PRICE SETTING UNDER UNCERTAINTY ABOUT INFLATION*

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ABSTRACT. We use 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. Consistent with empirical evidence, we find that monetary policy becomes more effective with less precise information about inflation. 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, monetary policy.

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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 that arises 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 academic 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 test 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 the inflation rate on firms' pricing decisions and the macroeconomy. First, we assess the empirical relationship between the degree of uncertainty about inflation and the cross-sectional dispersion of prices. We do so by exploiting an episode in which an economy experienced a regime switch from a regime with low volatility of inflation and access to credible public information about inflation to a regime in which the quality of inflation statistics was downgraded and inflation volatility increased. Using micro data, we find higher levels of observed price dispersion in a context with less precise inflation statistics and higher inflation volatility.

Then we formulate a general equilibrium model of price setting tailored to study our episode of analysis and calibrate it to match the empirical evidence. Consistent with Lucas' original argument, our model predicts that monetary policy becomes more effective in affecting the level of output when there is less precise public information about inflation. We provide empirical support for this prediction. We also 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 adequate inflation statistics.

Our 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. The higher degree of uncertainty about inflation was reflected in the cross-sectional dispersion of inflation forecasts, that increased significantly after the manipulation. We consider this event as an episode in which agents lost access to accurate aggregate information about the inflation rate. Simultaneously, during the period 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. The empirical analysis consists of a difference-in-difference estimation, in which Uruguay serves the purpose of the control group. 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.

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 publications of goods available for sale. Using data on posted prices of each publication and the categorization of the product, we compute series of price dispersion (measured as the coefficient of variation of prices) for all product categories, for both countries on a quarterly basis during the period 2003-2012. Controlling for observed 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.

Our empirical estimations yield a difference-in-difference coefficient that is positive and significant, indicating that less precise inflation statistics and higher inflation volatility were associated with an increase in observed price dispersion. The effect is also quite large in economic terms. The manipulation of inflation statistics and higher inflation volatility had associated an increase in the coefficient of variation of prices of 8.7% with respect to its mean. Later, we disentangle the effects of less precise inflation statistics and higher inflation volatility separately using a general equilibrium model.

We carry out robustness analysis to demonstrate that our results are robust to: the choice of the dependent variable (other alternative measures of price dispersion), the way we control for changes in inflation rates, alternative specifications and different sub-samples. Importantly, we still find a positive and significant effect when we shorten the post-manipulation period to a one or two-year window, when arguably there were no other major policies implemented that could have potentially affected price dispersion. We also find that the effect on price dispersion was permanent and gradually increasing over time. Additionally, using an analysis complementary to our difference-in-difference approach, we show that continuous

measures of uncertainty about inflation, such as the cross-sectional standard deviation of inflation expectations, are positively correlated with price dispersion in Argentina.

Having established our main stylized fact, we then formulate a general equilibrium model of price setting specifically tailored to understand the episode of analysis. In the model, 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. The model displays a source of money non-neutrality stemming from informational frictions. To reproduce the changes in policies observed in Argentina with our model, we implement a joint decrease in the precision of the aggregate price signal and increase in the volatility of monetary policy, and explore the effects on aggregate allocations.

We argue that the reaction of price dispersion and inflation volatility to a decrease in the precision of the aggregate price signal and an increase in monetary volatility provides a useful source of identification that allows us to disentangle the contributions of each of these policy changes. While price dispersion increases in response to both policy changes, inflation volatility decreases in response to a decrease in the precision of the aggregate price signal and increases in response to an increase in monetary volatility. These differential responses are due to the change in the weights that firms put into their signals when setting prices. A less precise aggregate price signal 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 price signal does not, and decreases inflation volatility since firms' prior does not respond to aggregate shocks whereas the aggregate price signal does. A more volatile monetary policy makes firms increase the weight attached to their idiosyncratic signals and the aggregate price signal, and reduce the weight attached to their prior since the latter becomes less informative. This increases price dispersion since idiosyncratic signals contain cross-sectional dispersion and the prior is common to all firms, and increases inflation volatility since firms increase the weight in all their signals, which respond to aggregate shocks.

To estimate and calibrate the underlying stochastic processes that govern the shocks in the model, we use panel data on wages from Argentina, panel data on the quantities sold in the online platform and moments of the aggregate price level. Additionally, we take advantage of the event that occurred in Argentina in order to discipline the most important model

parameters. More specifically, we use our estimated increase in price dispersion and the observed increase in inflation volatility to calibrate the implicit increase in the variance of the signal of aggregate prices and the change in the volatility of the money supply shock. Our calibrated model is then used to disentangle how much of the estimated increase in price dispersion is due to changes in these policies. 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 signal of the aggregate price level, 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.

Next we compare the effectiveness of monetary policy in an economy with a less precise signal of aggregate prices and higher volatility of the money supply process (that represents the economic context faced in Argentina after 2007) to that in an economy with a more precise signal and less volatile money supply (that represents the economic context in Argentina pre-2007). We find that monetary policy becomes more effective in the economy with more volatile monetary policy and a less precise aggregate price signal. Although a more volatile monetary policy is less effective in affecting output, a less precise aggregate price signal makes it more effective. Quantitatively, we find that the latter effect dominates. We test this model prediction by estimating an empirical VAR with money, prices and output variables from Argentina using a pre-2007 sub-sample and a post-2007 sub-sample. The identification of the VAR is informed by the timing of the model. We find that a money supply innovation in the estimated VAR on the post-2007 sample has associated a positive and significant effect on output, while the same money innovation has a much smaller effect on output that is not statistically significant in the estimated VAR using data from the pre-2007 sample.

Finally, we use our model to compute the welfare effects of not providing an accurate measure of aggregate prices. We find that these effects are negative and large. The representative household that lives in an economy with an accurate measure of aggregate prices requires a permanent decrease in consumption of 0.6% in order to be indifferent to living in an economy with a noisy signal of aggregate prices. This welfare cost is associated with a larger degree of misallocation of labor and consumption. 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. We find similar results if we use an alternative calibration strategy that targets moments computed using a restricted sample from 2003 to 2008, a period in which arguably there were no other major policies implemented.

The presence of such high welfare costs is related to the fact that the Argentinean economy is highly volatile. These welfare costs are significantly lower in less volatile economies. We illustrate this point by computing the same welfare exercise for a different parameterization of our model calibrated to match the US economy. The welfare cost of the same increase in the variance of the noise of the CPI signal in the US economy is equivalent to a permanent drop in consumption of only 0.17%. The main reason for the smaller welfare cost for the US is the fact that monetary policy is stable in this economy, which allows agents to predict reasonably well the rate of inflation just with their prior beliefs about the money supply process. In this context, reducing the accuracy of the signal of aggregate prices does not significantly undermine the prediction capacity of firms and thus does not 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 our 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) and Baley and Blanco (2016).[1] 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) and Angeletos and Pavan (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) show that welfare may decrease with more public information when the sources of information are endogenous, i.e. when agents learn from prices. Angeletos et al. (2016) show that the nature of the shocks driving business cycles are important in determining the social value of

[1]Other approaches to modeling informational frictions in price setting are models in which new information arrives in an exogenous staggered fashion, as in Mankiw and Reis (2002) and Klenow and Willis (2007), or models in which information is endogenously acquired and agents are rationally inattentive as in Reis (2006), Alvarez et al. (2011b), Alvarez et al. (2015) and Stevens (2015).

public information. We contribute to this literature by being the first paper that quantifies these welfare effects and showing that they are positive and large for volatile economies.

The remaining of the paper is organized as follows. Section 2 documents the episode of analysis, describes the data and assesses its representativeness of the overall economy. Section 3 discusses the empirical strategy, presents the main results and robustness exercises concerning the estimation of the relationship between higher uncertainty about inflation and price dispersion. Section 4 presents a general equilibrium model of price setting. A quantitative analysis of the model implications for price dispersion and the effectiveness of monetary policy is carried out in Section 5. Welfare results are presented in section 6. Finally, Section 7 concludes.

2. The Episode of Analysis and Data Description

This section begins by describing the episode of analysis, documents the evolution of dispersion in inflation forecasts and describes the sources of data used in the empirical analysis.

2.1. *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 being paid for CPI-linked government debt. The manipulation lasted for eight years and is being reverted at the time of the writing of this paper.[2] 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). In 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.[3] Since then, official inflation statistics were discredited by local and international media, international institutions and academic circles.[4]

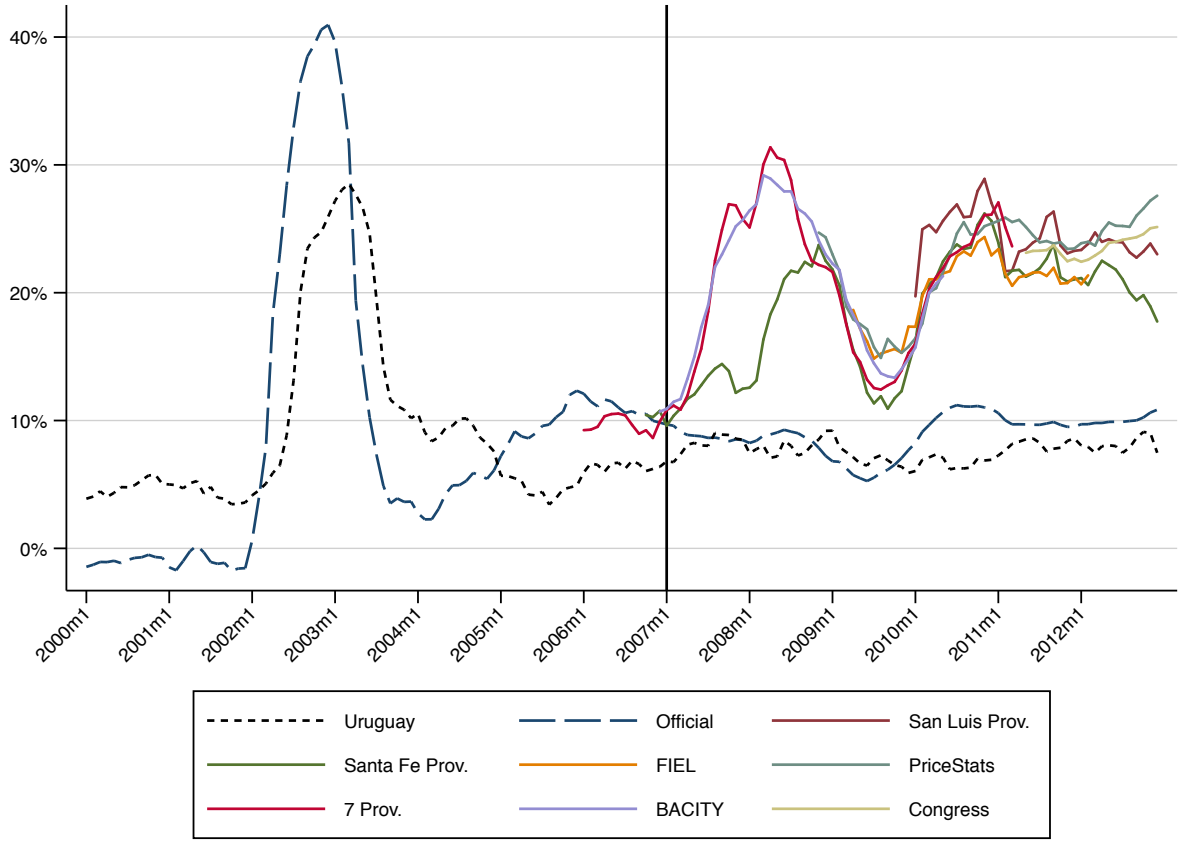
[2]The new government that took power in December 2015 is in the process of constructing a new CPI index.

[3]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. See Cavallo (2013) and Cavallo et al. (2016) for a detailed timetable of the event and the particular measures taken by the government.

[4]See, for example, *La Nacion*, February 10, 2007, *The Economist*, April 20, 2011 and IMF (2008). In 2012, the IMF censored Argentina for not providing adequate data on inflation.

In the absence of a trustworthy official measure of inflation, private and independent institutions gradually started monitoring the evolution of prices and reporting alternative measures of inflation. In addition, some individual provincial governments started reporting their local inflation statistics. As illustrated in Figure (1), 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. Notice that at the end of 2006 (right before the intervention of official statistics), the few alternative measures that were available were in line with the official measure. It is only after the manipulation takes place that the alternative measures begin to deviate from the official inflation statistics.

FIGURE 1. Inflation in Argentina Before and After Statistics Manipulation



Notes: This figure 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).

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. 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, PriceStat, another alternative measure, covered only online prices (see Cavallo (2013) for details on this last measure). One symptom of the smaller and less representative samples is the high dispersion observed among these measures. The difference between the highest and lowest inflation measures averaged five percentage points during the 2007-12 period (see Figure (1)). In addition, there was lack of consensus among economic agents concerning which of these alternative measures provided the best estimate of inflation.[5]

Figure (1) 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 average).[6] 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). These two differences across periods will be taken into account when disentangling the effect on price setting that can be attributed to information frictions.

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 (2a) shows the median of inflation expectations in Argentina that comes from a national household survey that started being conducted in 2006.[7] At the end of 2006, the median expected inflation was close to the official inflation rate. After the manipulation, the median expected inflation

[5]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.

[6]However, the highest levels of inflation in the past decade were observed in early 2003 in the aftermath of the economic crisis, when annual inflation peaked at 40%.

[7]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 participants answering the following question: "Comparing current prices with those in the next year, by which percentage do you

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 (2b) 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.

Given the approach we adopt in the empirical analysis, it is important to discuss here the broader economic context in which the manipulation of official statistics occurred. We argue that no other major changes in government policies nor in the macroeconomic scenario were observed 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 (A.1) in Appendix A 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 (A.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 (A.3a) 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. Figure (A.4) shows the sovereign spread of Argentina, which did not exhibit large changes until the onset of the global financial crisis. Finally, Figure (A.3b) compares the official exchange rate with the exchange rate obtained in the unofficial market.[8] 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, we carry out robustness analysis of all the main results of the paper (both

expect prices to increase on average in the next twelve months?". We thank Guido Sandleris for sharing the data.

[8]Data on expectations come from a survey conducted by the Central Bank 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.

the empirical analysis and the quantitative analysis of the model) by restricting our sample to the 2003-2008 period.

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. From 2003 to 2006 the government provided a *unique* and *credible* official measure of inflation and quarterly 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.

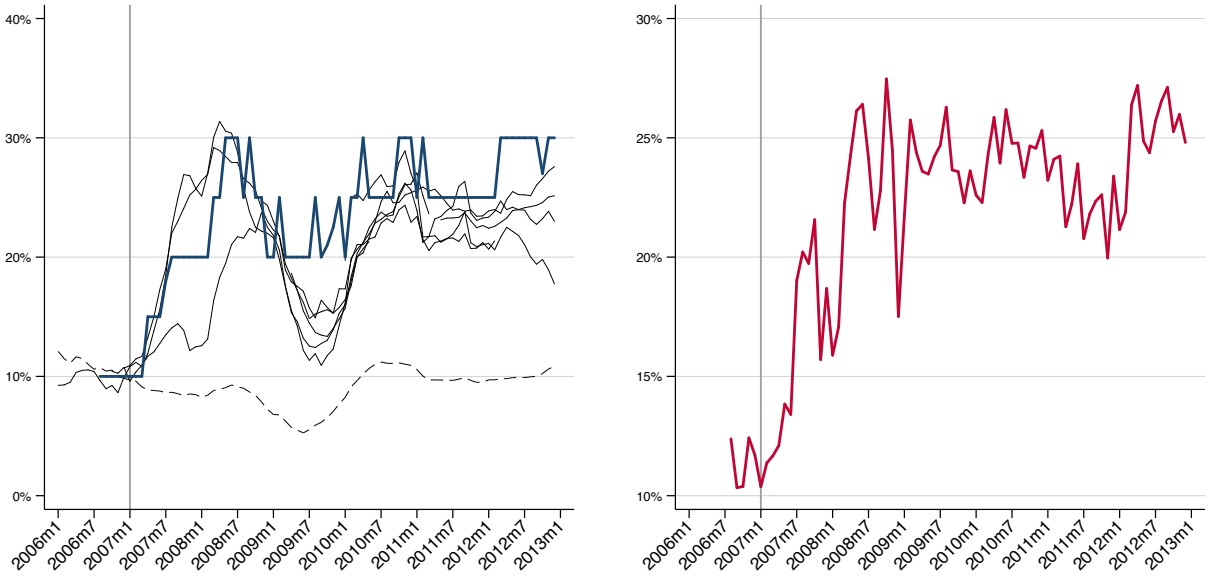
In the following empirical analysis we study the price setting behavior across these two regimes in Argentina. A natural question that arises is, how relevant is public information about aggregate inflation for price setting decisions? Recent papers have presented empirical evidence from *low-inflation* countries showing that different types of economic agents forecast higher inflation rates than actual rates and that these forecast exhibit substantial disagreement (see for example, Afrouzi et al. (2015) and Binder (2014)) suggesting that agents do not rely heavily on inflation statistics. This does not seem to be the case in high-inflation countries. Evidence presented by Cavallo et al. (Forthcoming) shows that in Argentina (where the cost of ignoring inflation is substantially higher) agents have a much stronger prior about the inflation rate than their counterparts in the US. This is consistent with the fact that in Argentina the median inflation expectation is quite aligned with realized inflation and inflation appears among the main concerns of the population in opinion polls. Additionally, Carrillo and Emran (2012) make use of a natural experiment to show that in Ecuador households rely on the CPI to form their market expectations.

2.2. *Data Description*

The data used for the analysis of price dispersion comes from the largest e-trade platform in Latin America that started its activities in 1999 and currently operates in 19 countries with 69.5 million users. The type of products traded in this platform are mostly durable products (see Figure (A.5) for a snapshot of the basket of products at two different points in time). In order to post goods in this platform, sellers generate a publication, 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

FIGURE 2. Inflation Expectations in Argentina

(A) Median Expected Inflation (B) Cross-sectional Standard Deviation



Notes: Panel (A) shows median expected inflation for the next 12 months for Argentina during the 2006-2012 period. The thin grey lines correspond to alternative measures of inflation in Argentina shown in Figure (1). The dashed line corresponds to the official inflation measure. Panel (B) shows the cross-sectional standard deviation of inflation expectations. The source of the data on inflation expectations is the Survey of Inflation Expectations developed by the Universidad Torcuato Di Tella.

groups. Once the buyer locates a good of interest, he can enter the publication and decide to make the purchase. Although the platform allows sellers to sell via auctions, a current search in the platform for notebooks shows that 99.5% of the goods are sold in a posted-price format. We obtained data for all the publications made in Argentina and Uruguay during the 2003-12 period. The inclusion of Uruguay serves the purpose of having a control country and is discussed further in the following section.

In our data, an observation consists of a publication made by a seller of a good(s). Some of the observed characteristics of a publication are: a description of the product, the product category, the type of the product (new or used), the posted price including its currency of denomination, the quantities available for sale, a seller identifier and the start and end date of the publication.

An important variable in the empirical analysis is the category of the product. The platform offers the possibility to the seller to categorize the good being sold according to a pre-specified set of choices. Each product is placed within a category tree that has five levels, which go from a broader to a more specific classification.[9] The first level of categories indicates broad product types such as computers, books and health/beauty. On the other extreme, the fifth level indicates very detailed products such as a Sony Vaio notebook with Intel Core i7 processor (for complete examples of the specification of each category level see Table (A1)). In some cases a detailed specification of the product is obtained even before the last level of category. For example, Table (A1) shows that an iPhone 5 with 16 GB of capacity can be identified with the categorization level 4. As one considers higher levels of category specification, the number of publications that are categorized under that level decreases. In particular, 92% of the total number of publications of new products are categorized in level 3 or higher (see Table (A1)).

Tables (A2) and (A3) in Appendix A 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).[10] 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). To make prices comparable across countries, we convert all prices to domestic currency using the spot nominal exchange rate on the day of the publication. To remove outliers, we drop all prices that are above US$10,000 or above the 99th percentile

[9]The category tree also contains two additional levels for a very narrow set of products. Since only 7% of the total number of publications contain categories specifications that go up to levels 6 or 7, we decided not to use those narrower classifications.

[10]The platform exhibits substantial price dispersion (see regression tables), even within narrowly specified categories at level 5. Part of this high level of price dispersion is explained by the fact that we cannot identify all goods uniquely so we need to rely on the category tree provided by the platform. However, these figures are also displaying price dispersion for a given type of good, which has also been found in other online platforms. For example, Gorodnichenko and Talavera (Forthcoming) use data from a price comparison website that operates in the US and Canada that allows them to uniquely identify goods. They find that, even when goods can be uniquely identified, the average standard deviation of log prices can be as high as 20% on a weekly basis. 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. (2016).

in each category-country group in a given year. Similarly, to remove outliers in the posted quantities we also winsorize the posted quantities at 100 units.

The entire data set includes more than 140 million publications made in both countries during the 2003-2012 period. On average, there are 2.9 million and 640 thousands new publications made in Argentina and Uruguay each quarter, respectively (this is consistent with the fact that the Argentinean economy is ten times as large as the Uruguayan economy). Most of the publications are concentrated in the last years of our sample as the number of publications grew at a rate of 8.8% annually on average given the rapid expansion of the site (see Figure (A.6)). Figure (A.7) shows the growth rates by category level 1 in Argentina and Uruguay. Despite heterogeneous growth rates in Uruguay at the beginning of the sample, on average, the number of publications grows at similar rates across categories.

The importance of this platform is illustrated by the fact that 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 items sold per quarter. The average publication lasts for 26 and 21 days in Argentina and Uruguay, respectively, and between 12% and 21% of all publications are effectively sold in the platform in each quarter.

We focus our analysis on the publications of new products, which represent around 46% of the total number of publications. By "new" goods we refer to goods without prior usage, and not new models/vintages. We restrict our sample to new goods for two reasons: i. to exclude the source of heterogeneity in prices of used products that comes from the products' previous usage by the seller and ii. to isolate one-time-sellers of used products that are less likely to consider the evolution of inflation when setting prices. However, in the robustness analysis, we also estimate the main specification using data of all goods posted in the platform.

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 publication is 1, the average quantity offered per publication is 10.8 (see Figure (A.8) for a histogram of the quantities available for sale by publication). 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 (A.9)).

Despite the large dimensions of the data set, one concern that arises is whether or not the pricing decisions made by users of this online platform are representative of the aggregate economy. As already shown in Figure (A.5), the basket of products offered in the platform

differs substantially from the representative basket of products and services included in the CPI (for example, the platform does not offer food nor services, which represent a large share in any basket of the CPI). To address this concern, we compare the implicit inflation rate from our data set with the evolution of measured aggregate inflation in Argentina. As shown in Figure (A.10), 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.[11]

3. Empirical Analysis

3.1. *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. 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.

Having established the two regimes and the control country we can discuss the estimation procedure. To obtain a measure of price dispersion, we compute the coefficient of variation of prices originally posted when the publication was made available for each category-country pair and each quarter in the sample period.[12] All variables are constructed at a quarterly frequency in order to have enough observations within category-country-quarter bins. However, in the Appendix we report the results obtained using the coefficient of variation measured on a monthly basis and the coefficient of variation of transacted prices (as opposed to originally

[11]The comparison is not favorable for the first quarters since the number of observations is much lower at the beginning of the sample and the composition of goods offered was more concentrated on fewer categories.

[12]The coefficient of variation is defined as the ratio of the sample standard deviation to the sample mean. This measure has the advantage of being dimensionless (in particular it does not depend on the currency in which prices are expressed). Alternative measures of price dispersion such as the standard deviation of the log of prices and inter-quartile ranges are also considered.

posted prices). Following this procedure gives us a panel of (at most) 36 observations for each category in each country.[13] Our baseline estimations are conducted using a dependent variable computed with products categorized at the level 3. This category level provides a sufficiently detailed level of product specification (bicycles, fridges, mattresses, watches and wines are examples of product specifications included in this level) while keeping 92% of all the observed publications of new products. For robustness purposes, we also conducted estimations using data with alternative category levels.

As part of the control variables in our baseline estimations, we include measures of observed inflation, output gap, devaluation rates 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.[14] The inclusion of inflation as a control variable is particularly relevant as inflation increased in Argentina at the time of the manipulation of 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. In the robustness analysis, we also include additional controls computed using data from the platform (such as the implicit inflation rate for each category, number of goods posted, among others). 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, our baseline difference-in-difference estimations are based on the following empirical model:

$$PriceDispersion_{cit} = \delta \mathbb{1}_{\{t \geq 2007\ ,\ c=Arg.\}} + \beta X_{ct} + \alpha_t + \alpha_{ci} + \varepsilon_{cit}, \tag{1}$$

where

[13] The panel is not balanced for all category levels, as some levels were introduced after 2003 and we do not always observe publications in all category levels and all quarters.

[14] Workhorse New-Keynesian models with price stickiness à la Calvo (1983) predict a positive relationship between inflation and price dispersion. 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 literature when presenting the results.

- $PriceDispersion_{cit}$ is the coefficient of variation of prices of all publications in a given quarter t, category i and country c,
- $\mathbb{1}_{\{t\geq 2007\ ,\ c=Arg.\}}$ is an indicator variable that equals 1 for quarters in years 2007 or after (post inflation statistics manipulation) interacted with an indicator variable that equals 1 for publications made in Argentina,
- X_{ct} is a vector that includes the annual inflation rate (for Argentina we use the official inflation measure until 2006 and the simple average of the available alternative measures after 2007), the cyclical component of 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,
- α_t are quarter fixed effects,
- α_{ci} are category-country fixed effects,
- ε_{cit} is an error term.

3.2. *Results*

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 (A.11) 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.

Table (1) reports our basic regression estimates that formally quantify the visual effect just described. Column (1) shows the results of the baseline estimation. The coefficient associated with the interaction between the indicator variable for Argentina and the indicator variable for the post-2007 period is positive and significant. The increase in price dispersion during a period of higher uncertainty about inflation associated with the manipulation of inflation statistics is large in economic terms. The difference-in-difference coefficient of 0.102 indicates that the price dispersion of products published in Argentina is 8.7% higher than average after the manipulation of inflation statistics.

Column (1) also reports the estimated coefficients associated with our macroeconomic control variables. Our estimates indicate a small and negative, albeit not statistically significantly different from zero, relationship between inflation and price dispersion (a 10 pp increase in inflation would reduce the coefficient of variation by 0.005). This evidence is at odds with the prediction of workhorse New-Keynesian models with Calvo pricing, but is consistent with Alvarez et al. (2011a), who find no relationship between inflation and price

dispersion in Argentina for low values of inflation (in line with those observed in our sample) and a positive elasticity for higher levels of inflation (larger than 30% per year). Our estimates are also consistent with the results presented in a paper by Nakamura et al. (2016), 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 (2015) 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 0.0186 and an increase in the volatility of the exchange rate of 10 pp increases the dependent variable by 0.0661. The latter effect could be explained by heterogeneous degrees of pass-through of the goods in the platform.

Next we provide robustness checks with respect to two main concerns: (1) the effect of inflation on price dispersion and (2) the effect of other policies that might have affected price dispersion. To assess the robustness of our results to the way inflation is included as a control variable, we estimate different specifications that vary in the functional form according to which inflation enters the regression equation. First, we re-estimate our 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 (2) of Table (1), 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 (3). 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 (4) shows the results. The coefficient decreases slightly, but remains significant. The effect of category-country specific inflation rate is negligible in magnitude, albeit significant at the 10% level. Finally, in the last column we perform a

TABLE 1. The Effect of Uncertainty About Inflation on Price Dispersion

	(1)	(2)	(3)	(4)	(5)
	Coef. Var.	Coef. Var.	Coef. Var.	Coef. Var.	Coef. Var.
$\mathbb{I}\{Arg\} \times \mathbb{I}\{Post\}$	0.102***	0.104***	0.099***	0.093***	0.114***
	(0.027)	(0.027)	(0.027)	(0.026)	(0.014)
π	-0.051	-0.341			0.433***
	(0.130)	(0.493)			(0.057)
π^2		0.808			
		(1.264)			
π_{arg}			-0.043		
			(0.131)		
π_{uru}			-0.263		
			(0.258)		
π_{ci}				-0.000*	
				(0.000)	
GDP Cycle	-0.878***	-0.978***	-0.982***	-0.927***	-0.650***
	(0.338)	(0.351)	(0.355)	(0.340)	(0.141)
Δ FX	-0.186***	-0.178**	-0.147*	-0.144**	0.298***
	(0.071)	(0.074)	(0.075)	(0.072)	(0.084)
Volatility FX	0.661***	0.605***	0.581***	0.586***	0.233***
	(0.130)	(0.137)	(0.156)	(0.145)	(0.043)
N	78982	78982	78982	75105	56212
Mean Arg.	1.167	1.167	1.167	1.167	1.167
Mean Uru.	0.975	0.975	0.975	0.975	-
Time FE	Yes	Yes	Yes	Yes	No
Categ.-Country FE	Yes	Yes	Yes	Yes	Yes
Specification	Baseline	2nd Deg. Inf.	Country Inf.	Categ. Inf.	Arg. only

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) includes inflation squared as an additional control. Column (3) allows the coefficient of inflation to be country-specific. Column (4) replaces the country-specific inflation rate by country-category-specific inflation rates computed using data from the platform. Column (5) uses observations from Argentina only. The estimation method used in all columns is OLS. Standard errors (in parentheses) are clustered at the Category-Country level. The mean values correspond to the mean of the dependent variable during the 2003-2006 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.

time series analysis in which we only use the time series variation in Argentina and discard Uruguay as the control group. We still observe a positive and significant coefficient with a point estimate similar to that obtained in the baseline specification.

A potential objection to our analysis is that the coefficient of interest could be capturing the effect of other major economic policies that can be potentially related to price dispersion. In the case of Uruguay, no major economic policies that could potentially affect price dispersion were put in place during our sample period. The case of Argentina is different. Together with the manipulation of inflation statistics there was an increase in inflation (for which we are controlling for in our estimations) and a potential increase in the level of uncertainty regarding monetary policy that is manifested in higher inflation volatility. Therefore, we will be flexible in the interpretation of our estimates from this section and discuss this further with the help of a quantitative model. Aside from these changes in monetary policy, we could also be capturing the effects of other policies non-related to monetary policy that could still have potentially affected price dispersion. In section (2.1) we argued that there were no additional policy changes during the first 2 years after the beginning of the manipulation of statistics in 2007 (see Figure (A.1)). Since then, the government implemented trade policies aimed at reducing trade and capital flows that had an impact on the nominal exchange rate. To isolate the potential effect of these other policies, we exploit the time dimension of the introduction of these different policies and estimate our baseline specification for shorter sample periods that end before 2012. Specifically, we estimate our 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 (2). The difference-in-difference coefficient is positive and significant in all subsamples. It increases from 0.054 during the first year to 0.102 when using the full sample. In the Appendix (see Table (A5)), we report results using a dependent variable constructed at a monthly frequency and results using data on transacted prices (as opposed to originally posted prices), which are similar but more precisely estimated.

To provide further evidence regarding the dynamics of our estimated effect, we include semester-specific dummy variables and their interactions with the indicator variable for Argentina in the baseline specification. The benefit of this specification relative to the one that restricts the sample to different sub-periods, is that it helps us 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

(3), 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 dispersion was cumulative over time increasing at a decaying rate. Importantly, we see that the effect attains its peak by the end of 2008, right before the government started implementing substantial changes in other policies.[15]

To sum up, we interpret our results in the following way. As previously discussed in section (2.1), 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 combine these point estimates with a structural model of price setting to disentangle the effects corresponding to each policy change.

3.3. *Robustness*

In this subsection, we present further analysis that helps us assess the validity of our results. We present robustness checks that dwell with three particular aspects: the estimation strategy, the choice of the dependent variable and the estimation sample.

We first 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 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

[15]The reason why the standard errors are larger for the pre-period is the fact that the sample size is much smaller in the earlier years (see Figure (A.6)).

TABLE 2. Robustness Analysis: Alternative Window Lenghts Post-2007

	(1)	(2)	(3)	(4)	(5)	(6)
	Coef. Var.	Coef. Var.	Coef. Var.	Coef. Var.	Coef. Var.	Coef. Var.
$\mathbb{I}\{Arg\} \times \mathbb{I}\{Post\}$	0.054*	0.054*	0.067**	0.088***	0.091***	0.102***
	(0.031)	(0.028)	(0.028)	(0.027)	(0.027)	(0.027)
π	-0.158	0.150	0.203	0.097	0.141	-0.051
	(0.191)	(0.160)	(0.154)	(0.132)	(0.133)	(0.130)
GDP Cycle	0.280	-0.727	-1.385**	-2.324***	-2.117***	-0.878***
	(0.868)	(0.715)	(0.549)	(0.523)	(0.453)	(0.338)
Δ FX	-0.457**	-0.370**	-0.302***	-0.244**	-0.159*	-0.186***
	(0.225)	(0.145)	(0.111)	(0.096)	(0.088)	(0.071)
Volatility FX	0.465***	0.533***	0.571***	0.579***	0.679***	0.661***
	(0.165)	(0.148)	(0.145)	(0.135)	(0.132)	(0.130)
N	25099	33341	43484	54776	66690	78982
Mean Arg.	1.167	1.167	1.167	1.167	1.167	1.167
Mean Uru.	0.975	0.975	0.975	0.975	0.975	0.975
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 lenght 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 mean values correspond to the mean of the dependent variable during the 2003-2006 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.

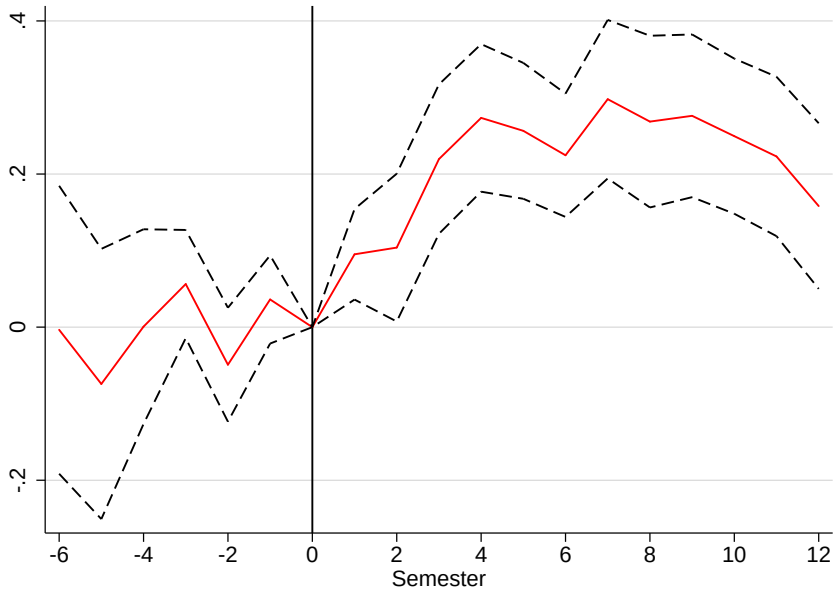
proxies of uncertainty during the period after the manipulation. Results are shown in the first two columns of Table (3). The coefficient associated with deviations of expected inflation is positive and significant (column (1)), and the coefficient associated with the standard deviation of inflation 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 3.2% with respect to its mean.

TABLE 3. 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	0.788^{***}											
	(0.126)											
SDev. Expectations		0.377^{**}										
		(0.162)										
$\mathbb{I}\{Arg\} \times \mathbb{I}\{Placebo\}$			-0.0463									
			(0.0405)									
$\mathbb{I}\{Arg\} \times \mathbb{I}\{Post\}$				0.231^{***}	0.359^{***}	0.0604^{***}	0.0947^{**}	0.124^{***}	0.0936^{***}	0.126^{***}	0.0847^{**}	0.131^{***}
				(0.0398)	(0.0243)	(0.0206)	(0.0394)	(0.0274)	(0.0236)	(0.0267)	(0.0369)	(0.0299)
N	43118	43118	18155	79558	78981	80230	80230	77865	47668	78982	24017	81104
Mean Arg.	1.167	1.167	1.167	1.239	1.064	0.805	1.857	1.152	0.704	1.167	1.057	1.241
Mean Uru.	-	-	0.975	1.287	1.457	0.796	1.666	1.006	0.682	0.975	1.008	1.109
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 publication 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 goods with prices posted in foreign currency, total number of posts, total number of posts 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 mean values correspond to the mean of the dependent variable during the 2003-2006 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.

FIGURE 3. The Effect of 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 treatment 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.

It could also be argued that statistical significance should be somewhat expected given the large dimension of our dataset. In order to strengthen the validity of our identified effect we designed a placebo test that consists of estimating our 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 (3). The difference-in-difference coefficient in this case is 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 publication), the standard deviation of log prices, the 75-25 interquartile range and the 90-10 percentile

range.[16] Results are shown in columns (4)-(7) of Table (3). 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 average of the dependent variable for the specification with the standard deviation of log prices, 19% for the specification with the weighted coefficient of variation, and 7% and 5% for the specifications of 75-25 and 90-10 percentile ranges.

In our main specification the dependent variable is computed by pooling prices set in local and foreign currency (converted at the spot exchange rate). One concern would 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 (3) deal with this concern. Columns (8) and (9) estimate the baseline specification in which the dependent variable is constructed using prices set in local and foreign currency only, respectively. In both cases we estimate a positive and statistically significant increase in prices dispersion of 11% and 13% 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 publications and the number of publications with prices set in local currency (all computed within each category-country-quarter bin). The estimated coefficient of 0.126 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 0.124 and significant at the 1% level (not shown due to space constraints).

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. An imperfect way to address this

[16]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.

concern is to estimate the effect on price dispersion allowing for differential effects across categories. More specifically, we estimate the main specification using data of prices at category level 3, but we interact the coefficient of interest $\mathbb{1}_{\{t\geq 2007\ ,\ c=Arg.\}}$ 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 21 effects (each corresponding to a group of goods categorized at level 1). Figure (A.12) in Appendix A presents the results. The estimated effect is positive for all but 3 categories (for these 3 categories the effects are not statistically significant). Of the remaining 18 positive effects, 11 are statistically significant at the 5% level. In the last column of Table (3) 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 (1.241 versus 1.167). However, we continue estimating a positive and significant increase in price dispersion of 10% relative to the mean.

TABLE 4. Robustness Analysis: Different Category Levels

	(1)	(2)	(3)	(4)	(5)
	Cat. 1	Cat. 2	Cat. 3	Cat. 4	Cat. 5
$\mathbb{I}\{Arg\} \times \mathbb{I}\{Post\}$	-0.0137	0.0873*	0.102***	0.167***	0.148**
	(0.134)	(0.0474)	(0.0271)	(0.0430)	(0.0707)
N	1670	19243	78982	129767	116732
Mean Arg.	2.323	1.518	1.167	0.883	0.683
Mean Uru.	2.198	1.384	0.975	0.758	0.710
Time FE	Yes	Yes	Yes	Yes	Yes
Categ.-Country FE	Yes	Yes	Yes	Yes	Yes

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. The estimation method used in all columns is OLS. Standard errors (in parentheses) are clustered at the Category-Country level. The mean values correspond to the mean of the dependent variable during the 2003-2006 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.

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 our 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 our baseline specification for category levels 1 to 5. Results are shown in columns (1)-(5) of Table (4). The coefficient of interest is positive and significant for category levels 2 to 5 and similar in magnitude. However, the estimated effects expressed as a fraction of the sample mean are increasing in the level of specificity of goods from 5% to 21%.[17] 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. Our model can shed light on the mechanisms behind these effects, so this discussion is reopened in section 6. Additionally, notice that in Table (A1) 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.

The final set of robustness analysis is presented in Tables (A4)-(A7) in the Appendix. Each table replicates the results shown here, but changing the way the coefficient of variation is constructed (on a monthly basis instead of quarterly) and the type of prices used (transacted prices as opposed to originally posted prices). By using transacted prices, we are implicitly giving more weight to the largest sellers in the platform who have more transactions (and therefore provide more data on prices when computing the coefficient of variation).[18] The entire set of results is robust to these two changes. For example, the point estimate of 0.102 from our main specification (column (1) in Table (1)) changes to 0.074 when using monthly data and 0.103 when using transacted prices, and is equally significant in all cases.

4. A Model of Price Setting With Incomplete and Noisy Information

In this section, we formulate a price-setting general equilibrium model with monopolistically competitive firms that have access to incomplete and dispersed information. Our 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 the availability

[17]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.

[18]This is not the case when using posted prices to construct the dependent variable, since originally each seller posts only one price even though he might have more than one transaction.

of public information on firms' pricing decisions. Firms make use of this noisy publicly-available signal of the aggregate price level, together with idiosyncratic information about their revenues and costs, to set their prices. Given their information set, firms cannot perfectly tell apart the realization of all the shocks in the economy. The presence of incomplete information gives rise to money non-neutrality, as noted in earlier works of Phelps (1970) and Lucas (1972).

Our episode of analysis is mapped into the model as a joint change in the precision of the aggregate price signal and in the volatility of monetary policy. We use our results from the previous section, together with the observed change in inflation volatility to disentangle the effects of each policy. Finally, we focus on a counterfactual economy that only experiences a change in the precision of the aggregate price signal.

4.1. *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

$$\mathbb{E}\left(\sum_{t=0}^{\infty}\beta^t\left[\frac{C_t^{1-\gamma}}{1-\gamma}-\int_0^1\Phi_{it}L_{it}\,\mathrm{d}i+\ln\left(\frac{M_t}{P_t}\right)\right]\right), \tag{2}$$

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

$$C_t=\left[\int_0^1\Psi_{it}^{1/\theta}C_{it}^{(\theta-1)/\theta}\,\mathrm{d}i\right]^{\theta/(\theta-1)}. \tag{3}$$

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

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

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 (2) 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 good of variety i. We characterize the solution to the household's problem by the set of first order conditions

$$(C_{it}): \qquad \beta^t C_t^{1/\theta-\gamma}\Psi_{it}^{1/\theta}C_{it}^{-1/\theta} = \lambda_t P_{it} \tag{4}$$

$$(L_{it}): \qquad \beta^t \Phi_{it} = \lambda_t W_{it} \tag{5}$$

$$(B_{it}): \qquad -\frac{\lambda_t}{1+i_t} + \mathbb{E}_t\left[\lambda_{t+1}\right] = 0 \tag{6}$$

$$(M_t): \qquad \frac{\beta^t}{M_t} = \lambda_t - \mathbb{E}\left[\lambda_{t+1}\right], \tag{7}$$

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

We assume that money supply follows the following stochastic process

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

Since we are interested in analyzing the effects of a one-time change in the variance of the innovations to money, σ_{mt}, we allow this parameter to depend on time in a deterministic way. Combining equations (6) and (7), and using the fact that the log of money supply follows a random walk process, generates a nominal interest rate given by

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

Given the linearity of preferences with respect to labor, equations (5), (6) and (7) imply

$$W_{it} = \kappa_t \Phi_{it} M_t \tag{8}$$

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.[19] Equations (4), (6) and (7) lead to a demand function for each variety given by

$$C_{it} = \Psi_{it} C_t^{1-\gamma\theta}\left(\frac{\kappa_t M_t}{P_{it}}\right)^{\theta}.$$

[19]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.

Replacing this expression in the Dixit-Stiglitz aggregator we obtain an expression for aggregate consumption

$$C_t = \left(\frac{\kappa_t M_t}{P_t}\right)^{1/\gamma},$$

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. Thus, the demand of each variety is given by

$$C_{it} = \Psi_{it}\left(\frac{P_{it}}{P_t}\right)^{-\theta}\left(\frac{\kappa_t M_t}{P_t}\right)^{1/\gamma}. \tag{9}$$

4.2. *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 (9). 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 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 $\mathcal{I}_{it}$ (which is defined below). By replacing the expressions that define the firm's demand (equation (9)) and the nominal wage (equation (8)) 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

$$P_{it} = \left(\frac{\theta\mathbb{E}_t\left(\Phi_{it}\left(\Psi_{it}(\kappa_t M_t)^{\frac{1}{\gamma}}P_t^{\theta-\frac{1}{\gamma}}\right)^{\frac{1}{\alpha}}\middle|\mathcal{I}_{it}\right)}{\alpha(\theta-1)\mathbb{E}_t\left(\Psi_{it}(\kappa_t M_t)^{\frac{1}{\gamma}-1}P_t^{\theta-\frac{1}{\gamma}}\middle|\mathcal{I}_{it}\right)}\right)^{\frac{1}{1+\frac{\theta}{\alpha}-\theta}}. \tag{10}$$

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

(1) conditional on the firm's information set, $\Phi_{it}\left(\Psi_{it}(\kappa_t M_t)^{\frac{1}{\gamma}}P_t^{\theta-\frac{1}{\gamma}}\right)^{\frac{1}{\alpha}}$ 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.

Taking logs to equation (10) we obtain[20]

$$p_{it} = const_{1t} + \frac{1}{1+\theta\left(\frac{1}{\alpha}-1\right)}\mathbb{E}_{it}\left[\left(\frac{1}{\alpha}-1\right)\psi_{it}+\phi_{it}\right] + \mathbb{E}_{it}\left[m_t\right] + \frac{\left(\theta-\frac{1}{\gamma}\right)\left(\frac{1}{\alpha}-1\right)}{1+\theta\left(\frac{1}{\alpha}-1\right)}\mathbb{E}_{it}\left[p_t - m_t\right], \tag{11}$$

where $const_{1t}$ is a constant that depends on time only to the extent that σ_{mt} is time-dependent (all constants presented hereon can be found in Appendix B). To simplify notation, we write $\mathbb{E}_{it}[\cdot]$ to refer to $\mathbb{E}_t\left[\cdot|\mathcal{I}_{it}\right]$. Similarly, we take logs to the equation defining the ideal price index to obtain

$$p_t = \log\left(\left(\int_0^1 \Psi_{it} P_{it}^{1-\theta}\,\mathrm{d}i\right)^{\frac{1}{1-\theta}}\right) = const_{2t} + \int_0^1 p_{it}\,\mathrm{d}i. \tag{12}$$

Equation (11) 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.

4.3. *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}^c and a wage bill signal s_{it}^w,

$$s_{it}^c = \psi_{it} + \frac{1}{\gamma}m_t + \left(\theta - \frac{1}{\gamma}\right)p_t, \tag{13}$$

$$s_{it}^w = \phi_{it} + m_t. \tag{14}$$

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

$$s_t^p = p_t + \sigma_{pt}\varepsilon_t^p \qquad \varepsilon_t^p \sim N(0,1). \tag{15}$$

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

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

in a deterministic way, since we are interested in analyzing the effects of a one-time change in this parameter.

In order to have information frictions in our 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:

$$p_{it} = const_{1t} + \frac{\left(\frac{1}{\alpha} - 1\right)}{1 + \theta\left(\frac{1}{\alpha} - 1\right)} s^d_{it} + \frac{1}{1 + \theta\left(\frac{1}{\alpha} - 1\right)} s^w_{it}.$$

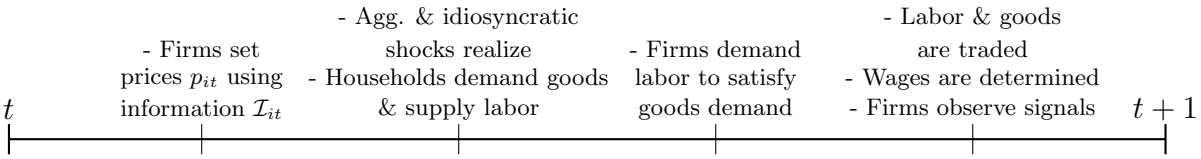
The firm's information set at the beginning of period t is thus characterized by the following filtration:

$$\mathcal{I}_{it} = \left\{ s^d_{it-s}, s^w_{it-s}, s^p_{t-s} \right\}_{s=1}^{\infty}.$$

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, Figure (4) describes the sequence of events that occur within each period in the model. 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.

FIGURE 4. Timing of Events



4.4. *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).[21] Then, the filtration $\mathcal{I}_{it}$ is replaced by

$$\hat{\mathcal{I}}_{it} = \left\{ s^d_{it-s}, s^w_{it-s}, s^p_{t-s}, \varepsilon^{\Phi}_{it-T-s}, \varepsilon^{\Psi}_{it-T-s}, \varepsilon^{m}_{t-T-s}, \varepsilon^{p}_{t-T-s} \right\}_{s=1}^{\infty}.$$

[21] In our quantitative analysis we choose T to be equal to 50 quarters.

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:

$$\begin{aligned}
\boldsymbol{\varepsilon}_{it}^{\Phi} &= \left(\varepsilon_{it-1}^{\Phi}, \varepsilon_{it-2}^{\Phi}, ..., \varepsilon_{it-T}^{\Phi}\right) \\
\boldsymbol{\varepsilon}_{it}^{\Psi} &= \left(\varepsilon_{it-1}^{\Psi}, \varepsilon_{it-2}^{\Psi}, ..., \varepsilon_{it-T}^{\Psi}\right) \\
\boldsymbol{\varepsilon}_{t}^{m} &= \left(\varepsilon_{t-1}^{m}, \varepsilon_{t-2}^{m}, ..., \varepsilon_{t-T}^{m}\right) \\
\boldsymbol{\varepsilon}_{t}^{p} &= \left(\varepsilon_{t-1}^{p}, \varepsilon_{t-2}^{p}, ..., \varepsilon_{t-T}^{p}\right)
\end{aligned}$$

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 $\boldsymbol{\Upsilon}_{\boldsymbol{\Psi}} \equiv \left(1, \rho_{\Psi}, \rho_{\psi}^{2}, \ldots, \rho_{\psi}^{T-1}\right)$, $\boldsymbol{\Upsilon}_{\boldsymbol{\Phi}} \equiv \left(1, \rho_{\Phi}, \rho_{\phi}^{2}, \ldots, \rho_{\phi}^{T-1}\right)$ and $\mathbf{1} = (1, \ldots, 1)$. Then, we can write the firm's optimal price as

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

where the common knowledge component of the firm's price, $\hat{p}_{it}$, is given by

$$\hat{p}_{it} = const_{3t} + m_{t-T-1} + \frac{1}{1 + \theta\left(\frac{1}{\alpha} - 1\right)}\left(\left(\frac{1}{\alpha} - 1\right)\rho_{\psi}^{T+1}\psi_{it-T-1} + \rho_{\phi}^{T+1}\phi_{it-T-1}\right).$$

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 $k_{t}^{x} = (k_{1t}^{x}, k_{2t}^{x}, ..., k_{Tt}^{x})$ for $x = \{m, p\}$ and the common knowledge component of the aggregate price, $\hat{p}_{t}$, is given by $\hat{p}_{t} = const_{4t} + m_{t-T-1}$. 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

$$p_{it} = \hat{p}_{it} + \frac{\left(\frac{1}{\alpha}-1\right)\sigma_\Psi \rho_\Psi}{1+\theta\left(\frac{1}{\alpha}-1\right)}\boldsymbol{\Upsilon}_{\boldsymbol{\Psi}}\mathbb{E}_{it}\left[\varepsilon_{it}^{\Psi}\right] + \frac{\sigma_\Phi \rho_\Phi}{1+\theta\left(\frac{1}{\alpha}-1\right)}\boldsymbol{\Upsilon}_{\boldsymbol{\Phi}}\mathbb{E}_{it}\left[\varepsilon_{it}^{\Phi}\right] + \left(\frac{1+\frac{1}{\gamma}\left(\frac{1}{\alpha}-1\right)}{1+\theta\left(\frac{1}{\alpha}-1\right)}\right)\sigma_{mt}\mathbf{1}\mathbb{E}_{it}\left[\varepsilon_t^m\right]$$
$$\left(\frac{\left(\theta-\frac{1}{\gamma}\right)\left(\frac{1}{\alpha}-1\right)}{1+\theta\left(\frac{1}{\alpha}-1\right)}\right)\left(k_t^m diag(\boldsymbol{\sigma}_{mt})\mathbb{E}_{it}\left[\boldsymbol{\varepsilon}_t^m\right] + k_t^p diag(\boldsymbol{\sigma}_{pt})\mathbb{E}_{it}\left[\boldsymbol{\varepsilon}_t^p\right]\right). \tag{16}$$

This expression can be replaced in the definition of p_t (equation (12)) to get

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

where we use our conjecture for equilibrium aggregate prices. We use the notation $\bar{\mathbb{E}}_t[\cdot]$ to denote $\int_0^1 \mathbb{E}_{it}[\cdot]\,\mathrm{d}i$. These conditional expectations are computed using the properties of the multivariate normal distribution. After computing them, the right-hand side of (17) 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. Since the implicit system of equations that define k_t^m and k_t^p is highly nonlinear we need to solve the model numerically. Further details on the computation of the expectations and the solution of the model are provided in Appendix B.

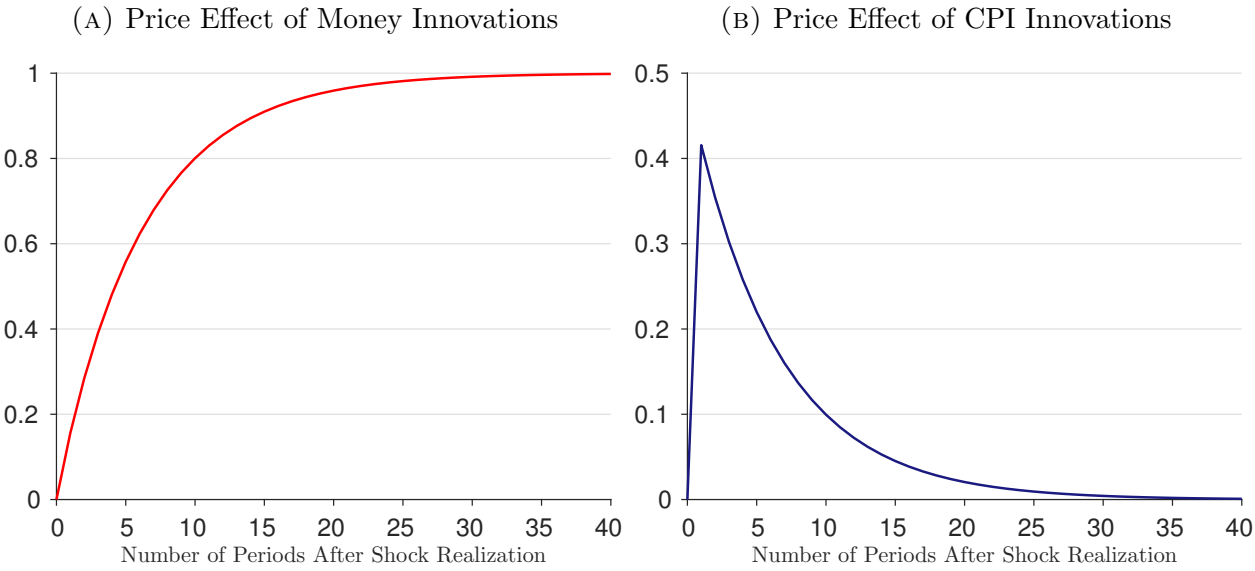
4.5. *Optimal Price Setting Under Uncertainty About Inflation*

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 our 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 (5a). The price adjustment 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).

A more novel result is shown in Figure (5b). Information innovations to the reporting of the aggregate price signal can affect aggregate prices and thus equilibrium allocations. 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 high price signal was the result of reporting noise and undo the original price increase.

FIGURE 5. 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 effect is normalized by the standard deviation of money. The second graph shows the response over time of aggregate prices to a unitary noise shock associated to the signal of prices. The effect is normalized by the standard deviation of the noise of the aggregate price signal. The parametrization corresponds to the 2007-12 calibration.

Next, we analyze the firms' price-setting behavior in more detail by describing how their optimal prices depend on their own signals. In Appendix B.2 we show that we can express idiosyncratic prices as a linear combination of idiosyncratic and aggregate signals

$$p_{it} \equiv \hat{p}_{it} + \Omega_t^c \left(\boldsymbol{s}_{it}^c - \hat{\boldsymbol{s}}_{it}^c\right) + \Omega_t^w \left(\boldsymbol{s}_{it}^w - \hat{\boldsymbol{s}}_{it}^w\right) + \Omega_t^p \left(\boldsymbol{s}_{it}^p - \hat{\boldsymbol{s}}_t^p\right),$$

where $\boldsymbol{s}_{it}^x = \left(s_{it-1}^x, s_{it-2}^x, ..., s_{it-T}^x\right)$ denotes the vector of signals of type $x = c, w, p$, and $\hat{\boldsymbol{s}}_{it}^x = \left(\hat{s}_{it-1}^x, \hat{s}_{it-2}^x, ..., \hat{s}_{it-T}^x\right)$ the common knowledge component of each signal.

Figure (B.1) plots the weights associated to the three signals used to set idiosyncratic prices as a function of the "vintage" of each signal (we refer to the coefficients in the vectors $\Omega_t^c, \Omega_t^w, \Omega_t^p$ as weights). 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.

4.6. *Price Dispersion and Inflation Volatility*

In this section we analyze the effects of changes in the variance of the noise of the aggregate price signal σ_{pt} and changes in the volatility of monetary policy σ_{mt} on price dispersion and the volatility of inflation. We argue that both changes have the same qualitative implications for price dispersion but different implications for inflation volatility. Hence, using these two moments can help us identify changes in these two parameters. Once the values of k_t^m and k_t^p are obtained, we can find analytic expressions for the cross-sectional price dispersion and the standard deviation of inflation, both of which can be found in Appendix B.4.

We first start analyzing 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 Figures (B.2a) and (B.2b)). 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 (B.3).

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). As σ_{pt} increases, the associated increase in price dispersion lowers. 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. 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 respond to aggregate shocks. 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 Figures (B.2c) and (B.2d)). 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 (B.3)). 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.

The fact that the reaction of inflation volatility is different in response to changes in σ_{pt} and σ_{mt} provides a source of identification that can help us disentangle the effect of each policy by studying the joint reaction of price dispersion and inflation volatility. Since we showed that inflation volatility increased in the period post-manipulation of inflation statistics, this evidence points towards σ_{mt} increasing in our episode of analysis.

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 regulate 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 the 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 our episode of analysis, which we replicate in the model as an unexpected and permanent change in both σ_{pt} and σ_{mt}.[22] In Section 6 we analyze the sensitivity of the

[22]We could also allow for a permanent change in μ. However, such a change in the model does not have an impact on price dispersion nor inflation volatility, which are our key identifying moments. Since prices

results by focusing on an alternative calibration that matches targets that were computed using data until 2008, before other macro policies were put in place.

The set of parameters can be categorized in 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 $(\rho_\Psi, \sigma_\Psi, \mu, \sigma_{mt}, \sigma_{pt})$. Model-based moments are computed by simulating multiple samples of 40 quarters (same length as in our 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 our 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 target moments.

The calibrated parameters are summarized in Table (5). 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). Given that there is no clear consensus in the literature about the value of this parameter, we 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)).

In order to estimate the process of the idiosyncratic labor costs we make use of the first order condition (equation (8)), which can be expressed (in logs) as

$$w_{it} = \log(\kappa_t) + \phi_{it} + m_t. \tag{18}$$

This equation links the process that governs the disutility of labor (and the aggregate shock) to idiosyncratic wages. In Appendix C.1, we show that we can use data on a panel of wages to estimate an autoregressive process for idiosyncratic wages and back out the underlying parameters that govern the process of the disutility of labor. Our estimation of the autoregressive process of w_{it} follows the approach in Floden and Lindé (2001) that allows for measurement error in wage data. We use data from the Argentinean Household Survey (*Encuesta Permanente de Hogares*), which is a rotating survey following workers for

are flexible, a change in μ would only imply a generalized change in the deterministic growth rate of all prices of the economy.

TABLE 5. Calibrated Parameters

Parameter	Before	Comments
From Literature		
β	0.99	
γ	2.00	
θ	7.00	
α	0.50	
Calibrated/Estimated		
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	0.800	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}	0.260	Estimated increase in price dispersion

4 waves. Appendix C.1 describes the estimation procedure and the data set. The point estimates are presented in Table (5). The estimated values of the autoregressive coefficient and the standard deviation for the innovations are 0.969 and 0.091, respectively.[23]

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 an annex data set that contains data on transactions (the date as well as quantities and price of each transaction) associated to an original publication in the main data set. We merge both sources of data and construct a time series variable that measures the number of quantities sold by a given seller in a given category in a given 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

[23]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.

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 of the regression with our main dataset. The resulting values of ρ_Ψ and σ_Ψ are 0.24 and 0.85, respectively. The reason why we choose these moments as targets is because equation (4) shows how preference shocks have a direct impact on idiosyncratic demand.

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 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.[24] 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 8.7% that we estimated in section 3. The calibrated values are $\sigma_p^{post} = 0.26$ and $\sigma_m^{post} = 0.036$. Allowing for a change in σ_p is crucial for the success of the calibration. If one 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.

We label the parametrization with σ_m^{pre} and σ_p^{pre} as the '2003-06 calibration', and the parametrization with σ_m^{post} and σ_p^{post} as the '2007-12 calibration'. Table (C2) in Appendix C.2 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.

5.2. *Disentangling the Increase in Price Dispersion*

We use our 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

[24] For values of σ_{pt} that are close to zero the solutions to equations (20) and (21) in the Appendix become numerically unstable due to problems of invertibility of near singular matrices.

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 (6) shows the transition dynamics of price dispersion in the model. The increase in price dispersion is gradual even though the policy changes are discrete. This is consistent with the estimates from our flexible specification shown in Figure (3) that also display a gradual increase in price dispersion. The reason for these dynamic effect in our 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. 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, observed price dispersion increases over time. According to our model, it takes approximately five years to reach the new steady state.

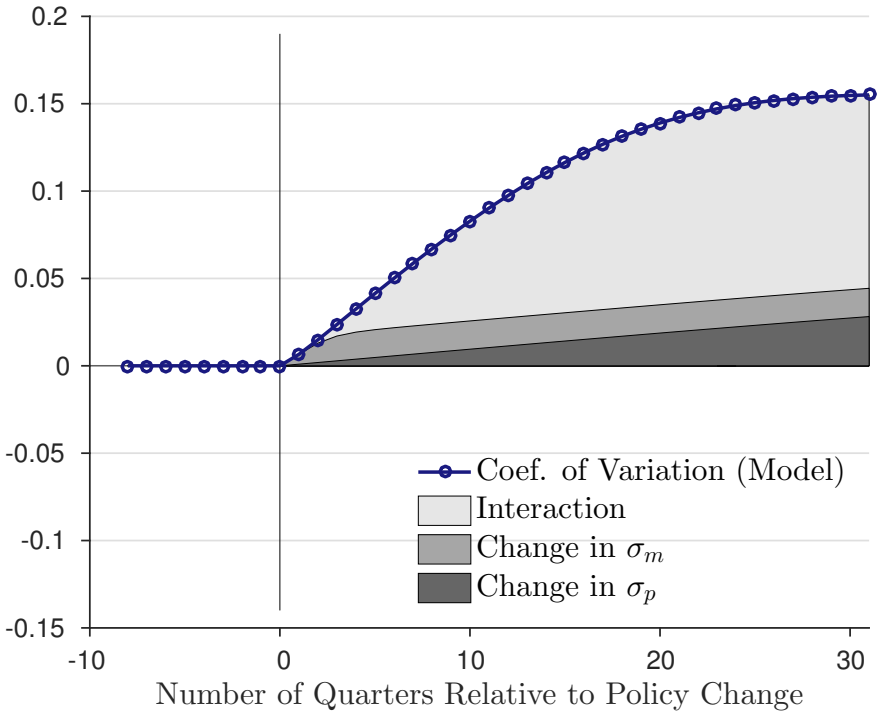
The model increase in price dispersion is mostly due to the interaction of the increase in monetary volatility and the decrease in the precision of the aggregate price signal. Of the total cumulative increase in price dispersion up to 6 years after the policy changes, 17% is due to the sole increase 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 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.

5.3. *Effectiveness of Monetary Policy*

In this subsection we study how the effectiveness of monetary policy changes after our episode of analysis both in the data and in the model.[25] In particular, we analyze the dynamics of the reaction of output to a money innovation in the data in the periods 2003-06 and 2007-12 and compare these reactions to the model implied reaction for the calibrated

[25]Our analysis of monetary policy corresponds to IRFs to monetary shocks using a given process of money supply. For an analysis of optimal monetary policy in the context of information frictions see Reis (2009), Lorenzoni (2010) and Angeletos et al. (2016).

FIGURE 6. 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).

economies in 2003-06 and 2007-12. Since we didn't target the effectiveness of monetary policy in the calibration, this analysis is useful to evaluate the performance of the model in other dimensions.

To estimate the effectiveness of monetary policy in the data we gather data on the stock of money, the aggregate price level and the level of output in Argentina for our sample period of 2003-12 and estimate an empirical VAR.[26] The stationary variables included are the growth rate of money, the real money balances and the level of output. Since our model does not admit a structural VAR representation, the following reduced form representation

[26]The stock of money is measured by the level of M2, the aggregate level of prices is obtained from our measure of inflation in Argentina (which corresponded to the official inflation until 2006 and the simple average of the alternative measures of inflation afterwards) and the level of output is measured by the de-trended real GDP.

is estimated

$$x_t = \mathbf{A_0} + \mathbf{A_1} x_{t-1} + u_t,$$

where $x_t' \equiv (m_t - m_{t-1}, m_t - p_t, y_t)$ and $u_t \sim N(\mathbf{0}, \mathbf{\Sigma})$. We constrain the money process to be a random walk as in the model by setting $a_{11} = a_{12} = a_{13} = 0$. Since we are interested in estimating the effect of a money innovation on the level of output we impose an ordering that is consistent with the timing of the model. We assume that innovations to the money process affect contemporaneously real balances and output, innovations to real balances affect contemporaneously output but not money supply, and innovations to output do not affect contemporaneously money supply nor real balances.[27] We perform estimations of the VAR for the subsamples 2003-06 and 2007-12, separately. Figure (7a) shows the response of output to the same money shock for both VARs. In the VAR estimated with observed data from the 2003-2006 period (pre-manipulation of statistics) we find no statistically significant effect of a money shock on output. In the VAR estimated with observed data from the 2007-2012 period (post-manipulation) we find a positive and significant effect that starts decaying gradually 4 quarters after the shock.

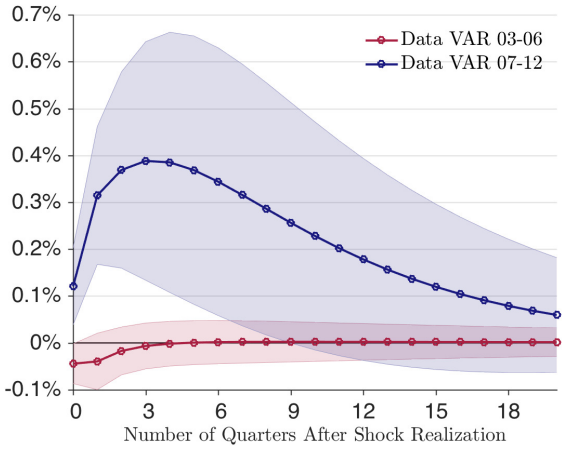
To maintain the symmetry we estimate the same VAR with simulated data from our model. We simulate data 200 times for 40 quarters for an economy that suffers a structural change in σ_p and σ_m in the 17th quarter. We estimate two VARs for each simulation, one using the first 4 years of simulated data (which corresponds to the 2003-2006 calibration) and another using the last 6 years (which corresponds to the 2007-2012 calibration).[28] Figure (7b) shows the average response of output to the same money shock in the VARs estimated with the first 4 years of the simulated data and in the VARs estimated with the last 6 years of simulated data. The reaction of output to a money shock is more persistent in the economy with more volatile monetary policy and less precise aggregate price signals. The impulse-response analysis delivers implications for the model and data that are qualitatively consistent. In both model and data, monetary policy becomes more effective in the economy post CPI manipulation.

[27] In Appendix C.3 we show that the key properties of the impulse responses to a monetary policy shock are robust to alternative VAR specifications and orderings.

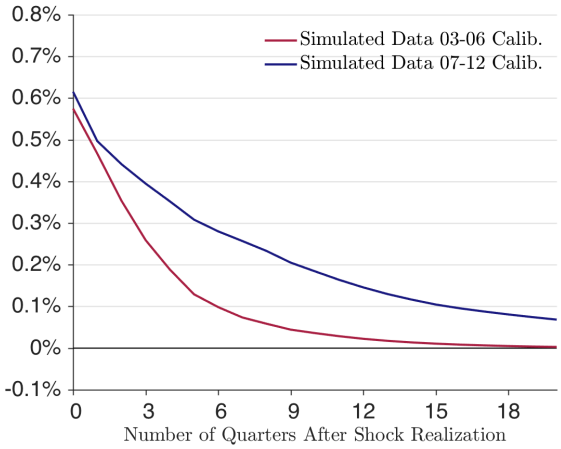
[28] Since output and real balances are co-linear in the simulated data, we exclude real balances from the estimated VAR and estimate a VAR with money growth and output with the same restrictions in the autoregressive matrix and the same ordering.

FIGURE 7. Output Response to Money Innovations: Model and Data

(A) Observed Data VARs



(B) Simulated Data VARs



Notes: These graphs compare the IRFs of output to a monetary innovation obtained from the VARs estimated with observed and model-simulated data for two periods of time, one in 2003-2006 and the other in 2007-2012. The left graph shows the IRFs estimated with observed data. The shaded area indicates the 95% confidence intervals. The right graph shows the average response of multiple VARs estimated with simulated data.

Why does monetary policy become more effective in the economy with more volatile monetary policy and less precise aggregate price signals? With a less precise aggregate price signal firms shift their weight to their common prior which makes prices less responsive to aggregate money shocks. This mechanism goes back to the original idea in Lucas (1972). The effect of a more volatile monetary policy actually makes monetary policy less effective since in this case firms shift weight from their prior to their signals, which respond to money shocks.[29] However, quantitatively the first effect dominates. In Appendix C.3 we disentangle the change in the effectiveness of monetary policy that is due to each policy change.

[29]Other researchers have studied how the effectiveness of monetary policy changes in times of higher uncertainty (see, for example, Vavra (2014) and Stevens (2015)). Our results refer to policy uncertainty rather than economic uncertainty, and show that different sources of policy uncertainty can lead to different effects on the ability of monetary policy to affect output.

6. Welfare Effects of Higher Uncertainty About Inflation

In this section we use our calibrated model to 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}.

Define the welfare effect of higher uncertainty about inflation, λ^P, as the percent change in the lifetime consumption stream required by an individual 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 an individual 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 $t = 0$).[30] Formally, 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. The underlying assumption under this exercise is that the change in the variance of the noise in the aggregate price signal is permanent.

Table (6) shows that not providing an accurate measure of the aggregate price level has associated significant welfare costs. The representative household living in an economy with an accurate measure of the aggregate price level requires a permanent decrease in consumption of 0.6% to be indifferent between living in an economy with a noisy aggregate price signal and an economy with an accurate aggregate price signal. When faced with a less precise signal of aggregate prices firms reduce the weight they put in the aggregate signal. This shift in the weights brings about a long-run increase in price dispersion of 9.7%, which is the result of firms decreasing the weights they put on this signal from 43% to 17%.

The presence of these welfare costs comes from the fact that less precise information about the aggregate state leads to a misallocation problem. With less accurate information firms

[30] 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 its unconditional mean zero.

TABLE 6. Welfare Effects of an Increase in σ_p

	Argentina Baseline	Argentina $\theta = 4$	Argentina $\theta = 10$	Argentina Calib 07-08	US
Weight CPI (σ_p^{pre})	43.3%	40.2%	44.3%	43.2%	46.8%
Weight CPI (σ_p^{post})	16.6%	24.1%	10.4%	22.5%	2.0%
Δ Price Dispersion	9.66%	5.98%	12.64%	9.15%	24.44%
Δ Welfare	-0.58%	-0.22%	-1.00%	-0.59%	-0.17%

Notes: The first line indicates the cumulative weight attached to the aggregate price signal for the 2003-06 calibration, differing by the value of θ in the columns. The second line is the same variable but for a calibration in which σ_p is set at σ_p^{post}. The third column is the variation in the coefficient of variation of prices in the steady state of the economy with σ_p^{post}. The last column is the welfare costs of increasing σ_p measured in consumption equivalent changes.

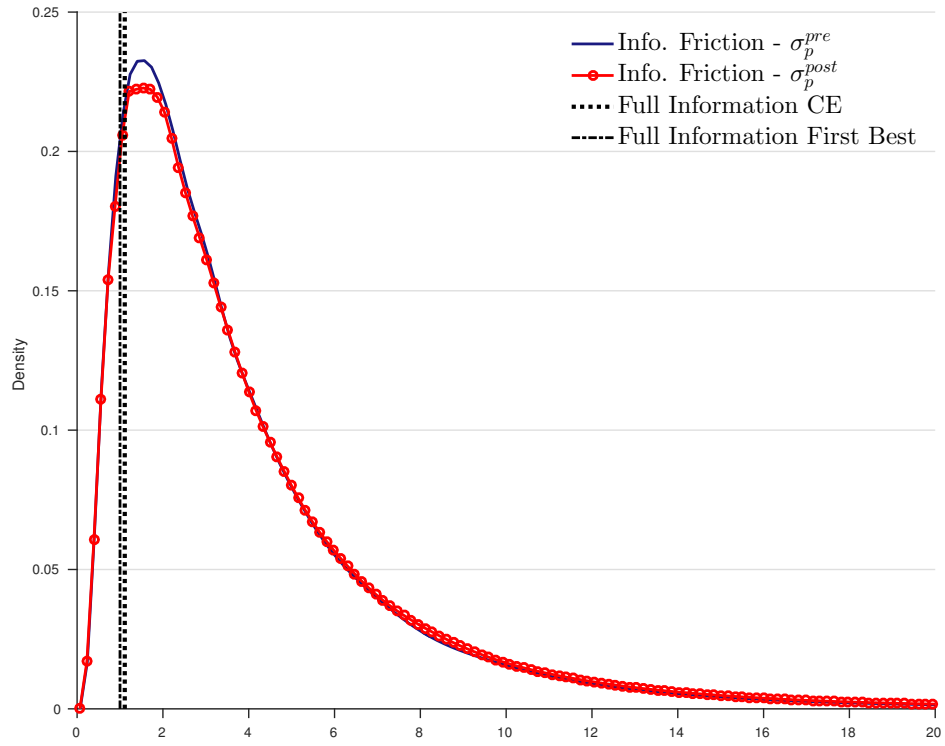
cannot have a good prediction of their idiosyncratic demand for goods and labor cost. This leads to a less precise price setting, which in turn causes a poor allocation of labor (and thus consumption) across varieties. We illustrate the misallocation problem using the concept of wedges between the marginal rate of substitution and the marginal rate of transformation. Define the wedge as

$$wedge_{it} = \frac{U_{c_{it}}/U_{l_{it}}}{Y_{l_{it}}} = \frac{C_t^{1/\theta-\gamma}\Psi_{it}^{1/\theta}C_{it}^{-1/\theta}}{\Phi_{it}\frac{1}{\alpha}C_{it}^{1/\alpha-1}}. \tag{19}$$

In a setting in which firms have full information, the first best of this economy is characterized by an allocation in which $wedge_{it} = 1$ for all i and t. This allocation is not the same as the allocation obtained in a competitive equilibrium with full information since the presence of monopolistic competition introduces an inefficiency that leads to underproduction in all varieties. The competitive equilibrium is characterized by an allocation in which $wedge_{it} = \theta/(\theta-1) > 1$ for all i and t. The introduction of dispersed and incomplete information leads to misallocation that shows mathematically as cross-sectional dispersion in $wedge_{it}$. Figure (8) shows the cross-sectional distribution of wedges in the first best, the economy with full information and the economy with informational frictions. In the economy with

a less precise aggregate price signal the histogram of wedges is more dispersed (although not visible in the figure, the distribution corresponding to the scenario with σ_p^{post} displays a much fatter tail than the distribution corresponding to the scenario with σ_p^{pre}).

FIGURE 8. The Effect of Higher Uncertainty About Inflation on Wedges



Notes: This figure plots 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 parametrization sets the value of σ_m as the average between its pre and post-policy change values, $\theta = 10$ and the remaining parameters to the calibrated values of the previous section.

We perform sensitivity analysis of our welfare calculations by changing θ, the elasticity of substitution between goods of different varieties. We consider alternative values of $\theta = \{4, 10\}$, as shown in the second and third columns of Table (6). The estimated welfare costs are increasing in the value of θ. 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.

Table (6) also reveals a positive relationship between the elasticity of substitution θ and its corresponding increase in price dispersion, which is qualitatively consistent with our empirical estimates of the relationship between higher uncertainty about the inflation rate and price

dispersion measured at different category levels. As shown in Table (4), the effect of higher uncertainty, measured as the percentage change of the coefficient of variation with respect to its sample average, is increasing in the level of categories. Higher levels of categories provide more specific groupings of products, which in turn can be interpreted as grouping goods with higher elasticities of substitution since they are more homogeneous. Therefore, the estimated higher effect for more specific categories can be mapped into higher effects on price dispersion that the model predicts for higher elasticities of substitution.

We also re-compute our welfare results by considering an alternative calibration that uses the target moments computed with data until 2007-08, before the global financial crisis and the implementation of the other policies discussed in section 2.1. Specifically, we calibrate the model with a similar strategy than in the baseline case, but targeting the volatility of inflation computed over the 2007-08 window and the increase in price dispersion estimated in the regression that uses data until 2008.[31] Inflation volatility during 2007-08 was 59% higher than that during 2003-06. Additionally, the estimated increase in price dispersion in the alternative regression was 4.6% (see Table (2), column 2). Table (C3) shows the calibrated parameters, and the goodness of fit of the targeted moments. The calibrated value of σ_m^{07-08} is 0.046, higher than the value of the baseline 2007-12 calibration, whereas the calibrated value of σ_p^{07-08} is 0.19, smaller than the value of the baseline 2007-12 calibration. This is consistent with the fact that while the targeted inflation volatility is higher, the estimated increase in price dispersion is lower than in the baseline case.

With this new calibration we analyze the welfare effects from changing σ_p from 0.02 to 0.19 in an economy in which the volatility of monetary policy is set at the average between σ_m^{pre} and σ_m^{07-08}. Results, shown in the fourth column of Table (6), indicate that the welfare losses are similar to those estimated in the baseline calibration. On the one hand, the fact that the value of σ_p^{07-08} is lower than in the baseline calibration points towards lower welfare losses. However, as we discuss in the next section, the fact that we analyze this effect in an economy with a higher monetary volatility leads to higher welfare losses. We find that these two effects offset each other quantitatively.

[31] When computing the model based moments we adjust the length of the simulations to be consistent with their data counterparts. We compute multiple simulations of 24 quarters in which the economy suffers a permanent change in σ_m and σ_p in the 17th quarter.

6.1. *Complementarities Between the Value of Information and Economic Volatility*

In this subsection, 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 re-do our main welfare exercise with a parametrization of our model calibrated to the US economy. For the US calibration, we leave the preferences parameters (β, γ, θ) and the productivity parameter α 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 (C4) in Appendix C.5.

The parameters that govern the demand shock and the labor supply shock are adapted from Burstein and Hellwig (2008). 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.[32] They calibrate their processes to match moments on prices and market shares using data from a large chain of supermarkets in Chicago. The resulting values (adjusted to reflect a quarterly calibration) are $\rho_\Psi = 0.28$, $\sigma_\Psi = 0.22$, $\rho_\Phi = 0.28$, $\sigma_\Phi = 0.08$.[33] 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). All the processes are less volatile in the US calibration compared to the Argentinean calibration. However, the most salient difference between Argentina and the US is the predictability of its monetary policy. The calibrated money supply process is more than twice as volatile in Argentina than it is in the US.

Next, we re-calculate our welfare analysis with the model calibrated to the US economy, with values for σ_p^{pre} and σ_p^{post} kept at the same values used in the Argentinean baseline calibration. This exercise can be interpreted as calculating the welfare effects of reducing the precision of the CPI signal by the same amount as in Argentina but for the US economy. The results are shown in the last column of Table (6). 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 0.17%. The reason for the significantly lower welfare effect found for the US economy is the fact that the aggregate monetary shock is already very well predicted with prior probabilities and without any Bayesian updating. Since the

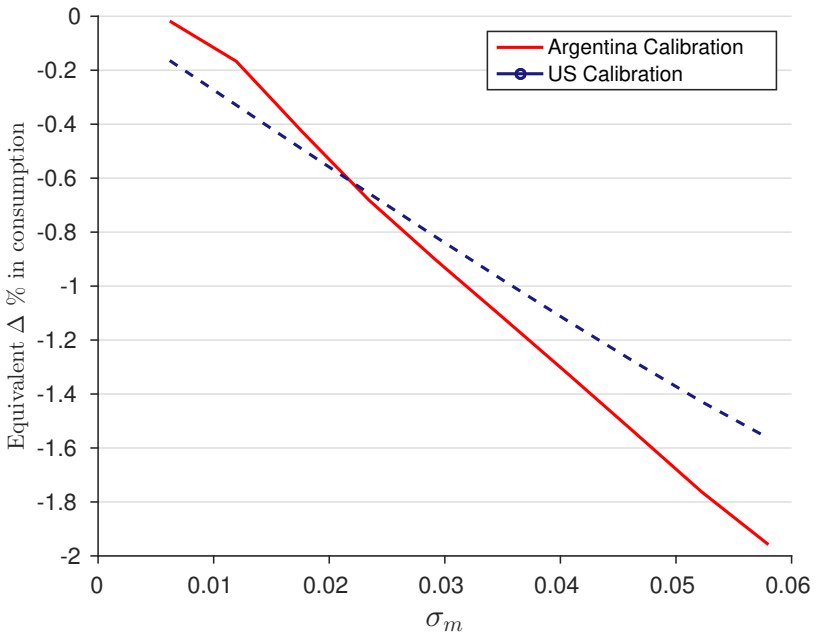
[32]The idiosyncratic cost shock in their model is a productivity shock that affects the marginal rate of transformation of each variety in the same way the shock to the disutility of labor does in our model.

[33]They calibrate the processes at a monthly frequency. We adjust the parameters of the AR processes by simulating data, computing the quarterly average and estimating an AR process with the quarterly data.

process of money supply is very stable, reducing the precision of the public signal that provides information about the aggregate state is not costly from an efficiency perspective. Firms would not be losing much accuracy in their pricing decisions by expecting money to grow at a constant rate μ every period.

This point is illustrated more generally in Figure (9), which plots the welfare effects of an increase in the standard deviation of the noise of the aggregate price signal from σ_p^{pre} to σ_p^{post} as a function of σ_m. The remaining parameters are set at the values of the baseline calibration for Argentina and the US. The negative welfare effects increase almost linearly with σ_m. For economies with monetary policy rules that are predictable, the welfare effects of not providing adequate inflation statistics are negligible. It is only for highly volatile economies with an unpredictable monetary policy that the provision of adequate statistics about inflation is highly valuable.

FIGURE 9. Economic Volatility and the Welfare Effects of Higher Uncertainty



Notes: This figure plots the welfare effect of a permanent increase in σ_p from σ_p^{pre} to σ_p^{post} as a function of σ_m, the volatility of the innovations of the money supply process. The remaining parameters are held constant and set at the values of the calibration for Argentina (solid line) and US (dotted line).

7. Conclusion

Making use of an episode in which economic agents lost access to relevant public information about the rate of inflation, this paper estimates the relationship between higher

uncertainty about the level of inflation and price dispersion. Our difference-in-difference approach indicates that in the face of a switch to a new regime with higher inflation volatility and without access to credible public inflation statistics, the coefficient of variation of prices in Argentina increased by 8.7% with respect to its mean.

We formulate a general equilibrium model of price setting tailored to study the episode of analysis and rationalize our empirical finding. The model allows us to disentangle the increase in price dispersion that can be attributed to worse public information and to the increase in the volatility of inflation. We find that neither effect can explain the entire estimated increase in price dispersion by itself, but the increase in price dispersion and the increase in the volatility of inflation can be jointly explained by an increase in the volatility of money supply and a decrease in the precision of the public signal.

Finally, our welfare analysis points toward quantitatively large welfare losses associated with not reporting an accurate CPI measure. Higher uncertainty about the aggregate level of prices leads to price dispersion, which in turn distorts the consumption basket of households. This last finding advocates for an adequate provision of public information about the level of prices and also about the macroeconomic state of the economy. However, we find these results to depend on the degree of volatility of an economy. For economies that conduct monetary policy according to predictable rules, these welfare losses appear to be negligible.

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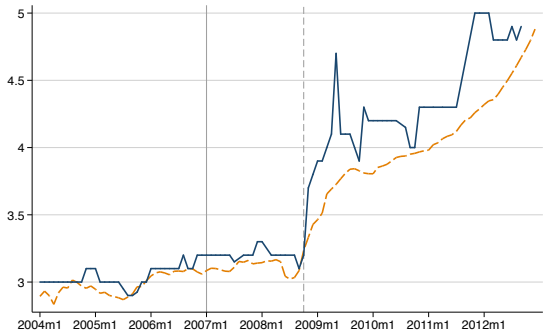
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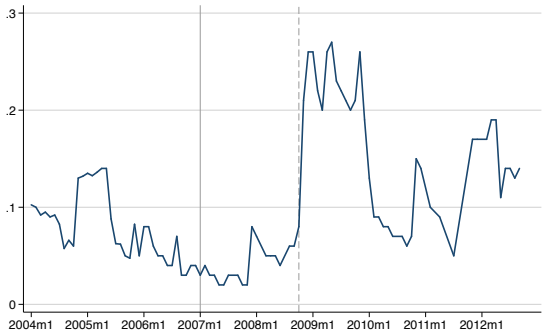
Appendix A. Empirical Appendix (For Online Publication)

Figure A.1. Observed and Expected Macroeconomic Policies in Argentina

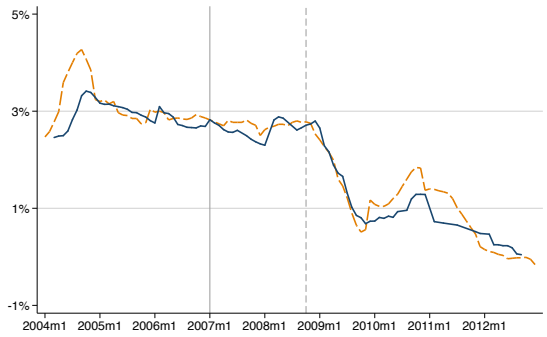
(A) Exchange Rate (Actual & Median Expectation)



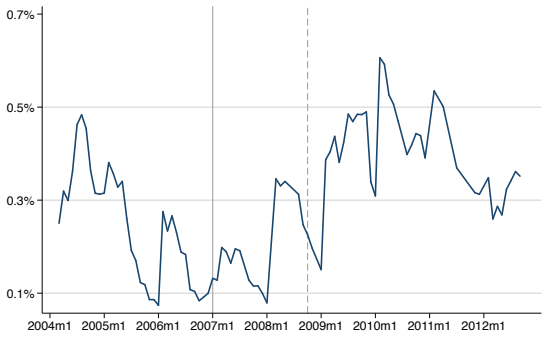
(B) Exchange Rate (Dispersion of Expectations)



(C) Fiscal Balance (Actual & Median Expectation)



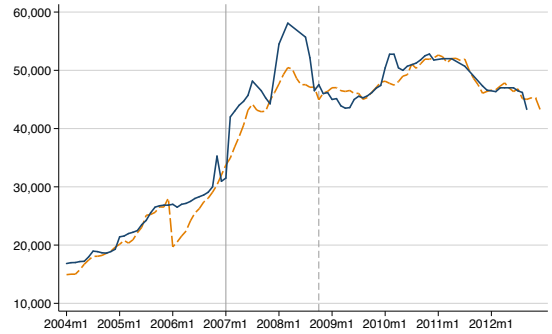
(D) Fiscal Balance (Dispersion of Expectations)



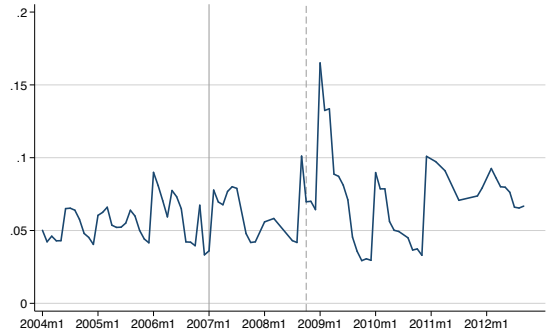
Notes: Panel (A) shows the observed exchange rate (dashed line) and the median expectation of the exchange rate at the end of calendar year (solid line). Panel (B) shows the cross-sectional standard deviation of expectations of the level of the exchange rate. Panel (C) shows the observed primary fiscal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

FIGURE A.2. Observed and Expected External and Financial Outlook in Argentina

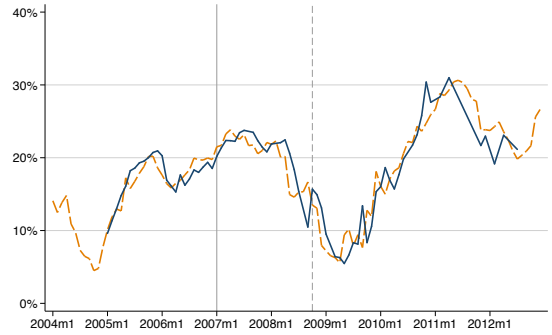
(A) Intl. Reserves (Actual & Median Expectation)



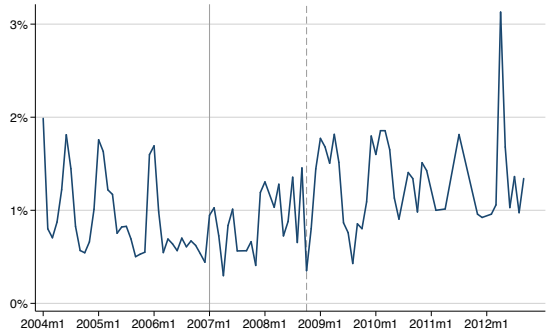
(B) Intl. Reserves (Dispersion of Expectations)



(C) Bank Deposits (Actual & Median Expectation)



(D) Bank Deposits (Dispersion of Expectations)



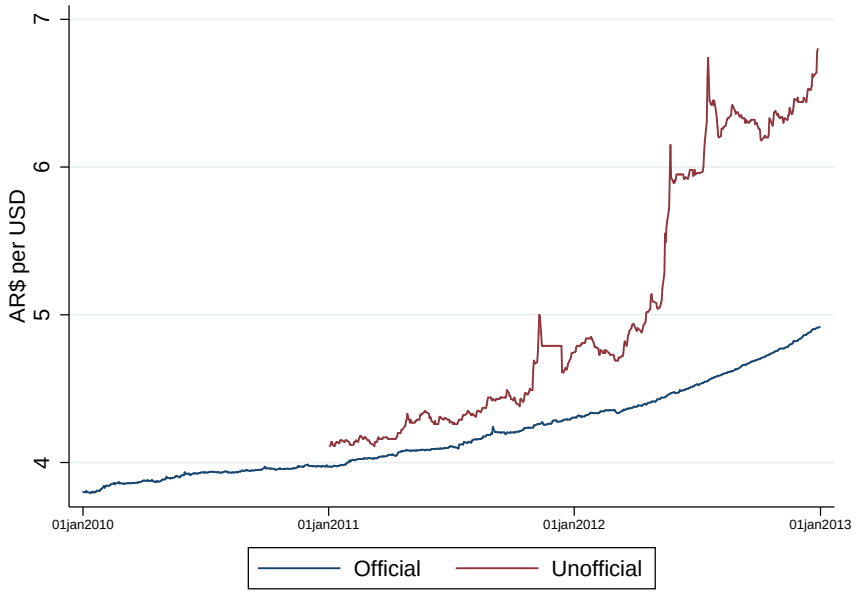
Notes: Panel (A) shows the observed stock of international reserves (dashed line) and the median expectation of the same variable at the end of calendar year (solid line). Both variables are measured in millions of dollars. Panel (B) shows the cross-sectional coefficient of variation of expectations 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 A.3. Additional Policies Implemented in Argentina

(A) Average Applied Tariff Rates

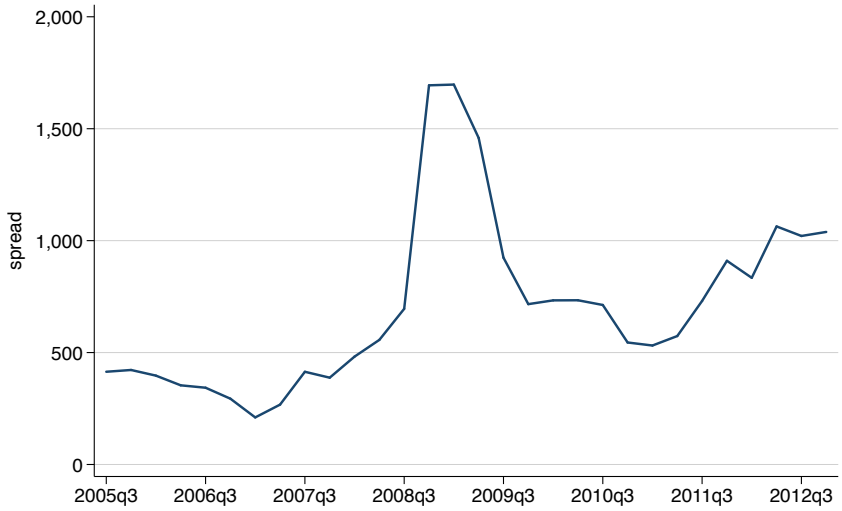


(B) Capital Controls in the FX Market



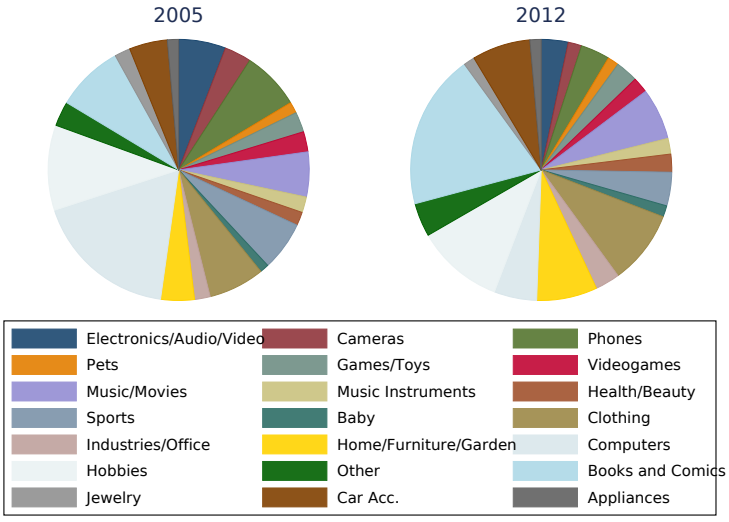
Notes: Panel (A) shows the average of effectively applied rates weighted by the product import shares corresponding to each partner country by year in Argentina. The data was obtained from the *World Bank*. Panel (B) compares the monthly official exchange rate (peso per dollar) with the unofficial exchange 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).

FIGURE A.4. Default Risk in Argentina



Notes: This figures 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.

FIGURE A.5. Changes in the Composition of Goods Sold over Time



Notes: This figure shows the change in the composition of the basket of goods sold in the online platform by presenting the composition of goods available for sale in 2005 and 2012. Goods are categorized according to the broadest level of categorization in the category tree.

TABLE A1. New Product Publications According to Maximum Category Level

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

Notes: This table shows the composition of publications of new products according to the maximum level of categorization available. The first (second) column shows the number (percentage) of total publications 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.

TABLE A2. Summary Statistics

Category	Avg. price		Std. price		% Foreign curr.		% New		Duration (days)	
	Arg.	Uru.	Arg.	Uru.	Arg.	Uru.	Arg.	Uru.	Arg.	Uru.
All goods	80.3	105.6	259.9	238.0	8	34	45	47	26	21
Electronics, audio and video	197.3	167.5	421.2	303.7	20	51	53	52	25	20
Cameras and accesories	177.1	189.1	315.3	229.7	26	63	52	57	25	21
Cellphones and phones	111.5	118.1	177.1	148.0	7	35	46	50	19	20
Pets	103.6	92.2	277.1	216.5	1	12	58	44	22	21
Games and toys	41.5	57.2	153.0	161.3	2	16	64	46	23	21
Videogames	82.4	80.9	141.3	127.9	9	34	37	37	19	20
Music and movies	13.8	19.7	23.8	55.0	4	13	36	37	31	25
Music instruments	354.5	261.9	534.3	422.3	18	52	37	22	24	20
Health and beauty	56.5	50.1	264.8	141.8	2	9	75	68	24	24
Sports and fitness	78.4	87.7	164.1	210.1	6	22	56	42	25	22
Babies	40.6	35.8	65.9	44.4	0	5	45	36	21	21
Clothing	25.6	28.1	54.3	81.4	1	6	53	45	22	20
Industries, office	295.7	270.8	826.6	688.2	4	23	52	44	26	23
Home, furniture, garden	86.6	95.0	175.4	202.7	1	8	55	42	25	23
Computers	140.3	149.1	315.1	275.7	24	59	48	58	23	20
Hobbies	18.0	29.3	47.0	104.0	4	17	37	23	25	23
Others	61.1	91.9	267.6	322.0	3	18	65	53	26	25
Books and magazines	10.3	20.1	21.5	53.2	1	6	18	29	36	27
Jewelry	122.8	168.3	322.7	296.9	21	38	53	44	26	23
Car accesories	93.1	99.0	219.0	208.1	3	26	51	43	27	24
Appliances	165.2	101.1	301.4	165.5	1	14	36	30	20	20

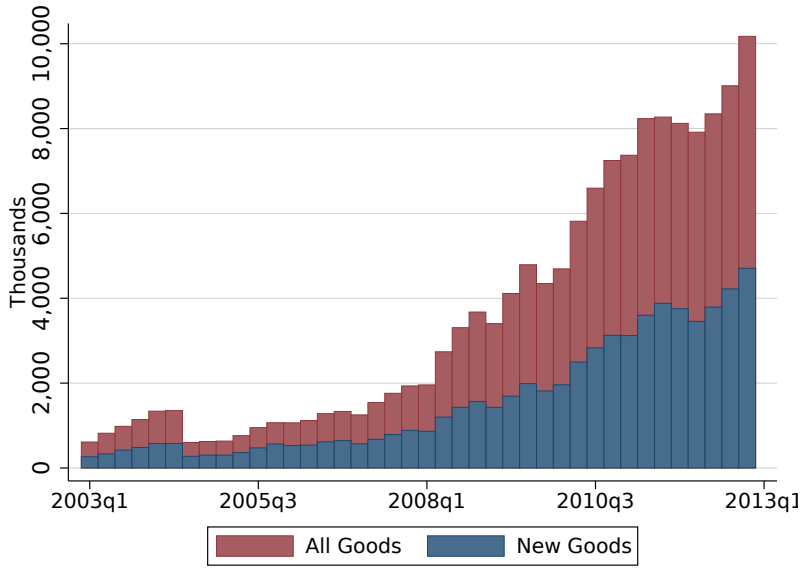
Notes: This table shows summary statistics of all the goods published in the platform (in Argentina and Uruguay separately) and by groups of goods categorized at level 1. The first two columns show the mean and standard deviation of prices in US dollars (prices set in local currency were converted using 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 publication is online.

TABLE A3. 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	2917.9	639.1	65.6	11.9	157.6	17.3	2325.1	235.6	22	12
Electronics, audio and video	106.9	28.7	11.2	2.1	41.5	3.4	207.8	14.0	32	13
Cameras and accesories	50.3	13.4	5.3	1.1	22.5	1.7	91.4	5.7	32	10
Cellphones and phones	120.6	42.3	15.4	3.5	40.0	5.2	206.3	27.4	35	18
Pets	37.6	10.1	4.5	1.2	10.9	2.1	43.1	9.0	30	19
Games and toys	83.4	13.2	3.5	0.7	17.8	1.4	78.2	5.1	22	12
Videogames	49.6	19.6	6.7	1.4	16.1	1.8	75.1	8.7	31	15
Music and movies	192.6	15.3	2.8	0.4	6.7	0.6	34.0	2.2	12	9
Music instruments	61.4	7.9	5.3	0.9	8.6	0.8	33.6	3.0	21	15
Health and beauty	66.4	10.3	3.7	0.6	19.2	1.6	81.3	5.5	27	11
Sports and fitness	128.0	28.6	10.1	2.2	37.1	3.8	161.8	15.2	30	14
Babies	39.2	8.3	3.2	0.6	8.5	0.8	34.7	3.1	25	14
Clothing	267.2	87.9	9.1	2.0	28.4	3.4	174.9	21.9	21	10
Industries, office	84.5	12.6	6.6	0.8	23.6	1.8	107.6	6.2	26	10
Home, furniture, garden	192.6	61.8	11.4	2.6	35.9	5.0	219.4	28.7	25	12
Computers	205.1	73.4	14.6	3.0	39.0	5.1	302.4	35.2	31	13
Hobbies	354.4	63.8	3.5	0.6	10.9	1.0	89.8	6.6	14	6
Others	112.0	20.5	6.1	1.5	17.2	2.4	67.9	8.1	15	11
Books and magazines	493.6	53.7	3.2	0.5	14.6	1.0	82.6	4.3	10	5
Jewelry	46.2	10.5	2.1	0.4	6.6	0.7	25.9	2.3	20	7
Car accesories	186.7	43.5	9.3	1.8	28.7	3.4	155.1	16.4	21	12
Appliances	39.6	13.6	6.7	1.6	14.6	1.9	52.1	6.9	33	16

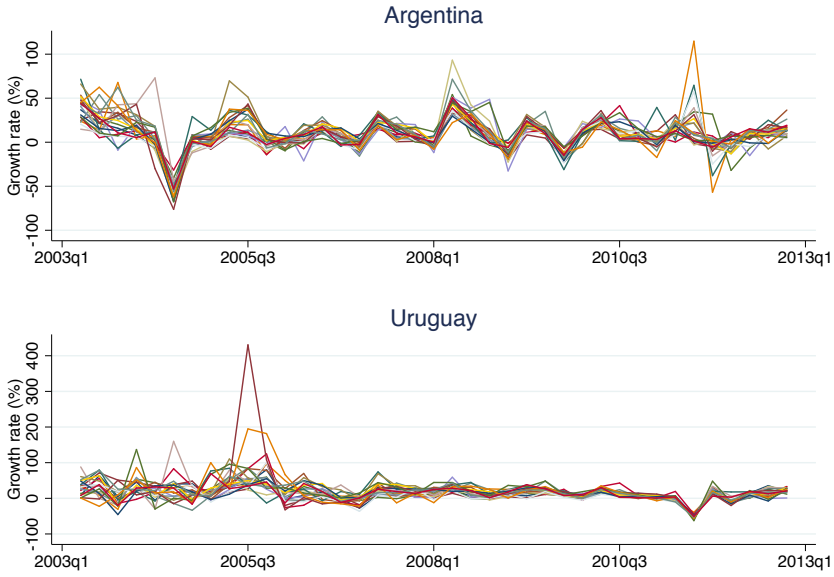
Notes: This table shows summary statistics of all the goods published in the platform (in Argentina and Uruguay separately) and by groups of goods categorized at level 1. The first two columns show the average number of new publications made per quarter (in thousands). The following two sets of columns 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.

FIGURE A.6. Number of Publications over Time (in Thousands)



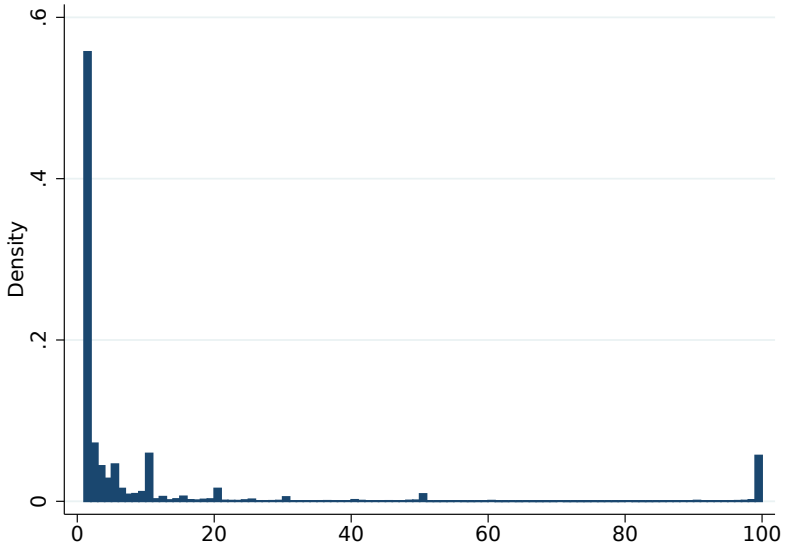
Notes: This figure shows the number of total publications made in the platform by quarter.

FIGURE A.7. Growth rates of Number of Publications over Time by Category



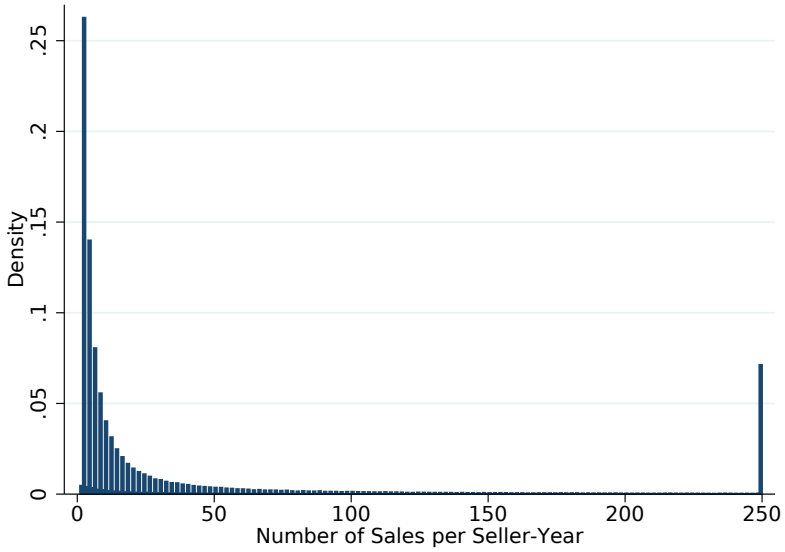
Notes: This figure shows the growth rates of the number of publications made each quarter by categories at level 1 in Argentina and Uruguay.

FIGURE A.8. Histogram of Quantities of New Goods Offered by Publication



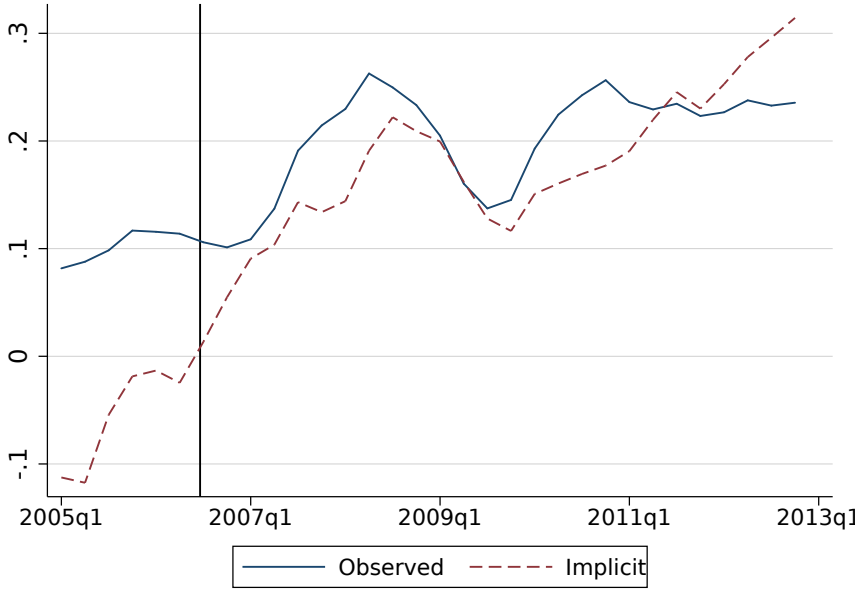
Notes: This figure shows the histogram of quantities of new goods available for sale by publication. We winsorize the number of units at 100.

FIGURE A.9. Histogram of Number of Sales of New Goods by Seller in 2012



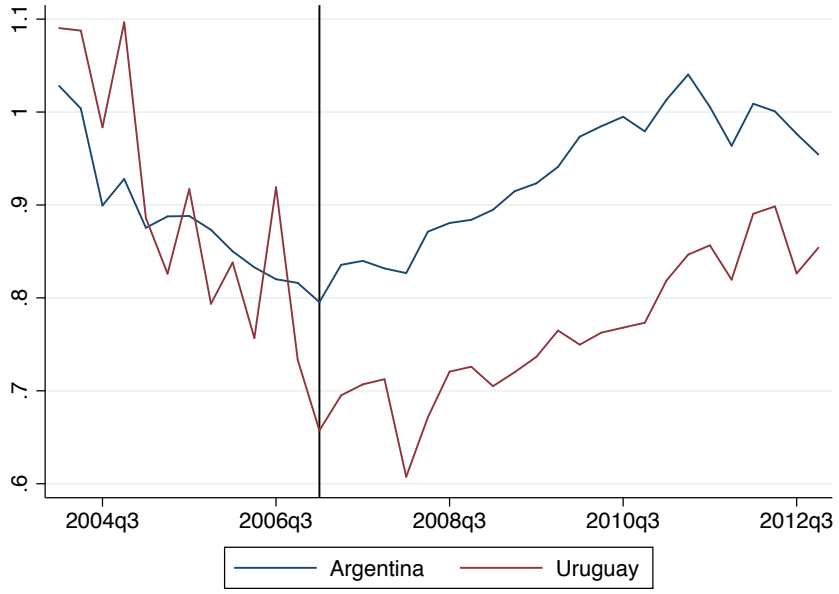
Notes: This figure shows the histogram of the number of sales of new goods by seller in 2012. We winsorize the number of publications at 250.

FIGURE A.10. Observed and Implicit Annual Inflation in Argentina



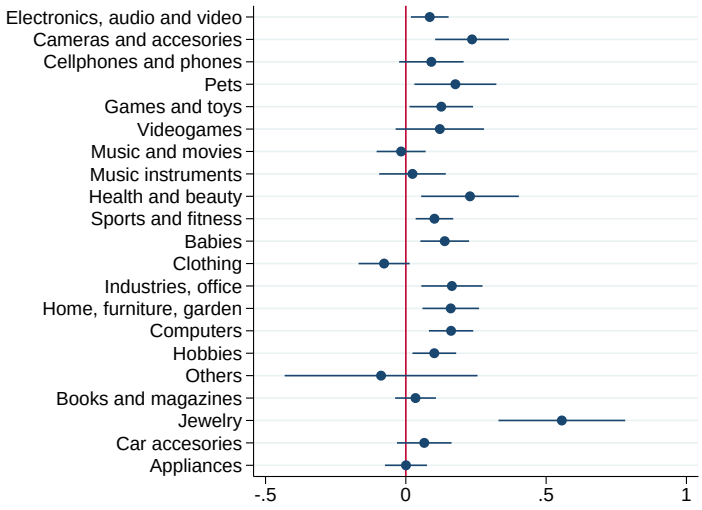
Notes: The observed inflation in Argentina is measured by official inflation statistics until 2006 and as the simple average of the alternative measures of inflation for 2007-12. The implicit inflation is computed as the average inflation rate across categories of level 3.

FIGURE A.11. 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.

FIGURE A.12. The Effect of Uncertainty by Categories



Notes: This figure shows the point estimates of a regression similar to the main specification using data of publications 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.

TABLE A4. The Effect of Uncertainty About Inflation on Price Dispersion

	(1)	(2)	(3)	(4)	(5)
	Coef. Var.	Coef. Var.	Coef. Var.	Coef. Var.	Coef. Var.
Panel A: Monthly Data					
$\mathbb{I}\{Arg\} \times \mathbb{I}\{Post\}$	0.074^{***}	0.078^{***}	0.068^{***}	0.069^{***}	0.118^{***}
	(0.023)	(0.023)	(0.022)	(0.022)	(0.012)
N	226484	226484	226484	221802	163510
Mean Arg.	1.107	1.107	1.107	1.107	1.107
Mean Uru.	0.910	0.910	0.910	0.910	-
Panel B: Bids Data					
$\mathbb{I}\{Arg\} \times \mathbb{I}\{Post\}$	0.103^{***}	0.093^{***}	0.113^{***}	0.118^{***}	0.036^{***}
	(0.028)	(0.028)	(0.031)	(0.031)	(0.012)
N	74850	74850	74850	70298	54993
Mean Arg.	1.016	1.016	1.016	1.016	1.016
Mean Uru.	0.973	0.973	0.973	0.973	-
Time FE	Yes	Yes	Yes	Yes	No
Categ.-Country FE	Yes	Yes	Yes	Yes	Yes
Specification	Baseline	2nd Deg. Inf.	Country Inf.	Categ. Inf.	Arg. only

Notes: The dependent variable in all columns is the coefficient of variation of prices within month or 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. Panel A presents the estimation results using a dependent variable constructed at a monthly level. Panel B presents the results corresponding to a dependent variable constructed using transacted prices (as opposed to originally posted prices). Column (1) is the baseline specification. Column (2) includes inflation squared as an additional control. Column (3) allows the coefficient of inflation to be country-specific. Column (4) replaces the country-specific inflation rate by country-category-specific inflation rates computed using data from the platform. Column (5) uses observations from Argentina only. The estimation method used in all columns is OLS. Standard errors (in parentheses) are clustered at the Category-Country level. The mean values correspond to the mean of the dependent variable during the 2003-2006 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.

TABLE A5. Robustness Analysis: Alternative Window Lenghts Post-2007

	(1)	(2)	(3)	(4)	(5)	(6)
	Coef. Var.	Coef. Var.	Coef. Var.	Coef. Var.	Coef. Var.	Coef. Var.
Panel A: Monthly Data						
$\mathbb{I}\{Arg\} \times \mathbb{I}\{Post\}$	0.045^{*}	0.045^{**}	0.046^{**}	0.059^{***}	0.066^{***}	0.074^{***}
	(0.025)	(0.023)	(0.022)	(0.023)	(0.023)	(0.023)
N	69485	93175	122379	155455	190391	226484
Mean Arg.	1.107	1.107	1.107	1.107	1.107	1.107
Mean Uru.	0.910	0.910	0.910	0.910	0.910	0.910
Panel B: Bids Data						
$\mathbb{I}\{Arg\} \times \mathbb{I}\{Post\}$	0.123^{***}	0.091^{**}	0.089^{***}	0.102^{***}	0.094^{***}	0.103^{***}
	(0.034)	(0.036)	(0.030)	(0.029)	(0.028)	(0.028)
N	22353	30301	40088	51115	62800	74850
Mean Arg.	1.016	1.016	1.016	1.016	1.016	1.016
Mean Uru.	0.973	0.973	0.973	0.973	0.973	0.973
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 month or 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. Panel A presents the estimation results using a dependent variable constructed at a monthly level. Panel B presents the results corresponding to a dependent variable constructed using transacted prices (as opposed to originally posted prices). Each column estimates the baseline specification, but differs in the subsample used. In each column we extend the lenght 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 mean values correspond to the mean of the dependent variable during the 2003-2006 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.

TABLE A6. 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.
Panel A: Monthly Data												
Gap Expectations	0.586***											
	(0.0625)											
SDev. Expectations		0.438***										
		(0.0712)										
$\mathbb{I}\{Arg\} \times \mathbb{I}\{Placebo\}$			-0.0393									
			(0.0276)									
$\mathbb{I}\{Arg\} \times \mathbb{I}\{Post\}$				0.204***	0.333***	0.0485***	0.0658*	0.118***	0.0654***	0.0927***	0.0570*	0.0733***
				(0.0333)	(0.0222)	(0.0177)	(0.0342)	(0.0238)	(0.0200)	(0.0222)	(0.0306)	(0.0236)
N	125858	125858	49944	229054	226483	232194	232194	221157	111597	226484	67545	235416
Mean Arg.	1.107	1.107	1.107	1.167	1.049	0.813	1.860	1.107	1.107	1.107	1.107	1.202
Mean Uru.	-	-	0.910	1.186	1.414	0.780	1.584	0.910	0.910	0.910	0.910	1.028
Panel B: Bids Data												
Gap Expectations	0.889***											
	(0.112)											
SDev. Expectations		0.417***										
		(0.157)										
$\mathbb{I}\{Arg\} \times \mathbb{I}\{Placebo\}$			-0.0375									
			(0.0506)									
$\mathbb{I}\{Arg\} \times \mathbb{I}\{Post\}$				0.105***	0.372***	0.0303	0.00258	0.0801***	0.108***	0.124***	0.108***	0.0623**
				(0.0289)	(0.0313)	(0.0270)	(0.0495)	(0.0300)	(0.0284)	(0.0280)	(0.0393)	(0.0257)
N	42435	42435	15733	74860	74850	75703	75703	73450	35547	74850	20246	78016
Mean Arg.	1.016	1.016	1.016	1.023	0.938	0.765	1.699	0.988	0.608	1.016	0.920	1.156
Mean Uru.	-	-	0.973	0.974	1.422	0.733	1.486	0.929	0.631	0.973	0.987	1.062
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 publication is weighted (by the number of units available for sale in Panel A and by the units sold per transaction in Panel B) 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 goods with prices posted in foreign currency, total number of posts, total number of posts 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 (11) 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 mean values correspond to the mean of the dependent variable during the 2003-2006 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.

TABLE A7. Robustness Analysis: Different Category Levels

	(1)	(2)	(3)	(4)	(5)
	Cat. 1	Cat. 2	Cat. 3	Cat. 4	Cat. 5
Panel A: Monthly Data					
$\mathbb{I}\{Arg\} \times \mathbb{I}\{Post\}$	-0.0289	0.0191	0.0737***	0.100***	0.0939*
	(0.118)	(0.0376)	(0.0225)	(0.0323)	(0.0484)
N	5006	56638	226484	352586	291150
Mean Arg.	2.296	1.460	1.107	0.843	0.670
Mean Uru.	1.941	1.230	0.910	0.715	0.671
Panel B: Bids Data					
$\mathbb{I}\{Arg\} \times \mathbb{I}\{Post\}$	0.0349	0.0461	0.103***	0.267***	0.459***
	(0.157)	(0.0502)	(0.0284)	(0.0408)	(0.0991)
N	1664	18509	74850	120760	104674
Mean Arg.	2.139	1.376	1.016	0.758	0.553
Mean Uru.	2.081	1.277	0.973	0.778	0.905
Time FE	Yes	Yes	Yes	Yes	Yes
Categ.-Country FE	Yes	Yes	Yes	Yes	Yes

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. Panel A presents the estimation results using a dependent variable constructed at a monthly level. Panel B presents the results corresponding to a dependent variable constructed using transacted prices (as opposed to originally posted prices). The estimation method used in all columns is OLS. Standard errors (in parentheses) are clustered at the Category-Country level. The mean values correspond to the mean of the dependent variable during the 2003-2006 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.

Appendix B. Theoretical Appendix (For Online Publication)

B.1. *Complete Characterization of p_{it}*

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

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

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

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

where

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

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

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

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

and

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

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

$$\begin{aligned}var\left(A_{it}|\mathcal{I}_{it}\right) &= var\left\{\sigma_\Phi\varepsilon_{it}^\phi+\sigma_\Phi\rho_\Phi\boldsymbol{\Upsilon_\Phi}\boldsymbol{\varepsilon_{it}^\phi}+\frac{1}{\alpha}\left(\sigma_\Psi\varepsilon_{it}^\psi+\sigma_\Psi\rho_\Psi\boldsymbol{\Upsilon_\Psi}\boldsymbol{\varepsilon_{it}^\psi}\right)\right.\\ &\left.+\frac{1}{\alpha}\left(\frac{1}{\gamma}diag(\boldsymbol{\sigma}_{mt})\boldsymbol{\varepsilon}_t^m+\frac{1}{\gamma}\sigma_{mt}\varepsilon_t^m+\left(\theta-\frac{1}{\gamma}\right)\left(k_t^m diag(\boldsymbol{\sigma}_{mt})\boldsymbol{\varepsilon}_t^m+k_t^p diag(\boldsymbol{\sigma}_{pt})\boldsymbol{\varepsilon}_t^p\right)\right)\right|\mathcal{I}_{it}\Big\}\\ &= \sigma_\Phi^2+\frac{\sigma_\Psi^2}{\alpha^2}+\frac{\sigma_{mt}^2}{\alpha^2\gamma^2}+\Delta_{\Sigma t}^1 var\left(\left[\boldsymbol{\varepsilon}_t^m\quad\boldsymbol{\varepsilon}_t^p\quad\boldsymbol{\varepsilon}_{it}^\psi\quad\boldsymbol{\varepsilon}_{it}^\phi\right]'\middle|\mathcal{I}_{it}\right)\Delta_{\Sigma t}^{1\,\prime},\end{aligned}$$

where

$$\Delta_{\Sigma t}^1 \equiv \left[\frac{1}{\alpha}\left(\frac{1}{\gamma}\mathbf{1}+\left(\theta-\frac{1}{\gamma}\right)k_t^m\right)diag(\boldsymbol{\sigma}_{mt})\quad\frac{1}{\alpha}\left(\theta-\frac{1}{\gamma}\right)k_t^p diag(\boldsymbol{\sigma}_{pt})\quad\frac{\sigma_\Psi\rho_\Psi\boldsymbol{\Upsilon_\Psi}}{\alpha}\quad\sigma_\Phi\rho_\Phi\boldsymbol{\Upsilon_\Phi}\right]$$

and

$$var\left(B_{it}|\mathcal{I}_{it}\right) = var\left\{\sigma_{\Psi}\varepsilon_{it}^{\psi} + \sigma_{\Psi}\rho_{\Psi}\boldsymbol{\Upsilon}_{\boldsymbol{\Psi}}\boldsymbol{\varepsilon}_{\boldsymbol{it}}^{\boldsymbol{\psi}} + \left(\frac{1}{\gamma}-1\right)\left(diag(\boldsymbol{\sigma}_{mt})\boldsymbol{\varepsilon}_{t}^{m} + \sigma_{mt}\varepsilon_{t}^{m}\right)\right.$$
$$\left. + \left(\theta - \frac{1}{\gamma}\right)\left(k_{t}^{m}diag(\boldsymbol{\sigma}_{mt})\boldsymbol{\varepsilon}_{t}^{m} + k_{t}^{p}diag(\boldsymbol{\sigma}_{pt})\boldsymbol{\varepsilon}_{t}^{p}\right)\right| \mathcal{I}_{it}\right\}$$
$$= \sigma_{\Psi}^{2} + \left(\frac{1}{\gamma}-1\right)^{2}\sigma_{mt}^{2} + \Delta_{\Sigma t}^{2}var\left(\left[\boldsymbol{\varepsilon}_{t}^{m} \quad \boldsymbol{\varepsilon}_{t}^{p} \quad \boldsymbol{\varepsilon}_{it}^{\psi} \quad \boldsymbol{\varepsilon}_{it}^{\phi}\right]' \middle| \mathcal{I}_{it}\right)\Delta_{\Sigma t}^{2}{}'$$

with

$$\Delta_{\Sigma t}^{2} \equiv \left[\left(\left(\tfrac{1}{\gamma}-1\right)\mathbf{1} + \left(\theta - \tfrac{1}{\gamma}\right)k_{t}^{m}\right)diag(\boldsymbol{\sigma}_{mt}) \quad \left(\theta - \tfrac{1}{\gamma}\right)k_{t}^{p}diag(\boldsymbol{\sigma}_{pt}) \quad \sigma_{\Psi}\rho_{\Psi}\boldsymbol{\Upsilon}_{\boldsymbol{\Psi}} \quad \mathbf{0}\right].$$

Finally,

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

B.2. *Conditional Expectations and Model Solution*

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 useful to also decompose the firm's signals into a common knowledge component and a filtering component

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

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 $(0, \tilde{k}_{t,1}^{x}, \ldots, \tilde{k}_{t,T-1}^{x})$ 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 $\left(\boldsymbol{\varepsilon}_{t}^{m}, \boldsymbol{\varepsilon}_{t}^{p}, \boldsymbol{\varepsilon}_{it}^{\psi}, \boldsymbol{\varepsilon}_{it}^{\phi}, \boldsymbol{s}_{it}^{c}, \boldsymbol{s}_{it}^{w}, \boldsymbol{s}_{t}^{p}\right)$ 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*

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

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 $\int_0^1 \boldsymbol{\varepsilon}_{it}^{\Psi}\,\mathrm{d}i = \int_0^1 \boldsymbol{\varepsilon}_{it}^{\Phi}\,\mathrm{d}i = 0$.

Replacing these results in the equilibrium condition (17), we obtain the following system of equations that form the fixed point that defines the equilibrium of the model:

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

$$k_t^p diag(\boldsymbol{\sigma}_{pt}) = \frac{1}{\left(1+\theta\left(\frac{1}{\alpha}-1\right)\right)}\left\{\left(\frac{1}{\alpha}-1\right)\sigma_\Psi\rho_\Psi\boldsymbol{\Upsilon}_{\boldsymbol{\Psi}}\Delta_3^{'} + \sigma_\Phi\rho_\Phi\boldsymbol{\Upsilon}_{\boldsymbol{\Phi}}\Delta_4^{'}\right. \tag{21}$$
$$+\left(\theta-\frac{1}{\gamma}\right)\left(\frac{1}{\alpha}-1\right)k_t^p diag(\boldsymbol{\sigma}_{pt})\Delta_{2t}^{'}$$
$$\left.+\left(\left(1+\frac{1}{\gamma}\left(\frac{1}{\alpha}-1\right)\right)\mathbf{1}diag(\boldsymbol{\sigma}_{mt})+\left(\theta-\frac{1}{\gamma}\right)\left(\frac{1}{\alpha}-1\right)k_t^m diag(\boldsymbol{\sigma}_{mt})\right)\Delta_{1t}^{'}\right\}\Delta_t^{-1}\Delta_{2t}.$$

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 (16), we can express idiosyncratic prices as a linear combination of idiosyncratic and aggregate signals

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

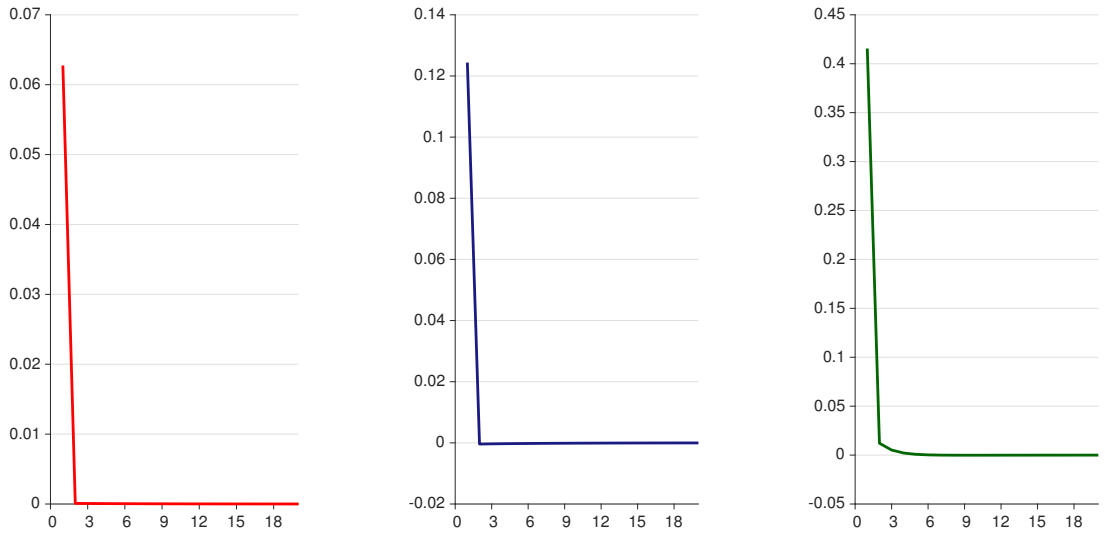
where

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

B.3. *Firms' Optimal Prices*

FIGURE B.1. Bayesian Weights on Signals

(A) Weight Attached to s_{it}^c (B) Weight Attached to s_{it}^w (C) Weight Attached to s_t^p



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 2007-12 calibration.

B.4. *Price Dispersion and Inflation Volatility*

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

$$Coef\ Var_t^i(p_{it}) = \left(\exp\left(var_t^i(p_{it})\right) - 1\right)^{1/2},$$

where

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

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

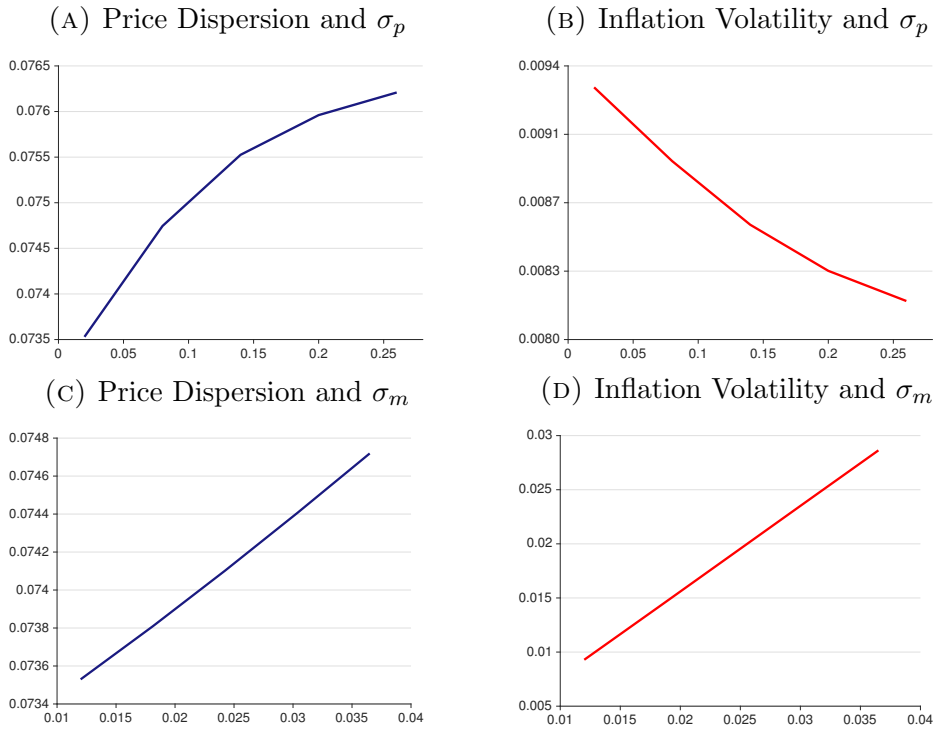
$$\hat{\boldsymbol{\varepsilon}}_t^i = \left(\varepsilon_{t-1}^i, \varepsilon_{t-2}^i, ..., \varepsilon_{t-T}^i, \varepsilon_{t-T-1}^i\right) \qquad for\ i = m, p,$$

$$v_m = \left(k_{m1}, k_{m2} - k_{m1}, ..., k_{mT} - k_{mT-1}, 1 - k_{mT}\right),$$

$$v_p = \left(k_{p1}, k_{p2} - k_{p1}, ..., k_{pT} - k_{pT-1}, -k_{pT}\right).$$

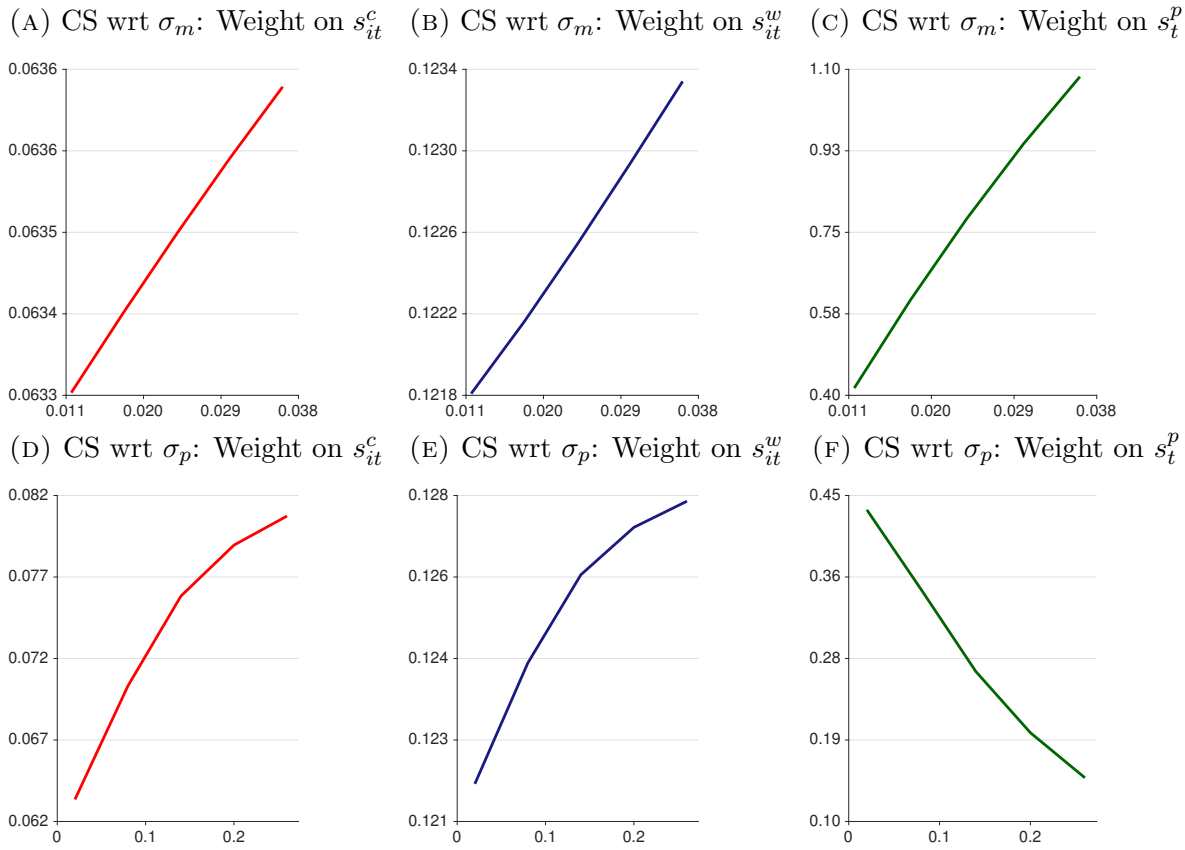
B.5. *Comparative Statics: Monetary Volatility and CPI-Precision*

FIGURE B.2. Price Dispersion and Inflation Volatility: Comparative Statics



Notes: The first two panels show the 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 second two panels show the price dispersion and volatility of inflation as a function of σ_m. The parametrization corresponds to the 2007-12 calibration.

FIGURE B.3. Cumulative Bayesian Weights on Signals: Comparative Statics



Notes: These graphs show the sum across age 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.

APPENDIX C. QUANTITATIVE APPENDIX (FOR ONLINE PUBLICATION)

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 (18) and adding measurement error as well as individual controls we re-express the joint process for wages and disutility of labor shocks as

$$w_{it} = \boldsymbol{\chi} \boldsymbol{X_{it}} + \phi_{it} + \sigma_\upsilon \upsilon_{it}$$
$$\phi_{it} = \rho_\Phi \phi_{it-1} + \sigma_\Phi \varepsilon^\Phi_{it},$$

where υ_{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_{it}^2, $tenure_{it}$,$education_{it}$, etc.) and a set of aggregate time dummies (that capture the effect of the aggregate money shock in our model).

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_υ we use observations from workers that were continuously employed to construct the following moment conditions

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

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

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_υ	0.1168	(0.0014)

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

C.2. *Model Fit and Comparative Statics*

TABLE C2. Goodness of Fit of Targeted Moments

Target	Data	Model
ρ_c	0.24	0.18
σ_c	0.85	0.86
Avg. Inflation	0.03	0.03
SDev. Inflation Pre-Episode	0.009	0.009
SDev. Inflation Post-Episode	0.013	0.014
Δ CV	0.09	0.08

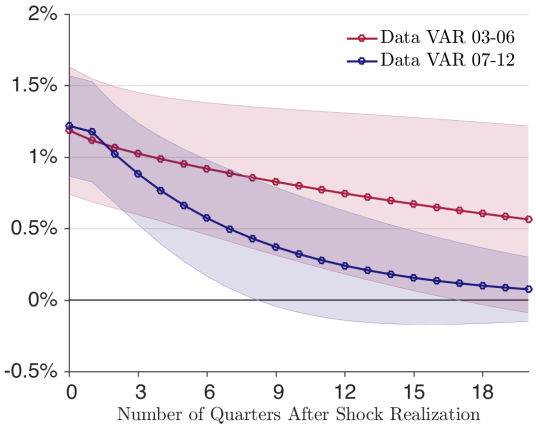
Notes: Data moments correspond to the sample 2003-2012. Model moments correspond to simulated data for 40 quarters for an economy that suffers a change in σ_p and σ_m in the 17th quarter. ρ_c and σ_c refer to the point estimates of estimating an AR(1) process for quantities. Δ CV refers to the percent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

C.3. *Effectiveness of Monetary Policy*

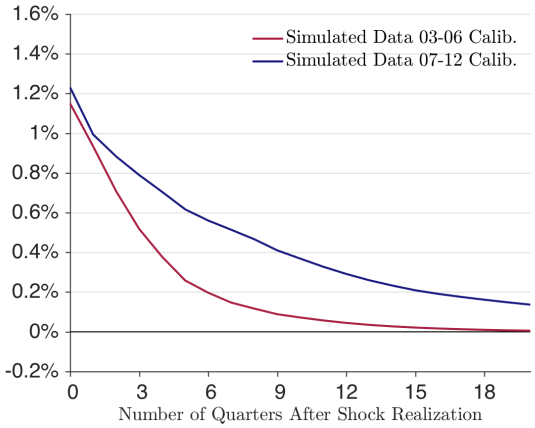
In this appendix we provide additional results regarding the VAR analysis. First, we show the response of real balances to a money supply shock. Results are shown in Figure (C.1). Real balances increase after a money shock in the VARs estimated with observed data and in the VARs estimated with model-simulated data. In VARs estimated with data for 2003-2006 and 2007-2012 the reaction of money balances to a money shock is not statistically different. In the VARs estimated with model-simulated data the positive reaction of money balances is more persistent in the VARs estimated with from the model with the 2007-2012 calibration.

FIGURE C.1. Real Balances Response to Money Innovations

(A) Observed Data VARs



(B) Simulated Data VARs



Notes: These graphs compare the IRFs of real balances to a monetary innovation obtained from the VARs estimated with observed and model-simulated data for two periods of time, one in 2003-2006 and the other in 2007-2012. The left graph shows the IRFs estimated with observed data. The shaded area indicates the 95% confidence intervals. The right graph shows the average response of 200 VARs estimated with simulated data.

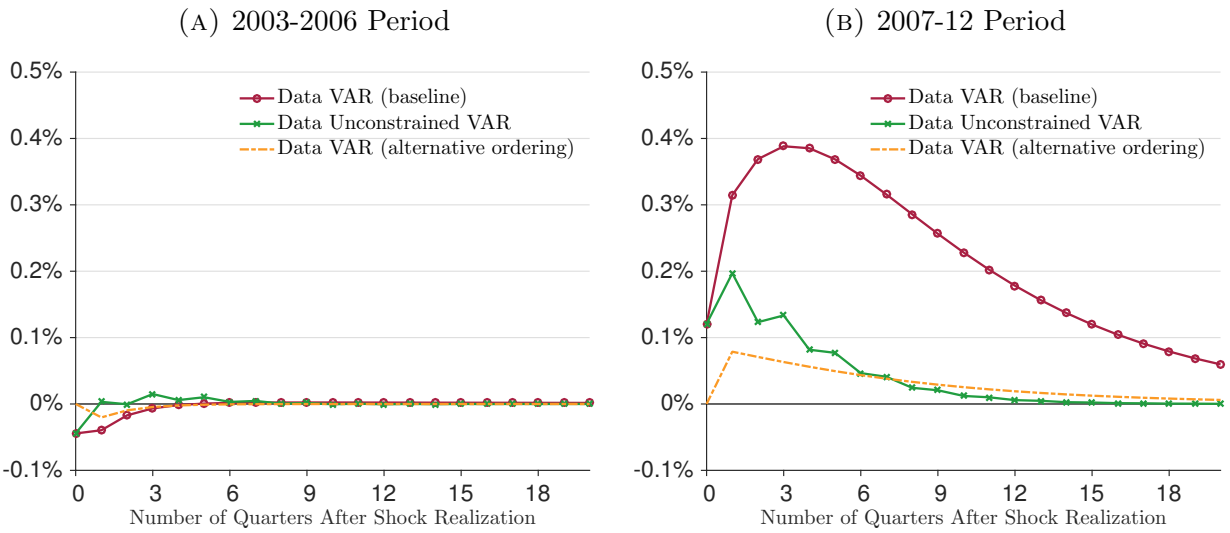
Second, we assess the robustness of the response of output to a money shock to alternative VAR specifications and ordering assumptions. Regarding the ordering assumptions we compute the IRFs assuming a reverse ordering along the lines of Christiano et al. (2005). In particular, we perform a Cholesky decomposition according to which innovations to output affect contemporaneously money and real balances and output, innovations to real balances affect contemporaneously money but not output, and innovations to money do not affect contemporaneously output nor real balances. We refer to this ordering as the 'alternative ordering'.

We also estimate an alternative VAR in which we do not impose any restriction in the autoregressive matrix $\mathbf{A_1}$. By not restricting the coefficients in $\mathbf{A_1}$, we are allowing for a monetary policy rule that depends on lagged levels of prices and real activity. We then compute the response of output to a money shock for this specification using the baseline ordering assumption. We denominate this specification as the 'Unrestricted VAR'.

Figure (C.2) shows the output effects of an innovation to the money process for the baseline VAR specification estimated with observed and simulated data and compares the results to the same IRF estimated for the 'Unrestricted VAR' and the VAR with the 'alternative

ordering' assumption. Result from these additional specifications are consistent with the baseline VAR.

FIGURE C.2. Output Response to Money Innovations: Alternative VARs

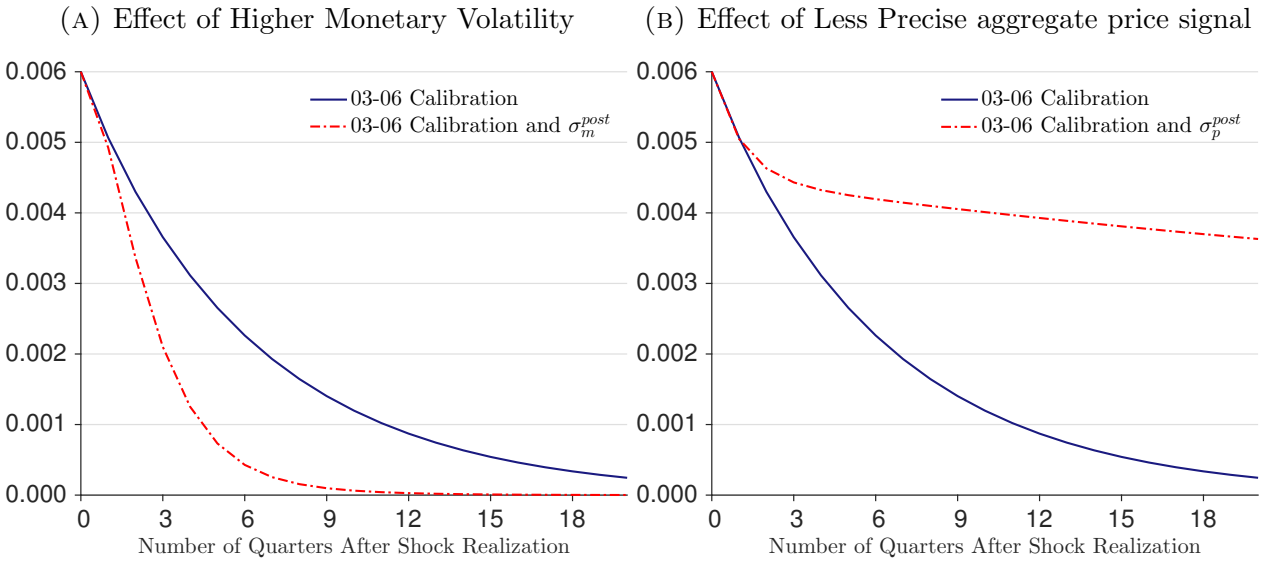


Notes: These graphs compare the IRFs of a monetary innovation obtained from alternative specifications of the data-based VAR in two periods of time, one in 2003-2006 (left) and the other in 2007-2012 (right).

Finally, we assess the reasons behind the increase in the effectiveness of monetary policy in the model economy post-policy changes. The effect of the increase in monetary volatility goes in the opposite direction to the effect of the decrease in the precision of the aggregate price signal. While monetary policy becomes less effective in the context of a more volatile money process, it becomes more effective in the context of a less-precise aggregate price signal. This is shown in Figure (C.3) that shows the reaction of output to a money shock in the steady state of an economy with the 2003-2006 calibration and compares it to that in the steady state of an economy in which we change σ_m and σ_p, one at a time.[34] In the economy with a more volatile money process, the same money shock has an effect on output that dissipates after the year. In the economy with only a less-precise aggregate price signal the same shock produces an effect on output that fails to dissipate even after 5 years.

[34]Similar results are obtained if we do the VAR analysis with simulated data.

FIGURE C.3. IRF of Money Innovations on Aggregate Output



Notes: The right graph shows the output reaction to a money shock in the steady state of the model under two different parametrizations, one corresponding to the 2003-06 calibration and another one in which σ_p is increased to σ_p^{post}. The left graph shows the same variables for two different parametrizations, one corresponding to the 2003-06 calibration and another one in which σ_m is increased to σ_m^{post}.

C.4. *Alternative 2007-08 Calibration*

TABLE C3. New Parameters and Goodness of Fit of Targeted Moments

Parameters		
σ_m^{07-08}	0.047	
σ_p^{07-08}	0.190	
Targeted Moments	Data	Model
SDev. Inflation Post-Episode	0.015	0.014
Δ CV Pre-Post	0.05	0.05

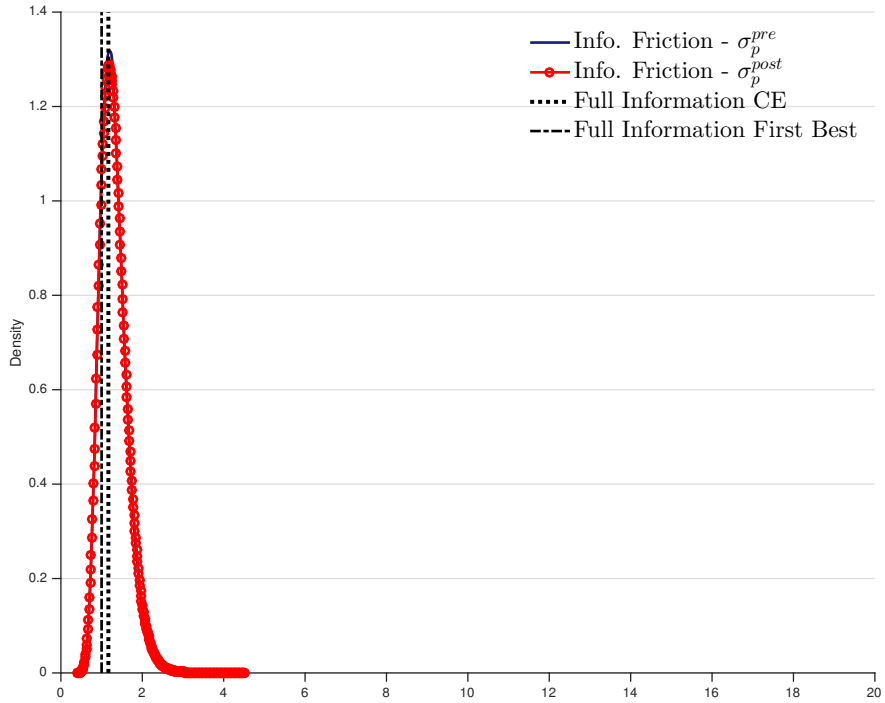
Notes: All the remaining parameters are set as in the 2003-06 Calibration. 'SDev Inflation Post-Episode' refers to the standard deviation of inflation. Its data moment is computed for the 2007-08 period. Δ CV Pre-Post refers to the percent increase in the coefficient of prices. Its data moment is computed as the point estimate of the regression with the 2003-08 sample. Model moments correspond to simulated data for 24 quarters for an economy that suffers a change in σ_p and σ_m in the 17th quarter.

C.5. *US Calibration*

TABLE C4. 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	0.800	0.229
Money Process		
μ	0.033	0.006
σ_m^{pre}	0.012	0.006
σ_m^{post}	0.036	0.006

FIGURE C.4. Wedge Dispersion in the US Calibration



Notes: This figure plots 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 parametrization uses $\theta = 10$ and the remaining parameters from the calibration of the US economy.