%	−0.71%	−0.14%	−0.71%

Notes: The first and second lines indicate the cumulative weight attached to the aggregate price signal for the calibrations pre- and post- policy change, respectively. The third line is the variation in the coefficient of variation of prices in the both steady states, and the last line is the welfare costs of the policy change measured in consumption equivalent changes. The first column corresponds to the baseline calibration. The second and third column correspond to Alternative Calibrations 1 and 2 in Table C3. In these three columns σ_m is set at the average of σ_m^{pre} and σ_m^{post}. The fourth and fifth columns correspond to the baseline calibration in which the initial $\sigma_m = \sigma_m^{pre}$. The first four columns analyze a single change in σ_p and the last column analyzes a joint change in σ_p and σ_m.

0.71%, significantly higher than the one obtained from changing only σ_p in an economy with monetary volatility set at σ_m^{pre}, which is the relevant benchmark.

C.4 US Calibration

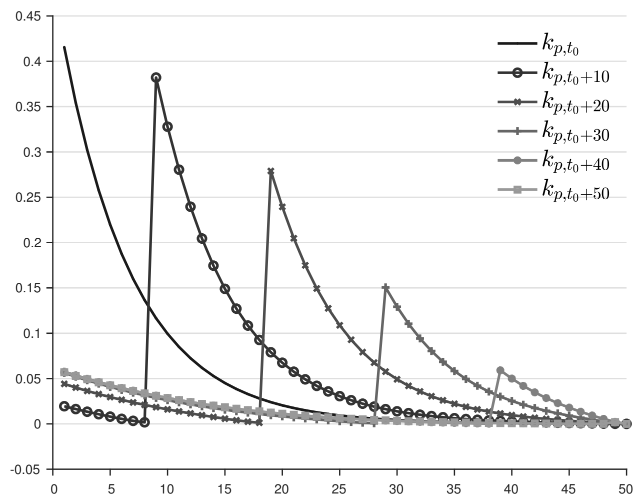
The parameters that govern the demand shock and the labor supply shock are adapted from Burstein and Hellwig (2008), who calibrate their processes to match moments using US price data. In that paper, the authors use the same structure of demand shocks. Idiosyncratic cost shocks play an analogous role in their model to our disutility of labor shocks. The idiosyncratic cost shock in their model is a productivity shock that affects the marginal rate of transformation of each variety in the same way the shock to the disutility of labor does in our model. The resulting values (adjusted to reflect a quarterly calibration) are $\rho_\Psi = 0.28$, $\sigma_\Psi = 0.22$, $\rho_\Phi = 0.28$, $\sigma_\Phi = 0.08$. The parameters that govern the money supply process were calibrated to match the standard deviation of inflation and average inflation in the US obtained from Golosov and Lucas (2007).

Table C5: US Calibration

Parameter	Argentina	US
Labor Supply Shock		
ρ_Φ	0.969	0.278
σ_Φ	0.091	0.084
Goods Demand Shock		
ρ_Ψ	0.500	0.278
σ_Ψ	0.780	0.229
Money Process		
μ	0.033	0.006
σ_m^{pre}	0.012	0.006
σ_m^{post}	0.036	0.006

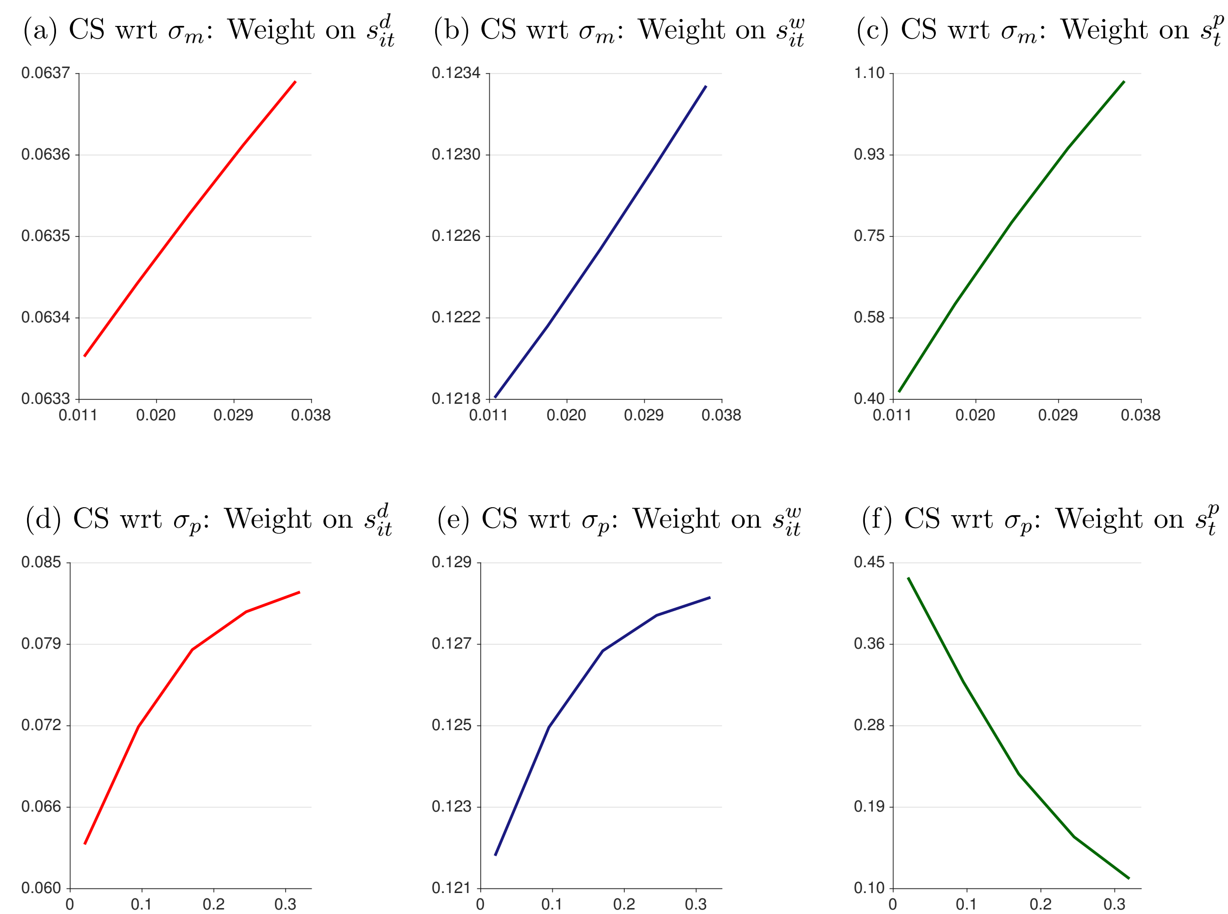
C.5 Additional Figures

Figure C.1: The Effect of a Higher σ_p: Transition Dynamics



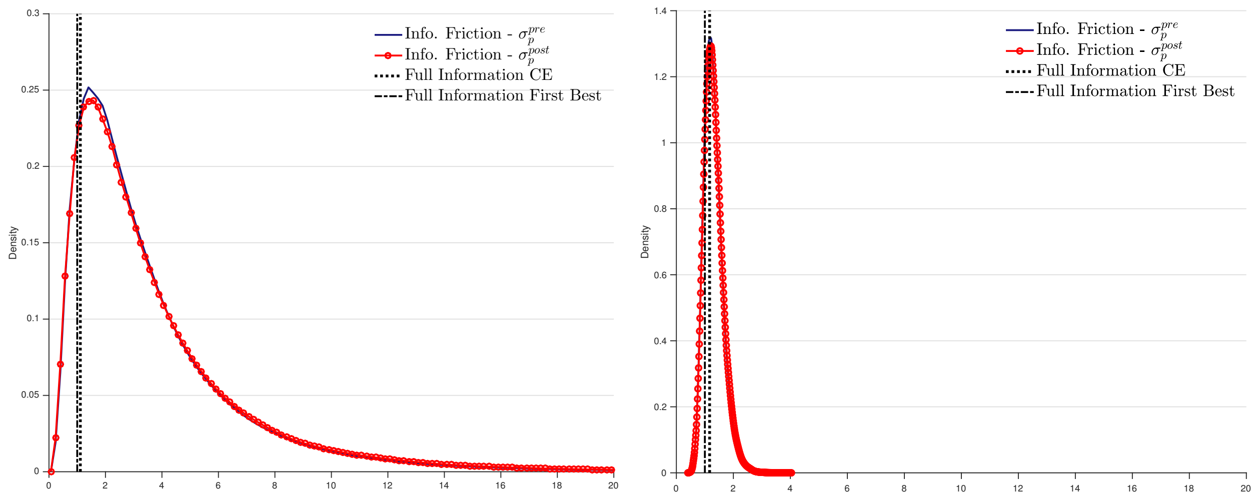
Notes: This graph shows the vector of the loadings of the aggregate price on the innovations of the aggregate public signal, k_{pt}. The x-axis is the vintage of the signal (the larger the value, the older the signal). The different lines show how the loadings change during the transition, assuming that at period t_0 there is a permanent increase in σ_p. The spikes in the graph illustrate how the aggregate price respond to noise in signals with high σ_p and reflect the fact that firms not only place more weight in their idiosyncratic signals but also on past signals of the aggregate price level that were not contaminated by the high-variance noise.

Figure C.2: Cumulative Bayesian Weights on Signals: Comparative Statics



Notes: These graphs show the sum across vintages (from 1 to T) of all the weights attached to each component of $\boldsymbol{s}_{it}$. The top panels plot them as a function of σ_m and the bottom panels plots them as a function of σ_p. All the remaining parameters are set at the values of the 2007-12 calibration.

Figure C.3: The Effect of Higher Uncertainty About Inflation on Wedges

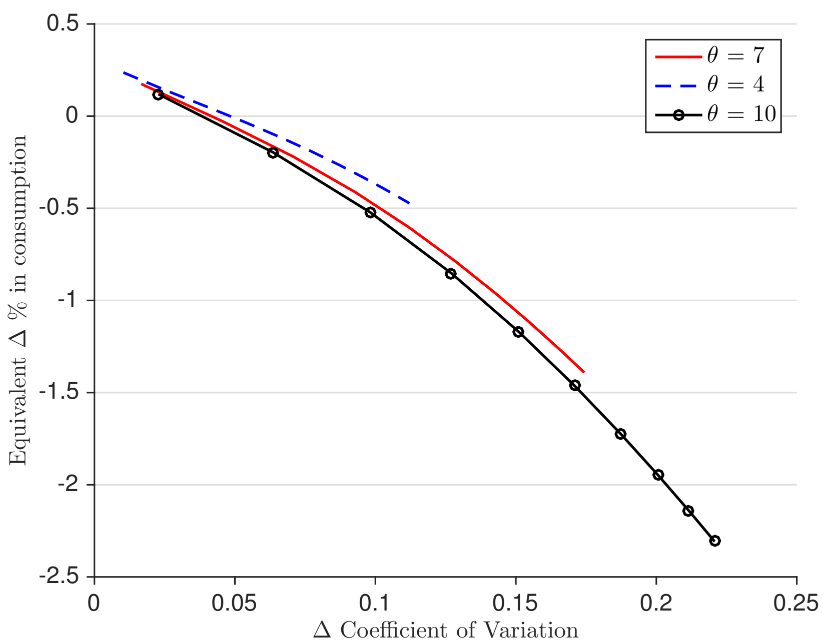


(a) Argentina Calibration

(b) US Calibration

Notes: These figures plot the histogram of wedges across-varieties for the model with low and high σ_p. In the case of the first best and competitive equilibrium with full information there is no dispersion across wedges. The left panel uses the calibration for Argentina with σ_m set at the average between its pre and post-policy change values and $\theta = 10$. The right panel uses the calibration for the US with $\theta = 10$.

Figure C.4: Welfare and Price Dispersion: Robustness Analysis



Notes: This figure plots the welfare effect of a permanent increase in σ_p as a function of the percent change in the coefficient of variation of prices such an increase generates. The results are presented for three values of the elasticity of substitution.

D Additional Models and Analytical Results

In this section, we analyze the model presented in Hellwig (2005). We make two points with this analysis. First, we analytically demonstrate the effects of a noisier public signal and of higher monetary volatility, on price dispersion and on the volatility of inflation. Second, we show that our model-based identification strategy is also valid with alternative information structures. Without loss of generality, there is only one period in the model.

Households

There is a continuum of identical infinitely-lived households whose preferences are defined over a continuum of varieties of goods C_i, a continuum of variety-specific labor supply L_i and real money balances $\frac{M}{P}$. The problem of a household is given by:

$$\max_{\{C, L_i\}} \mathbb{E}\left(\log C + \log\left(\frac{M}{P}\right) - \int_0^1 L_i \, \mathrm{d}i\right)$$

subject to

$$\int_0^1 P_i C_i \, \mathrm{d}i + M = \int_0^1 W_i L_i \, \mathrm{d}i + \Pi + T,$$

where C is the Dixit-Stiglitz composite of individual goods with elasticity of substitution θ

$$C = \left[\int_0^1 C_i^{\frac{\theta-1}{\theta}} \, \mathrm{d}i\right]^{\frac{\theta}{\theta-1}},$$

Π represents the aggregate profits from the ownership of firms, T are lump sum transfers of money from the central bank, W_i is the wage paid by the firm that produces variety i and P_i is the price of good of variety i. We assume that money supply follows the following stochastic process

$$\log(M) = m_0 + \epsilon_m \qquad \epsilon_m \sim N(0, \sigma_m^2).$$

The demand for each variety obtained from the maximization problem is given by

$$C_i = \frac{M}{P}\left(\frac{P_i}{P}\right)^{-\theta}, \tag{22}$$

where $P = \left(\int_0^1 P_i^{1-\theta} \mathrm{d}i\right)^{1/(1-\theta)}$ is the ideal price index.

Firm's Problem

There is a continuum of firms, each of which sells one variety of the consumption good indexed by i. Firms are monopolistically competitive and face the demand derived from the household's problem given by equation (22). The production function of the firm is given by

$$Y_i = L_i^{\alpha} \qquad \text{with} \qquad \alpha < 1.$$

The firm's problem is to maximize expected profits

$$\Pi = \max_{\{P_i\}} E_i \left[P_i C_i - L_i W_i | \mathcal{I}_i\right],$$

where $\mathbb{E}_i\left[\cdot|\mathcal{I}_i\right]$ denotes the expectation operator conditional on the firm-specific information set $\mathcal{I}_i$ (which is defined below). The optimal price, expressed in logs[35], is given by

$$p_i = c_0 + (1 - c_1)E_i(m) + c_1 E_i(p),$$

where

$$\begin{aligned} c_0 =& \frac{1}{1+\theta\frac{1-\alpha}{\alpha}}\left\{\log\left[\frac{\theta}{\alpha(\theta-1)}\right] + \frac{1}{2}var_i\left[\frac{1}{\alpha}m + \frac{(\theta-1)\,p}{\alpha}\right] - \frac{1}{2}var_i\left[(\theta-1)\,p\right]\right\}, \\ c_1 =& \frac{1}{1+\theta\frac{1-\alpha}{\alpha}}(\theta-1)\left(\frac{1-\alpha}{\alpha}\right). \end{aligned}$$

[35]The natural logarithm of capital letters is denoted by small letters: $x = \log X$.

Firm's Information Structure

In order to maintain similar information frictions as in the baseline model, we assume that firms make pricing decisions before observing demand and hiring workers. However, firms have access to idiosyncratic and aggregate signals about the monetary shock m:

$$s_a^m = m + \epsilon_a \qquad \epsilon_a \sim N\left(0, \sigma_a^2\right)$$
$$s_i^m = m + \epsilon_i \qquad \epsilon_i \sim N\left(0, \sigma_i^2\right),$$

where s_a^m is the aggregate signal and s_i^m is firm i's idiosyncratic signal of m. Thus, the firm's information set at the beginning of the period is characterized by the following filtration:

$$\mathcal{I}_i = \{s_a^m, s_i^m\}.$$

Given this information set, firms face a signal-extraction problem in which they are not able to perfectly disentangle the realization of all aggregate and idiosyncratic shocks. The reason is that the number of signals observed per period (s_a^m and s_i^m) is lower than the number of aggregate and idiosyncratic shocks (ϵ_a, ϵ_i and ϵ_m).

Solution

In order to find the equilibrium of the model, we conjecture that the equilibrium aggregate price level follows

$$p = k_0 + k_m\epsilon_m + k_p\epsilon_a.$$

This conjectured solution implies that aggregate prices fully reflect the common knowledge component k_0, and that they react to innovations to the money supply and to the noise of the aggregate price signal according to k_m and k_p, respectively. Using this conjecture and the expression of the optimal price, the aggregate price level is given by

$$p = const_1 + (1 - c_1)\int_0^1 E_i(\epsilon_m)\,\mathrm{d}i + c_1\int_0^1 E_i(k_m\epsilon_m + k_p\epsilon_a)\,\mathrm{d}i.$$

In order to compute the expectation terms, we make use of the fact that the vector $(\epsilon_m, \epsilon_a, s_a^m, s_i^m)$ is jointly normally distributed. Thus,

$$p = const_1 + \frac{\left((\sigma_a^{-2} + \sigma_i^{-2})(1 + c_1(k_m - 1)) + \sigma_m^{-2} c_1 k_p\right) \epsilon_m}{\sigma_m^{-2} + \sigma_a^{-2} + \sigma_i^{-2}}$$
$$+ \frac{\left(\sigma_a^{-2}(1 + c_1(k_m - 1)) + (\sigma_i^{-2} + \sigma_m^{-2}) c_1 k_p\right) \epsilon_a}{\sigma_m^{-2} + \sigma_a^{-2} + \sigma_i^{-2}}.$$

This expression can be replaced in the conjecture of p to obtain the following equilibrium conditions:

$$k_m = \frac{(\sigma_a^{-2} + \sigma_i^{-2})(1 + c_1(k_m - 1)) + \sigma_m^{-2} c_1 k_p}{\sigma_m^{-2} + \sigma_a^{-2} + \sigma_i^{-2}}$$

and

$$k_p = \frac{\sigma_a^{-2}(1 + c_1(k_m - 1)) + (\sigma_i^{-2} + \sigma_m^{-2}) c_1 k_p}{\sigma_m^{-2} + \sigma_a^{-2} + \sigma_i^{-2}}.$$

The main benefit of this setup is that we can explicitly solve for k_m and k_p:

$$k_m = \frac{\sigma_a^{-2} + (1 - c_1)\sigma_i^{-2}}{\sigma_a^{-2} + \sigma_m^{-2} + (1 - c_1)\sigma_i^{-2}}$$

and

$$k_p = \frac{\sigma_a^{-2}}{\sigma_a^{-2} + \sigma_m^{-2} + (1 - c_1)\sigma_i^{-2}}.$$

Therefore, in equilibrium firms set their prices according to

$$p_i = const_2 + \frac{\sigma_m^{-2} m_0 + \sigma_a^{-2} s_a^m + \sigma_i^{-2}(1 - c_1) s_i^m}{\sigma_m^{-2} + \sigma_a^{-2} + \sigma_i^{-2}(1 - c_1)} \tag{23}$$

and the aggregate price level is given by

$$p = const_3 + \frac{(\sigma_a^{-2} + \sigma_i^{-2}(1 - c_1))\epsilon_m + \sigma_a^{-2}\epsilon_a}{\sigma_m^{-2} + \sigma_a^{-2} + \sigma_i^{-2}(1 - c_1)}. \tag{24}$$

The following propositions summarize the key results.

Result 1. *The weight k_m is increasing in σ_m, and decreasing in σ_i and σ_a. On the other* *hand, the weight k_p is increasing in σ_m and σ_i, and decreasing in σ_a.*

Proposition **2.** *Price dispersion is increasing in σ_a and σ_m. The volatility of inflation is increasing in σ_m and decreasing in σ_a.*

Proof. We have shown that the coefficient of variation of prices is a monotonically increasing function of the cross sectional variance of prices, which is given by:

$$var^i(p_i) = \sigma_i^2 \left(\frac{\sigma_i^{-2}(1-c_1)}{\sigma_m^{-2} + \sigma_a^{-2} + \sigma_i^{-2}(1-c_1)} \right)^2$$

It is easy to verify that $var^i(p_i)$ is increasing in σ_a^2 and σ_m^2. Similarly, the volatility of inflation is defined as

$$var(p) = k_m^2 \sigma_m^2 + k_p^2 \sigma_a^2.$$

Then, we have the result that

$$\frac{\partial var(p)}{\partial \sigma_m} = 2k_m \sigma_m^2 \frac{\partial k_m}{\partial \sigma_m} + 2k_m^2 \sigma_m + 2k_p \sigma_a^2 \frac{\partial k_p}{\partial \sigma_m} > 0,$$

since both k_m and k_p are increasing in σ_m. The sign of the derivative of the volatility of inflation with respect to σ_a is not obvious. On the one hand, firms put less weight on the noise of the aggregate signal when σ_a increases. On the other hand, firms pay attention to a more noisy aggregate signal when σ_a increases. This tension between both effects can be noted in the first line of the following equation. However, we show that the first effect dominates, so:

$$\begin{aligned} \frac{\partial var(p)}{\partial \sigma_a} &= 2k_m \sigma_m^2 \frac{\partial k_m}{\partial \sigma_a} + 2k_p \sigma_a^2 \frac{\partial k_p}{\partial \sigma_a} + 2k_p^2 \sigma_a \\ &= \frac{-2\sigma_a^{-3}}{\sigma_m^{-2} + \sigma_a^{-2} + \sigma_i^{-2}(1-c_1)} \left(\sigma_m^{-2} + \sigma_a^{-2} + 3\sigma_i^{-2}(1-c_1) \right) < 0. \end{aligned}$$

□

The previous proposition shows that in a simplified version of our model, all of the main predictions discussed in the paper still apply. The direct effect of a higher σ_a is that firms put less weight on the aggregate signal and focus more on the prior m_0 and on idiosyncratic information (see equation (23)). Thus, aggregate prices become less responsive to the monetary shock and the noise of the aggregate signal (see equation (24)). Since firms need to forecast the prices set by other firms, the fact that other firms are paying less attention to the aggregate signal, makes each firm want to pay even less attention to it as well. This feedback effect means that when σ_a increases, k_p decreases at a higher rate, so that $k_p\sigma_a$ ends up declining too. Thus, price dispersion is increasing and the volatility of inflation is decreasing in σ_a.

When the monetary shock becomes less predictable (i.e., higher σ_m), firms pay more attention to both the idiosyncratic and the aggregate signal and less attention to the prior (see equation (23)). Thus, the aggregate price reflects more the aggregate signal and becomes more volatile (see equation (24)). Also, since firms shift the weight away from the common prior in part to the idiosyncratic signal, price dispersion is increasing in the volatility of the monetary shock.

The welfare effects of σ_a are thoroughly described in Theorem 2.i in Hellwig (2005), which states that equilibrium welfare is strictly decreasing in σ_a. By affecting the response of aggregate prices to the monetary shock (and thus inflation volatility), a less precise public signal (higher σ_a) decreases the volatility of aggregate prices (and thus output). However, when σ_a is higher, firms rely more on their idiosyncratic signals, whose cross-sectional variations translates into higher price dispersion. Theorem 2.i in Hellwig (2005) shows that the latter effect dominates, so welfare is unequivocally decreasing in σ_a.

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