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Inflation Volatility and Economic Development: Evidence from Nigeria

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Abstract

We use monthly time-series data on the prices of 96 individual products in the 37 states of Nigeria to analyze the factors that drive inflation volatility. Among the significant determinants of volatility are average inflation rates, transport and communication infrastructure, consumer access to credit markets and urbanization. However, there is substantial heterogeneity across products in the relative importance of these factors.

JEL classification: E31, O11

Key words: Inflation, Volatility, Uncertainty, Nigeria

1. Introduction

A highly volatile rate of inflation has the potential to do great economic harm. With nominal contracts, uncertainty about future prices is likely to entail higher risk premia and unanticipated changes in the distribution of wealth. These costs mean that for a given average inflation rate, higher inflation volatility can depress economic growth (Elder, 2004; Fatás and Mihov, 2005; Grier and Grier, 2006). There is a large body of economic theory and econometric evidence dealing with impact of monetary policy on inflation volatility (for example, Gali and Monacelli, 2005; Leduc and Sill, 2007). Historically, weak institutions have been blamed for both high average inflation and high inflation volatility in developing countries, and close attention has been paid to the consequences for inflation volatility of alternative macroeconomic policy regimes (Bleaney and Fielding, 2002; Rother, 2004; Aisen and Veiga, 2006).

As a consequence, many developing countries have already instituted (or are in the process of instituting) reforms designed to reduce the level and variability of monetary growth. In Africa, the 14 members of the CFA Franc Zone are committed to a monetary system in which their central banks operate what is in effect a currency board arrangement based on the Euro. Their neighbours in ECOWAS, including Nigeria, are discussing a similar system. South Africa has adopted western-style inflation targeting. Political crises do still lead to hyperinflation, as in Zimbabwe, but such cases are now the exception rather than the rule. In an era of relative monetary stability, what factors are likely to determine the level of inflation volatility? Does economic development bring more or less volatility? What can the government do to reduce volatility further?

In this paper we address these questions using monthly price data on 96 specific items in the 37 states of Nigeria. The focus on disaggregated prices mirrors recent work on price variation in industrialized countries based on barcode level data (for example Broda and Weinstein, 2008). For each item, we model the state-specific economic characteristics that are associated with a relatively high or low level of inflation volatility. We avoid the traditional focus on aggregate inflation volatility for two reasons. Firstly, developing countries tend to have a more unequal distribution of income and therefore more heterogeneity in consumption. An aggregate consumer price index masks this heterogeneity; moreover, it weights the consumption of the rich more than that of the poor (Ley, 2005). Goni *et al*. (2006) find that in Latin America the consumer price index typically reflects the consumption patterns of the top quintile of the income distribution, and is not informative about the cost of living of the poor. In order to shed light on the volatility of prices facing heterogeneous consumers, we need to examine volatility in the prices of specific types of commodity. Secondly, many consumers in developing countries are also producers; their welfare is affected by volatility in the prices of the specific commodity or commodities they are selling on local markets. We therefore need to examine volatility in this subset of commodity prices.

The focus on differences across states within a single country (albeit the most populous country in Africa) means that we are sure that the differences are not a consequence of heterogeneous monetary policy. All the states face the same macroeconomic environment; nevertheless, we will see that there are substantial differences between them in terms of inflation volatility, some of which are due to observable state-specific characteristics. Some of these characteristics are beyond the influence of public policy, but others are a direct consequence of patterns of local public spending. Our results therefore shed light on those dimensions of non-monetary policy that can affect inflation volatility. Before discussing the data, we briefly review the literature relating to the determinants of inflation volatility.

2. Background

A large part of the literature on inflation volatility in industrialized countries is concerned with the potential link between the level of inflation and its conditional variance, an idea dating back to Friedman's Nobel Prize lecture of 1977 and formalised by Ball (1992). The link arises when monetary policy is more uncertain with high inflation than with low inflation. GARCH models fitted to aggregate price data for the USA, Israel and the UK indicate that periods of high inflation are also periods of high conditional variance in inflation (Brunner and Hess, 1993; Ungar and Zilberfarb, 1993; Kontonikas, 2004). Internationally, the evidence for ARCH effects is mixed, but there is strong evidence that countries with high inflation have significantly higher levels of inflation volatility on average (Baillie *et al*., 1996; Davis and Kanago, 1998).

If the link between the level of inflation and inflation volatility is entirely a consequence of variations in the degree of monetary policy uncertainty, then we should not see such a link in a cross-section of states within a country, all of which face the same monetary policy environment. However, there are other reasons for a link that are unrelated to monetary policy. Álvarez *et al*. (2006) find that prices of individual commodities in the Euro area are somewhat more persistent when moving downwards than they are when moving upwards. This is consistent with evidence that small increases in costs are more likely to lead to a price adjustment than small decreases (Peltzman, 2000). Such asymmetry features in a number of theoretical papers, including the consumer search models of Benabou and Getner (1993) and Lewis (2005). A corollary of the asymmetry in price stickiness is that the degree of persistence exhibited by a particular price series will be negatively correlated with its average inflation rate: when average inflation is high, reductions in price are hardly ever called for. Dias *et al*. (2004)

report evidence for such an effect. In this case there will be a positive relationship between average inflation and inflation volatility. Moreover, this is an effect relating to the unconditional variance of inflation, not to the conditional variance featuring in the GARCH models discussed above: the asymmetric response to a change in costs does not necessarily depend on whether the change was anticipated. We might expect that the relationship between the average level of inflation and the degree of persistence is attenuated at very high inflation rates; however, for lower inflation rates there is no strong *a priori* reason to suppose a particular functional form to the relationship.

The link between average inflation and inflation volatility may well be an important feature of the data; however, variations in sample average inflation rates across commodities and across states are likely to arise because of asymmetric shocks beyond the control of the policymaker. Nevertheless, inflation volatility might also respond to other characteristics of states reflecting their relative levels of economic development, some dimensions of which are at least partly a consequence of public policy. The three main types of characteristic are as follows. Discussion of the measurement of these characteristics is left to the following section.

1. *Market infrastructure, competitiveness and menu costs*. With higher menu costs, an individual producer (or a group of producers in the same local market charging the same price for a particular commodity) will adjust its price less frequently but by a larger amount.[1] For a given constant rate of money growth, the rate of growth of prices charged by that producer will be more variable when menu costs are higher. Moreover, menu cost effects are likely to be larger in less competitive markets. Akerlof and Yellen (1985) show that the profits lost through failing to adjust output prices in response to a shock to costs are lower in monopoly than in a Bertrand duopoly. In a similar vein, Rotemberg and Saloner (1987) demonstrate that a monopolist is less likely to adjust prices when costs change than are firms competing in duopoly markets.[2]

   We should note that the impact of menu costs on inflation volatility is reversed in models with imperfect competition and staggered price adjustment. In this case, a smooth rate of money growth translates into zero aggregate inflation volatility, since a constant fraction of producers are adjusting their price each period. With lower menu costs this fraction increases, so when there is a temporary shock to money growth a

[1] That is, when it faces increases in costs or in demand. The preceding discussion indicates that small reductions in costs or in demand may not stimulate any price adjustment at all.

[2] Empirical evidence for these theories in relation to the financial services market is provided by Hannan and Berger (1991) and Arbatskaya and Baye (2004).

larger proportion of this shock is translated into an inflation shock. Therefore, inflation is more volatile with lower menu costs. This characteristic is a feature of many New Keynesian models, for example Devereux and Yetman (2002). In empirical models of *aggregate* inflation volatility, such a model is likely to be highly relevant. However, when we are looking at the price of a particular commodity in a particular location, this is much less likely to be the case. Firstly, the number of producers is likely to be much smaller; secondly, the cross-price elasticity of demand between producers is likely to be very high, so there is less scope for staggered price setting. In our case, higher menu costs are likely to be associated with higher inflation volatility.

We cannot measure menu costs directly, but we can identify characteristics of states that are likely to increase local competitiveness and reduce the impact of menu costs on price-setting behavior. Such characteristics might include the quality of transport and communication infrastructure that reduces the segmentation of local markets and increases competition between suppliers in different locations.

2. *Access to credit markets*. Both across and within developing countries, there is a great deal of variation in the fraction of consumers with access to credit markets. The extent of credit market access could affect the volatility of aggregate demand and therefore of inflation. However, the direction of the effect is ambiguous. On the one hand, access to credit could be used by individual households to maintain a smooth consumption path in the presence of income volatility, in which case wider access to credit should be associated with lower inflation volatility. On the other hand, there is reason to believe that bank lending increases sharply during booms (Bernanke *et al*., 1998; Borio *et al*., 2001). In this case, procyclical bank lending policies could amplify the effects on consumption and inflation volatility. If the extra lending during booms is to existing customers, then states where more households have access to credit markets may experience higher consumption and inflation volatility.
3. *Urbanization*. In a particular area, the impact on local prices of idiosyncratic variations in supply and demand may depend on the size of that area. When a relatively large market experiences an idiosyncratic shift in supply or demand, the mitigating influence of arbitrage with neighbouring markets may be relatively weak. For example, Rátfai (2003) finds that the speed of convergence of a city’s prices to the national mean is a negative function the city’s size.

Several of the mechanisms in (1-3) above – for example, consumption smoothing and inter-city arbitrage – can be described either in terms of the response of prices to aggregate shocks, or in terms of the response to predictable variations in aggregate supply and demand. They can motivate either a model of the conditional variance of inflation, or a model of the unconditional variance. However, economic costs are more likely to arise from uncertainty about inflation than they are from predictable variations in prices. Therefore, it will be important to compare empirical results using a conditional variance measure of volatility with results using an unconditional variance measure. In the following section we first present the Nigerian price data used to measure inflation volatility, and then show how variations in volatility across states are related to the characteristics that we have identified.

3. Modelling Inflation Volatility

3.1 The Nigerian price data

Our data comprise monthly prices for 96 individual retail items in the 37 states of Nigeria over 2001-2006. These are a subset of the prices reported by the Nigerian National Bureau of Statistics and available online at www.nigerianstat.gov.ng/nbszip/retail.zip; we use the prices of all products that are reported consistently in each state. (The main product type completely excluded from our analysis is alcohol, the sale of which is illegal in some states in northern Nigeria.) For each product in each state, we have 72 monthly observations on the price level and 71 observations on the monthly inflation rate. The products in our sample are listed in Table 1.

The products listed cover all of the main components of consumption. Table 1 aggregates the 96 products into eight general categories: main staples, other loose food, packaged food, household goods, fuel and light, medical supplies, rent and services,[3] and clothing and footwear. The first category forms a relatively large fraction of the consumption of the poor, and production of products in the first two categories forms a substantial fraction of the income of the rural poor. These products are commonly sold in small local markets. Other products are more likely to be sold only in stores in urban centres. The 96 price series are for specific homogeneous items, the characteristics of which will exhibit little or no variation over time and space. Hence, we are sure that our results are free from any aggregation bias. The items do not constitute the components of a consumer price index, but are representative of the main types of goods and services consumed in Nigeria.

[3] The services are hotel accommodation and a blood test; all of the other items in this category are rents for various types of accommodation. Exclusion of the two service items does not make any substantial change to the results for this category that are reported below.

Table 1: Products Included in the Sample

Main staples

1kg guinea corn
1kg millet
1kg rice (imported)
1kg rice (local)
1kg white gari
1kg white maize
1kg yams
1kg yellow gari

Other loose food

1kg bananas
1kg beef steak
1kg brown beans
1kg carrots
1kg cooking salt
1kg dried mud fish
1kg fresh tomatoes
1kg irish potatoes
1kg melon seeds
1kg okra
1kg onions
1kg oranges
1kg sweet potatoes
1kg white beans
1 litre palm oil
1 litre vegetable oil
6 kolanuts
Box of a dozen eggs
Chicken (agricultural)
Chicken (local)
Single egg

Packaged food & cigarettes

125g tin of Titus Brand sardines
170g tin of Peak Brand evaporated milk
2kg bag of Semovita Golden Penny
30cl can of 7Up
30cl can of Coca Cola
50g box of Lipton tea
50g tin of Nescafé coffee
400g tin of Cerelac
400g tin of Peak Brand powdered milk
450g tin of Bournvita
500g packet of macaroni
500g packet of Quaker Oats
500g bag of St Louis sugar
Bottle of Maltina
Packet of 30 B&H cigarettes
Packet of Cabin Brand biscuits
Tin of Blue Band margarine
Tin of Derica tomato paste

Medical supplies

15ml bottle of iodine
Bottle of Benylin
Bottle of Glaxo Multivite
Bottle of Nivaquine
Packet of 3 Fansidar tablets
Packet of 6 Combantrin tablets
Packet of 60 Glaxo Multivite tablets
Packet of Panadol tablets
Tin of Andrews Liver Salts

Rent & services

1 month rent (bungalow)
1 month rent (flat)
1 month rent (room with parlour)
1 month rent (room)
Blood test
Night in a hotel room

Household goods

20 sheets Star Brand corrugated iron
20” Panasonic colour television
2A school exercise book
34” plastic bucket
4 litre tin of gloss paint
4 litre tin of Nigerlux emulsion paint
50kg bag of Elephant Brand cement
85g bar of Lux toilet soap
200g packet of Omo detergent
Bic biro
Cock Brand charcoal iron
Dunlop bicycle tyre
Foam pillow
Bar of Key Brand household soap
Michelin car inner tube (175 SR 14)
New General Maths textbook
Philips electric iron
Roll of toilet paper
Singer sewing machine
Vita foam mattress 6’ × 4.5’

Clothing & footwear

1 yard of khaki drill
1 yard of poplin
10 yards of embroidery lace
10 yards of guinea brocade
6 yards of Ankara wax print
Acrylic men’s singlet
Pair of Bata Brand men’s shoes
Pair of Bata Brand women’s shoes

Fuel & light

1 litre engine oil
Box of matches
Gallon can of kerosene
Litre can of kerosene
Packet of 8 candles

Table 2: Summary Statistics

product category	*mean monthly inflation rates (%)*	*s.d. of mean monthly inflation rates across products*	*mean bivariate correlation of inflation rates*
all products	0.82	0.31	0.16
main staples	0.87	0.17	0.33
other loose food	1.03	0.23	0.20
packaged food	0.75	0.24	0.28
household goods	0.58	0.18	0.11
fuel & light	1.10	0.50	0.24
medical supplies	0.71	0.26	0.06
rent & services	1.09	0.29	0.21
clothing & footwear	0.62	0.21	0.10

Table 2 provides some basic summary statistics for the inflation data. Let π_{ijt} stand for product *j* inflation in state *i* between month *t*-1 and month *t* (in percent). The first element of the first row of the table shows overall mean inflation in the sample:

$$\overline{\pi} = \frac{1}{37}\sum_{i=1}^{i=37}\frac{1}{96}\sum_{j=1}^{j=96}\frac{1}{71}\sum_{t=2}^{t=72}\pi_{ijt} \tag{1}$$

The second element in the first row of the table shows the standard deviation of the product-specific means, i.e. $\sqrt{\frac{1}{95}\sum_j\left(\frac{1}{37}\sum_i\frac{1}{71}\sum_t\pi_{ijt}-\overline{\pi}\right)^2}$. The third element in the first row of the table shows an average bivariate correlation coefficient. Defining average inflation for product *j* in state *i* as:

$$\pi_{ij} = \frac{1}{71}\sum_{t=2}^{t=72}\pi_{ijt} \tag{2}$$

we compute time-series correlation coefficients for every pair of products (*j*,*k*), i.e., $corr([\pi_{ijt}-\pi_{ij}],[\pi_{ikt}-\pi_{ik}])$. The figure shown is the average of these correlation coefficients across all pairs, indicating the extent to which inflation rates for the different products are correlated, on average. Subsequent rows in the table show corresponding statistics for the eight product categories instead of the set of all 96 products.

The table shows that although average inflation in Nigeria (0.82% per month) is low by historical standards, it is still higher than in the typical industrialised economy. Moreover, there is substantial variation in the mean inflation rate both within and across product categories. Within the sample, the most inflationary product category (fuel and light) experienced an average inflation rate almost twice that of the least inflationary category (household goods). Moreover, the standard deviation within each category is between 20% and 40% of the corresponding category mean. The heterogeneity in average inflation rates is matched by quite low correlations of monthly inflation rates across products. Across all products, the average correlation is only 16%; even in the most homogeneous category (main staples), the correlation is only 33%.

It follows that both the change in the cost of living experienced by a particular household in a particular month and the overall level of inflation volatility that the household faces depend very much on its consumption patterns. This has implications for both the type of econometric model that we apply to the data and the way we interpret the results. In the statistical analysis that follows we must allow for heterogeneous dynamics in the evolution of inflation in each product and in each state. We must also allow for heterogeneity across products in the factors that determine inflation volatility. On the basis of this analysis, we can then compare the determinants of inflation volatility in different products, and draw conclusions about the determinants of inflation volatility overall. However, in interpreting conclusions about the determinants of inflation volatility on average, we must remember that individual households may deviate some way from the average.

3.2 The volatility model

In this section we examine, product by product and state by state, the magnitude of inflation volatility over time. We consider both unconditional inflation volatility and the magnitude of inflation shocks, since it is possible that some changes in inflation can be anticipated, in which case the associated costs may be smaller. With these two volatility measures, we explore whether there are any systematic differences across states in the level of inflation volatility, and whether these differences can be explained by economic characteristics of the states. One potentially important characteristic is the average rate of inflation in the state: as noted in section 2, high mean inflation may be associated with a high level of inflation volatility. However, the underlying level of economic development in the state may also play a role.

We begin with some notation. The standard deviation of inflation for product *j* in state *i*, which serves as our basic unconditional volatility measure, is:

$$V_{ij} = \sqrt{\frac{1}{70}\sum_{t=2}^{t=72}\left(\pi_{ijt} - \pi_{ij}\right)^2} \tag{3}$$

Alongside this definition of inflation volatility, we will be using a conditional volatility measure, based on an estimated inflation shock. The inflation shock for a particular product in a particular state in month *t* is defined as the residual ε_{ijt} in the following regression equation:

$$\tilde{\pi}_{ijt} = \theta_{ij}^{0} + \theta_{ij}^{1}\tilde{\pi}_{ijt-1} + \theta_{ij}^{2}\tilde{\pi}_{jt-1} + \theta_{ij}^{3}\tilde{\pi}_{t-1} + \theta_{ij}^{4}\left[p_{ijt-1} - p_{jt-1}\right] + \theta_{ij}^{5}\left[p_{jt-1} - p_{t-1}\right] + \theta_{ij}^{6}m_{t-1} + \theta_{ij}^{7}\Delta m_{t-1} + \theta_{ij}^{8}y_{t-1} + \theta_{ij}^{9}\Delta y_{t-1} + \varepsilon_{ijt} \quad (4)$$

where $\tilde{\pi}_{ijt}$ indicates the deseasonalised value of π_{ijt}, $\tilde{\pi}_{jt}$ is the deseasonalised average inflation rate for product j across all 37 states,[4] and $\tilde{\pi}_{t}$ is the deseasonalised rate of growth of the Nigerian consumer price index. The log-price levels corresponding to these inflation rates are p_{ijt}, p_{jt} and p_{t} respectively. m_{t} is the log of deseasonalised real M1 and y_{t} the log of deseasonalised real GDP, both constructed using data in the Nigerian *Monthly Bulletin of Statistics*.[5] The θ_{ij} are fixed parameters. Table 3 provides summary statistics for the parameter estimates in these 96 × 37 regression equations. There is considerable variability in the size, sign and significance of individual parameter estimates. However, a common feature in almost all regressions is that the dominant effect is the price convergence across states, captured by $-\theta_{ij}^{4}$. Using the shocks we have estimated, we construct a conditional inflation volatility measure:

$$U_{ij} = \sqrt{\frac{1}{69}\sum_{t=3}^{t=72}\left(\varepsilon_{ijt}\right)^{2}} \quad (5)$$

Table 3: Sample Statistics for the θ_{ij} Coefficients

coefficient on	*mean*	*s.d.*
π_{ijt-1}	-0.039	0.206
π_{jt-1}	-0.257	0.383
π_{t-1}	0.275	0.993
p_{ijt-1} - p_{jt-1}	-0.650	0.340
p_{jt-1} - p_{t-1}	-0.238	0.341
m_{t-1} - p_{t-1}	-0.045	0.318
$\Delta[m_{t-1} - p_{t-1}]$	0.197	0.355
y_{t-1}	-0.235	0.437
Δy_{t-1}	0.163	0.385

[4] This is an unweighted mean. If instead we use a weighted mean, with weights based on population sizes in different states, the results are very similar to those reported here.

[5] Monthly GDP figures are interpolated from annual GDP and monthly industrial production data.

Table 4: Inflation Volatility ($\overline{V}_i, \overline{U}_i$) and Average Inflation ($\overline{\pi}_i$) by State

state	$\overline{V}_i$	$\overline{U}_i$	$\overline{\pi}_i$
Abia	0.1564	0.1378	0.7747
Adamawa	0.1766	0.1580	0.7103
Akwa Ibom	0.1813	0.1630	0.9615
Anambra	0.1799	0.1577	0.7400
Bauchi	0.1787	0.1568	0.9208
Bayelsa	0.1924	0.1651	0.7905
Benue	0.1846	0.1602	0.9087
Borno	0.1701	0.1415	0.5355
Cross River	0.1744	0.1574	0.8970
Delta	0.1816	0.1586	0.9066
Ebonyi	0.1841	0.1648	0.9114
Edo	0.1682	0.1494	0.8972
Ekiti	0.1799	0.1623	0.8563
Enugu	0.2129	0.1872	0.8584
Gombe	0.1815	0.1593	0.8266
Imo	0.1996	0.1727	0.7463
Jigawa	0.1865	0.1636	0.8652
Kaduna	0.1786	0.1591	0.7411
Kano	0.1731	0.1564	0.7198
Katsina	0.1841	0.1610	0.8552
Kebbi	0.1787	0.1567	0.8315
Kogi	0.1922	0.1689	0.7642
Kwara	0.1930	0.1682	0.9117
Lagos	0.1837	0.1603	0.8095
Nassarawa	0.1764	0.1554	0.8289
Niger	0.1889	0.1640	0.8011
Ogun	0.1897	0.1704	0.8932
Ondo	0.1837	0.1614	0.8188
Osun	0.1862	0.1639	0.6129
Oyo	0.1743	0.1614	0.8129
Plateau	0.1815	0.1603	0.8082
Rivers	0.1834	0.1695	0.9017
Sokoto	0.1858	0.1597	0.8377
Taraba	0.1816	0.1641	0.8675
Yobe	0.1969	0.1767	0.8038
Zamfara	0.1823	0.1643	0.8651
Abuja	0.1863	0.1653	0.6582

Overall, there is substantial variation in the level of inflation volatility across states. Table 4 illustrates some of this variation, showing average levels of inflation volatility (that is, $\overline{V_i} = \frac{1}{96}\sum_j V_{ij}$ and $\overline{U_i} = \frac{1}{96}\sum_j U_{ij}$) and average inflation rates (that is, $\overline{\pi_i} = \frac{1}{96}\sum_j \pi_{ij}$) for each state. It can be seen that $\overline{U_i}$ constitutes a large fraction of $\overline{V_i}$ in most cases; that is, a large proportion of total volatility is made up of unanticipated shocks. The cross-state correlation between $\overline{V_i}$ and $\overline{U_i}$ is 0.93, so our regression results are unlikely to vary enormously between the two volatility measures. Nevertheless, there are large differences in $\overline{V_i}$ and $\overline{U_i}$ between states. The largest observations of $\overline{V_i}$ and $\overline{U_i}$ (Enugu) are 36% greater than the smallest (Abia). Some of the volatility of inflation for a particular product in a particular region may be explained by the corresponding average level of inflation, for the reasons discussed in section 2. However, the proportion of the cross-state variation in inflation volatility explained by average inflation rates is not that large. For example, the correlation coefficient for $\overline{V_i}$ and $\overline{\pi_i}$ is only 0.12; for $\overline{V_i}$ and $\overline{\pi_i}$ it is 0.25. What else might explain the variation in inflation volatility?

Tables 6-8 provide some answers to this question. They report summary results from regression equations explaining the volatility of inflation in each product across states. In addition to average inflation, the regressions include a number of state-specific characteristics.[6] The characteristics are as follows.

1. *Market infrastructure*. As noted in section 2, better infrastructure is likely to increase the degree of competition in local markets, which will increase the frequency of price adjustments and (probably) reduce inflation volatility. Following the suggestion of Kovanen (2006), we include two variables in the regression that capture transport infrastructure: the log of the total length of sealed roads in a state and the log of the total length of unsealed roads, both measured in kilometres per hectare. We also include two variables that capture communication infrastructure: the adult literacy rate and log of the number of different languages spoken *per capita*.[7] Communication between suppliers and customers will be more expensive if they cannot read, or do not speak the same language. In principle, telecommunications infrastructure could also have an impact. However, the number of people with access to a cellphone and the number of landlines

[6] The data used in these regressions are from the Nigerian *Annual Abstract of Statistics* 2006 and from National Bureau of Statistics datasets available online at www.nigerianstat.gov.ng.

[7] The number of different languages spoken *per capita* is a proxy for the ethnolinguistic fractionalisation rate, that is, the probability that two individuals selected at random will speak different languages. Unfortunately, fractionalisation data are not available for individual Nigerian states.

per capita is still very low in much of Nigeria. When such variables are added to the regression equation they are not statistically significant.

2. *Access to credit markets*. As noted in section 2, the impact of credit market access on inflation is uncertain *a priori*. The National Bureau of Statistics collects data on the fraction of households reporting access to formal sector credit markets. These figures are typically very low, with a mean of 10.5% across all the states. Direct measures of access to informal sector credit markets are not readily available for the whole of Nigeria. However, access to such markets is likely to depend on a household's access to collateral, which will be correlated with its level of wealth. We have data on average *per capita* income levels in each state, and on the incidence of poverty: self-reported poverty, a headcount measure of those falling below the official Nigerian poverty line, and a headcount measure based on a poverty line of two PPP-adjusted US Dollars *per capita per diem*. Average *per capita* income and the poverty line measures of poverty turn out not to be significant determinants of V_{ij} and U_{ij}; however, the self-reported poverty rate does. We will report the results of regressions employing this last measure of poverty, and discuss briefly the results using alternative measures. Note that if there is a procyclical lending effect, it is more likely to be at work during predictable booms and recessions, and therefore to be a characteristic of V_{ij} rather than of U_{ij}.
3. *Urbanization*. As noted in section 2, volatility could be larger in highly urbanized states. For this reason, we include the state's population density, measured as the number of people per hectare, among the set of explanatory variables.

These state-specific characteristics are included alongside average inflation rates in regression equations for all 96 products. The 96 regression equations are of the form:

$$V_{ij} = \beta_j^0 + \beta_j^1 \pi_{ij} + \beta_j^2 (\pi_{ij})^2 + \beta_j^3 ln(unsealed\ roads\ per\ ha)_i + \beta_j^4 ln(sealed\ roads\ per\ ha)_i + \beta_j^5 ln(languages\ per\ capita)_i + \beta_j^6 (literacy\ rate)_i + \beta_j^7 (credit\ access\ rate)_i + \beta_j^8 (poverty\ rate)_i + \beta_j^9 ln(population\ density)_i + \xi_{ij} \qquad (6)$$

and similarly for U_{ij}. The β_j are fixed parameters and ξ_{ij} is a regression residual. β_j^1 and β_j^2 capture the effect of mean inflation on inflation volatility. We allow for a quadratic functional form, but have no strong priors about the values that these two parameters will take. Higher order polynomial terms in π_{ij} are not statistically significant.

When we fit equation (6) to the data, the residuals in many of the 96 regressions contain large outliers, and it is unlikely that ξ_{ij} is always normally distributed; as noted in Tables 5-7, the Jarque-Bera test for normally distributed residuals can be rejected at the 5% level in a substantial fraction of regressions. We therefore check the robustness of our results by using both OLS and LAD to fit equation (5) to the data. LAD results are reported alongside OLS ones in Table 5; the LAD results corresponding to the OLS results in Tables 6-7 are recorded in Appendix 1. The differences between the two sets of coefficients are generally quite small, apart from the β_j^1 and β_j^2 coefficients, as discussed below.

Table 5 provides the broadest overview of our results, by reporting mean values of the regression coefficients across all 96 equations (that is, $\overline{\beta^p} = \frac{1}{96}\sum_j \beta_j^p$ for p = 1,…,9). There are four sets of mean values, using both V_{ij} and U_{ij} with both OLS and LAD. Alongside these means are corresponding standard errors, computed using a bootstrap.[8] On average, our regressors explain just under 40% of the variation in V_{ij} and just over 40% of the variation in U_{ij}. Our broad overview in Table 5 indicates the characteristics of the *average* product in our sample. However, this average is calculated for 96 representative products, not for elements of a consumer price index, nor is it to be interpreted as indicating the determinants of overall inflation volatility for the average consumer. Nevertheless, the results in the table indicate whether our conjectures about the determinants of inflation volatility are correct. More detailed results are presented in Table 6-7, which show averages for the eight different product categories. We discuss each table in turn.

In Table 5, we see for the average product a convex relationship between inflation volatility and average inflation, with little difference between the OLS and LAD estimates. In all four sets of results, the values of $\overline{\beta^1}$ are insignificantly different from zero, implying that the volatility-minimizing inflation rate is insignificantly different from zero. However, the values of $\overline{\beta^2}$ are all significantly greater than zero, indicating that inflation volatility increases with the average inflation rate. The estimated convexity of this relationship is somewhat greater for the LAD estimates than it is for the OLS estimates, and greater for U_{ij} than for V_{ij}. Our estimates of $\overline{\beta^2}$ vary between 1.3 (OLS estimates with V_{ij}) and 2.2 (LAD estimates with U_{ij}). It remains to be seen in Tables 6-7 how much variation there is around these averages.

In Table 5, the signs of the coefficients on all of the market infrastructure variables are consistent with our priors. All of the standard errors around the mean coefficients in the OLS regressions are very low, being based on 96 × 37 observations, so all four market infrastructure

[8] The figures are calculated using the ANALYZ command in TSP 5.0.

variables are statistically significant at the 1% level for both V_{ij} and U_{ij}. The standard errors in the LAD regressions are somewhat higher; nevertheless, all of the market infrastructure variables except languages *per capita* are significant at the 5% level. Point estimates of the mean coefficient values vary very little between the OLS and LAD estimates, or between the V_{ij} and U_{ij} regressions. A 1% increase in the total length of either kind of road is associated with a reduction in volatility of slightly less than one percentage point. (The standard deviation of both of the log road length variables is just over 0.7, corresponding to a difference in volatility of over 50 percentage points.) A 1% increase in the number of languages *per capita* is associated with an increase in inflation volatility of around 0.2 percentage points. (The standard deviation of the log language number variable is 1.2, corresponding to a difference in volatility of around 25 percentage points.) A percentage point increase in literacy is associated with a reduction in V_{ij} or U_{ij} of around three percentage points, and the standard deviation of the literacy rate is 16 percentage points.

Coefficients on the rate of access to formal sector credit are positive, suggesting that lending to households is procyclical. A percentage point increase in credit access is associated with a rise in V_{ij} of around five percentage points, and the standard deviation of the credit access rate is six percentage points. The magnitude of the effect on U_{ij} is half as large, but still statistically significant when OLS is used. Also consistent with the procyclical lending hypothesis are the negative coefficients on self-reported poverty. A percentage point increase in the poverty rate is associated with a reduction in volatility of over three percentage points, and the standard deviation of the poverty rate is eight percentage points. However, replacing this poverty measure with the any of the alternative measures produces an insignificant coefficient (although there is no substantial change in the size and significance of other coefficients). Moreover, the correlation between self-reported poverty and the other poverty measures is very low. This anomaly in the Nigerian poverty data is beyond the scope of the present study, and one should exercise caution in interpreting the self-reported poverty coefficients.

Finally, consistent with our priors, there is a positive and statistically significant coefficient on population density in all cases. A 1% increase in population density is associated with a rise in V_{ij} of just over one percentage point, and with a rise in in U_{ij} of just under one percentage point. (The standard deviation of the log population density variable is 0.6, corresponding to a difference in volatility of around 60 percentage points.) One explanation for this effect is a weakening of inter-state arbitrage effects in more urbanized states.

Table 5: Mean Coefficient Values with Bootstrapped Standard Errors

	V_{ij} regressions				U_{ij} regressions			
	OLS		LAD		OLS		LAD	
	estimate	*s.e.*	estimate	*s.e.*	estimate	*s.e.*	estimate	*s.e.*
$intercept$	7.985	*0.351*	5.012	*7.109*	7.222	*0.277*	7.887	*7.349*
π_{ij}	0.589	*0.064*	-0.073	*1.174*	-0.060	*0.050*	-0.323	*1.234*
$(\pi_{ij})^2$	1.291	*0.025*	1.898	*0.500*	1.930	*0.020*	2.219	*0.492*
$ln(unsealed\ roads)_i$	-0.806	*0.024*	-0.977	*0.491*	-0.829	*0.019*	-0.796	*0.521*
$ln(sealed\ roads)_i$	-0.935	*0.018*	-1.003	*0.354*	-0.728	*0.013*	-0.694	*0.337*
$ln(languages\ p.c.)_i$	0.208	*0.011*	0.135	*0.226*	0.243	*0.009*	0.208	*0.216*
$literacy\ rate_i$	-3.414	*0.099*	-3.724	*2.176*	-1.769	*0.083*	-2.429	*2.100*
$credit\ access\ rate_i$	4.829	*0.188*	4.718	*3.485*	2.703	*0.132*	1.599	*3.352*
$poverty\ rate_i$	-3.576	*0.112*	-3.736	*2.333*	-3.435	*0.089*	-3.729	*2.180*
$ln(pop.density)_i$	1.118	*0.028*	1.264	*0.561*	0.878	*0.022*	0.845	*0.545*
mean R^2	0.387				0.436			
mean σ	0.040				0.033			
proportion of cases with Jarque-Bera test significant at 5%	0.188				0.167			

Table 6: Mean Coefficient Values in the V_{ij} Regressions for Different Product Categories

Bootstrapped t-ratios are in italics. Significant coefficients are shown in bold; anomalous coefficients are shaded grey.

	main staples	*other loose food*	*packaged food*	*household goods*	*fuel & light*	*medical supplies*	*rent & services*	*clothing & footwear*
$intercept$	**15.671**	**16.253**	**5.521**	**2.440**	**10.881**	1.542	1.248	**9.341**
	3.459	*23.319*	*5.482*	*3.056*	*2.200*	*0.420*	*0.204*	*3.584*
π_{ij}	**4.822**	**2.594**	0.064	**-1.768**	**8.004**	**-3.347**	-0.179	**-1.375**
	6.457	*3.548*	*0.228*	*-2.753*	*5.468*	*-6.779*	*-0.262*	*-5.816*
$(\pi_{ij})^2$	**-0.699**	-0.161	**3.503**	**1.349**	**-2.320**	**1.836**	**2.271**	**2.752**
	-2.254	*-0.384*	*19.870*	*2.988*	*-2.423*	*5.928*	*5.516*	*19.307*
$ln(unsealed\ roads)_i$	-0.141	**-0.476**	**-0.589**	**-1.295**	**-0.904**	**-2.520**	**-1.152**	**-0.855**
	-0.694	*-13.430*	*-10.864*	*-31.511*	*-3.216*	*-12.693*	*-3.583*	*-6.116*
$ln(sealed\ roads)_i$	-0.489	**-0.892**	**-0.688**	**-1.242**	-0.641	**-0.741**	**-0.765**	-0.279
	-1.649	*-21.572*	*-9.882*	*-23.958*	*-1.882*	*-2.679*	*-2.003*	*-1.728*
$ln(languages\ p.c.)_i$	**0.554**	**0.264**	**0.479**	**0.232**	0.272	**-0.470**	-0.333	**0.242**
	4.104	*10.358*	*12.803*	*8.155*	*1.494*	*-3.552*	*-1.596*	*2.499*
$literacy\ rate_i$	-2.088	**-5.985**	**-1.180**	**-1.567**	-1.854	**-14.008**	-2.086	**2.148**
	-1.608	*-31.936*	*-3.606*	*-6.565*	*-1.237*	*-13.116*	*-1.299*	*2.991*
$credit\ access\ rate_i$	**7.246**	**7.275**	**2.002**	**6.044**	**12.218**	-2.611	5.791	2.230
	3.559	*20.456*	*3.681*	*14.330*	*4.392*	*-1.216*	*1.735*	*1.527*
$poverty\ rate_i$	1.629	**-3.342**	**-1.883**	**-6.500**	**-9.425**	**-9.981**	1.780	0.281
	1.231	*-13.288*	*-4.883*	*-20.398*	*-4.359*	*-6.551*	*0.686*	*0.270*
$ln(pop.\ density)_i$	**1.069**	**1.274**	**1.007**	**1.519**	**0.897**	**1.602**	-0.508	**1.017**
	3.164	*23.463*	*11.619*	*23.213*	*2.188*	*4.841*	*-1.097*	*4.924*
mean R^2	0.292	0.367	0.470	0.376	0.405	0.479	0.356	0.291
mean σ	0.038	0.043	0.019	0.040	0.041	0.044	0.075	0.041
proportion of cases with Jarque-Bera test significant at 5%	0.125	0.190	0.111	0.250	0.400	0.111	0.286	0.125

Table 7: Mean Coefficient Values in the U_{ij} Regressions for Different Product Categories

Bootstrapped t-ratios are in italics. Significant coefficients are shown in bold; anomalous coefficients are shaded grey.

	main staples	*other loose food*	*packaged food*	*household goods*	*fuel & light*	*medical supplies*	*rent & services*	*clothing & footwear*
$intercept$	**19.251**	**10.940**	**4.921**	**2.787**	6.157	3.464	6.550	**7.181**
	5.667	*17.442*	*6.598*	*4.742*	*1.437*	*1.045*	*1.355*	*3.369*
π_{ij}	**2.162**	1.162	-0.026	**-1.750**	**4.220**	**-2.334**	-0.231	**-1.305**
	3.516	*1.753*	*-0.142*	*-3.501*	*3.603*	*-5.453*	*-0.436*	*-6.986*
$(\pi_{ij})^2$	**0.575**	**0.900**	**3.613**	**1.952**	-0.399	**2.003**	**2.298**	**3.205**
	2.397	*2.537*	*27.437*	*5.425*	*-0.527*	*6.851*	*7.202*	*27.213*
$ln(unsealed\ roads)_i$	0.111	**-0.546**	**-0.496**	**-0.999**	**-1.136**	**-1.742**	**-0.564**	**-0.635**
	0.699	*-17.852*	*-13.095*	*-28.403*	*-4.804*	*-8.767*	*-2.143*	*-5.327*
$ln(sealed\ roads)_i$	-0.114	**-1.020**	**-0.812**	**-1.181**	**-0.996**	**-0.577**	-0.605	**-0.574**
	-0.512	*-26.863*	*-16.062*	*-28.918*	*-3.643*	*-2.150*	*-1.869*	*-4.147*
$ln(languages\ p.c.)_i$	**0.400**	**0.274**	**0.548**	**0.295**	**0.449**	**-0.473**	-0.270	**0.315**
	3.813	*12.387*	*19.959*	*13.500*	*2.996*	*-3.703*	*-1.499*	*3.601*
$literacy\ rate_i$	-0.175	**-3.674**	**-0.861**	**-0.895**	0.256	**-10.392**	1.700	**2.811**
	-0.176	*-21.516*	*-3.832*	*-4.829*	*0.204*	*-10.039*	*1.316*	*4.613*
$credit\ access\ rate_i$	2.587	**5.921**	**1.711**	**4.366**	**9.601**	-3.728	-2.177	-0.355
	1.560	*18.528*	*4.066*	*12.760*	*4.186*	*-1.939*	*-0.886*	*-0.285*
$poverty\ rate_i$	-0.825	**-3.128**	**-1.852**	**-5.205**	**-8.959**	**-8.424**	-0.290	0.328
	-0.775	*-14.093*	*-6.023*	*-21.749*	*-4.909*	*-5.771*	*-0.146*	*0.374*
$ln(pop.\ density)_i$	0.400	**1.100**	**1.063**	**1.287**	**1.074**	**0.972**	**-1.230**	**0.958**
	1.488	*22.814*	*17.325*	*24.969*	*3.175*	*3.166*	*-3.337*	*5.210*
mean R^2	0.336	0.416	0.549	0.387	0.513	0.491	0.417	0.368
mean σ	0.030	0.036	0.016	0.032	0.032	0.036	0.066	0.036
proportion of cases with Jarque-Bera test significant at 5%	0.125	0.143	0.167	0.150	0.400	0.000	0.429	0.125

Table 6 shows the mean coefficient values in the OLS estimates of the V_{ij} equation for the eight different product categories separately. The sample sizes underlying these means are considerably smaller, and the standard errors correspondingly larger. In several cases, individual coefficients are insignificantly different from zero. We therefore report bootstrapped t-ratios alongside the mean coefficient values; those coefficients significantly different from zero at the 5% level are written in bold type.

Of all the coefficients in the table, the most heterogeneous are those on average inflation (β_j^1 and β_j^2). Five of the product categories exhibit the convexity implicit in the values of $\overline{\beta^1}$ and $\overline{\beta^2}$ in Table 5: packaged food, household goods, medical supplies rent and services, and clothing and footwear. However, the shape of the function implicit in the average values of β_j^1 and β_j^2 varies considerably across these categories. Moreover, the relationship between volatility and average inflation is concave for main staples and fuel and light, and linear for other loose food. Coefficients for individual products within each category (not reported here) are also very heterogeneous, but with a sample of 37 observations in each case the estimates are rather imprecise. This means that we cannot generalise about the impact of average inflation on inflation volatility, other than to say that it is positive. Any relationship at the aggregate level masks considerable diversity at the product level.

The other regression coefficients in Table 6 exhibit somewhat more homogeneity across product types. All of the coefficients on road length are negative. The largest effects are in household goods and medical supplies; the smallest are in main staples (the only category for which there is no statistically significant road length coefficient). With the basic food crops, for which there are likely to be many local village markets at a short distance from each other, physical transport infrastructure is less important than with manufactured goods, which are likely to be available only in the main urban centres. By contrast, the positive coefficient on the number of languages *per capita* is largest for main staples and smallest for household goods. (For medical supplies it is one of two instances in Table 6 of a coefficient “wrongly” signed and significantly different from zero; there is no obvious explanation for this anomaly.) The communication problems associated with a multiplicity of languages appear to be largest in relation to basic food crops sold in local village markets. The final variable associated with transport and communication is the literacy rate. In this case the coefficients are negative for all product categories except clothing and footwear (the second anomaly); the largest coefficient is again in medical supplies.

All of the coefficients on the credit access variable are either positive and significant or insignificantly different from zero. If these coefficients are interpreted as procyclical lending effects, then the largest effects are in the case of fuel and light, main staples and other loose food, in other words, basic, non-luxury, non-durable items. However, this pattern is not replicated in the relative sizes of the poverty coefficients, another reason to be somewhat cautious in interpreting the poverty variable.

Finally, the population density coefficient is positive and significant for all categories except rent and services. Among the other categories, household goods and medical supplies again register the largest coefficients, just over 1.5; other coefficients are very close to unity.

Table 7 shows the mean coefficient values in the OLS estimates of the U_{ij} equation for the eight different product categories separately. The coefficients in this table are generally quite close to those in Table 6, except those on average inflation (β_j^1 and β_j^2). With average inflation effects, there is more homogeneity across product categories in the case of U_{ij} than there is in the case of V_{ij} . The average inflation effect is significantly convex in all cases except fuel and light, for which the effect is approximately linear. However, there is still considerable variation in the size of β_j^1 and β_j^2 across product categories. Overall, there are no simple stylized facts about the relationship between average inflation and inflation volatility, except that higher inflation usually leads to higher volatility. Nevertheless, the several channels through which economic development impacts on inflation volatility are apparent across almost all product categories. Better transport and communication infrastructure – as captured by road length, literacy and linguistic homogeneity – lead to lower inflation volatility. On the other hand, better access to credit leads to higher inflation volatility. (The credit access coefficients in Table 7 are smaller than those in Table 6, as one would expect if the effect is a result of procyclical lending; however, the difference is not that large.)

4. Summary and Conclusion

Analysis of monthly time-series data on the prices of 96 individual products in the 37 states of Nigeria reveals some of the non-monetary factors that drive inflation volatility. Overall, better transport and communication infrastructure, as captured by road length, literacy and linguistic homogeneity, are associated with lower inflation volatility in a state. However, more extensive access to credit facilities is associated with higher inflation volatility, as is urbanization. There is some positive association between average inflation and inflation volatility; however, the shape of the relationship varies considerably from one product to another. Since most changes in inflation are unanticipated, these results apply equally to conditional and unconditional inflation volatility.

Some types of public spending on infrastructure and development, for example road building and literacy programmes, are therefore likely to reduce inflation volatility. This constitutes a substantial extra benefit not usually accounted for in traditional cost-benefit analysis of development projects. On the other hand, public expenditure designed to widen and deepen financial development, for example extending credit access, is likely to increase inflation volatility. The overall welfare benefits of any such expenditure are likely to be much reduced without measures to limit their impact on inflation volatility.

These general conclusions must be tempered by an understanding of the heterogeneity across products in the response of inflation volatility to different dimensions of economic development. For example, variation across states in the average level of conditional inflation volatility for main staples depends only on mean inflation and the level of linguistic diversity, which is likely to be largely beyond the influence of public policy (Table 7). None of the development factors within the scope of public policy has any significant influence on the average level of inflation volatility for main staples. This means that the very poor, for whom main staples make up a large fraction of consumption, and the rural poor, for whom main staples are a major source of income, are likely to benefit less (on average) from infrastructure development that reduces overall inflation volatility. The households with most to benefit (on average) from the lower inflation volatility associated with better infrastructure are those for whom the general household goods in Table 1 make up a relatively large fraction of total expenditure. These households are likely to be some way up the income distribution. However, comments about average effects for product categories need also to be modified by an acknowledgement of variation in the magnitude of effects within each product category, as reflected in the sizeable standard errors on some of the coefficients in Tables 6-7. In order to predict with any precision the level of inflation volatility faced by a specific household, and the sensitivity of that volatility to public policy, we need detailed information about that household’s consumption patterns.

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Appendix 1: LAD Coefficients Corresponding to OLS Coefficients in Tables 6-7

LAD coefficients for V_{ij}

	main staples	*other loose food*	*packaged food*	*household goods*	*fuel & light*	*medical supplies*	*rent & services*	*clothing & footwear*
$intercept$	14.477	9.765	7.026	-2.591	10.112	4.089	-9.783	8.346
π_{ij}	3.624	3.392	-2.053	-2.491	6.938	-4.247	-0.801	-1.410
$(\pi_{ij})^2$	-0.121	-0.336	5.103	2.171	-1.873	2.817	2.691	2.521
$ln(unsealed\ roads)_i$	-0.465	-0.555	-0.389	-1.543	-1.017	-2.307	-1.523	-0.822
$ln(sealed\ roads)_i$	-0.368	-1.245	-0.677	-1.269	-0.589	-1.105	-2.188	0.136
$ln(languages\ p.c.)_i$	0.753	0.087	0.448	0.041	0.308	-0.112	-0.491	-0.113
$literacy\ rate_i$	-1.049	-6.407	-1.046	-1.497	-3.568	-13.425	-5.875	1.747
$credit\ access\ rate_i$	7.140	8.381	2.168	4.400	10.252	-0.833	1.275	5.011
$poverty\ rate_i$	3.269	-3.827	-1.524	-6.424	-6.882	-10.420	-4.299	1.220
$ln(pop.density)_i$	1.398	1.317	1.015	1.371	1.577	2.203	0.805	0.430

LAD coefficients for U_{ij}

	main staples	*other loose food*	*packaged food*	*household goods*	*fuel & light*	*medical supplies*	*rent & services*	*clothing & footwear*
$intercept$	19.158	9.695	9.176	0.831	7.336	16.650	-1.184	5.027
π_{ij}	2.534	1.595	-1.602	-2.135	2.863	-1.806	-0.106	-1.327
$(\pi_{ij})^2$	0.332	0.791	4.099	2.805	0.485	2.289	2.222	3.156
$ln(unsealed\ roads)_i$	-0.224	-0.514	-0.218	-0.991	-1.274	-1.240	-1.053	-0.672
$ln(sealed\ roads)_i$	0.028	-1.126	-0.550	-1.250	-0.227	-0.201	-1.676	-0.426
$ln(languages\ p.c.)_i$	0.475	0.197	0.454	0.176	0.279	-0.005	-0.300	0.141
$literacy\ rate_i$	-0.994	-3.719	-0.452	-0.614	-0.784	-13.053	-2.363	1.408
$credit\ access\ rate_i$	4.378	5.018	0.430	2.958	6.584	-2.188	-8.639	-0.814
$poverty\ rate_i$	-2.067	-3.981	-1.857	-5.679	-4.622	-7.429	-5.572	2.267
$ln(pop.density)_i$	0.607	0.851	0.722	1.076	0.916	1.367	0.013	0.867