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Decomposing inflation using micro-price-level data: South Africa's pricing dynamics

Franz Ruch* Neil Rankin † Stan du Plessis‡

June 22, 2016

Abstract

Inflation, or the general increase in prices, is the result of many unobserved adjustments. Only a fraction of prices change in a month. Some of those prices haven't changed for over a year while others changed last month. Some are rising or falling faster than others. Some goods are on sale while others are not. These dynamics matter a lot in themselves as they describe pricing behaviour. But they also matter for economic theory forming the foundation of how these prices, and hence inflation, are predicted and forecast. We used a never-before analysed dataset of consumer goods prices to decompose inflation into the fraction of price changes (extensive margin), both increases and decreases, and the magnitude of those price changes (intensive margin). We found the following properties of pricing dynamics in South Africa. First, the average fraction or prices changing from 2009 to 2015 is 27.8 per cent, while the median change is only 12.5 per cent. The average fraction of prices changing per month can vary anywhere between 37 and 18 per cent. There is also substantial heterogeneity between products and over months. Second, the average magnitude of price changes 0.83 per cent, or just under 10 per cent annualised. Multiplying the extensive and intensive margins mean that monthly inflation averages 0.25 per cent, or 3.0 per cent annualised. Third, the variance in monthly inflation is explained mainly by the extensive margin, or the fraction of prices changing. This suggests that inflation in South Africa is state-dependent, rather than time-dependent. Fourth, the variance of inflation is mainly due to price increases (explains 70%). Fifth, sales prices account for only around four per cent of prices but help lower inflation from 4.8 per cent annualised to 3 per cent.

JEL Classification: E31, D40, C55

Keywords: frequency of price changes; pricing microdata; decomposing inflation

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Non-technical summary

Inflation, or the general increase in prices, is the result of many unobserved adjustments. Only a fraction of prices change in a month. Some of those prices haven't changed for over a year while others changed last month. Some are rising or falling faster than others. Some goods are on sale while others are not. These dynamics matter a lot in themselves as they describe pricing behaviour. But they also matter for economic theory forming the foundation of how these prices, and hence inflation, are predicted and forecast.

To address these underlying dynamics we introduce a decomposition of South African goods inflation into the fraction of prices changing in a specific month, and the magnitude of price changes. These are further decomposed into the magnitude and fraction of prices which are increasing and decreasing. Decompositions of this nature provide economists with the underlying price dynamics needed to both replicate the empirical properties found in consumer prices as well as make choices on which models better fit this data. Models of micro-founded pricing dynamics generally fall into two categories: time-dependent or state-dependent, each having significantly different implications for pricing behaviour. Time-dependent models rely on firms setting prices every n^{th} period (as in Taylor, 1999) or randomly (as in Calvo, 1983) while state-dependent models are based on firms which face a cost to change prices and hence only change prices once the change is larger than a "menu cost" (as in Mankiw, 1985). The role and incidence of sales can also have important implications for the decomposition of inflation, as sales can be an vital source of price flexibility at least on price decreases.

The results of the decomposition of inflation reveal the following properties in South Africa. First, the average fraction of prices changing, or the extensive margin, is 27.8 per cent but this can vary anywhere between 37 and 18 per cent in any particular month. This implies that prices change on average (median) every 3.6 months. The median frequency of price changes is 12.5 per cent implying that prices change every 8 months at the median. There is substantial heterogeneity between products and over time with the distribution having moderate positive skewness and heavy tails (excess kurtosis). Second, the magnitude of price changes, or the intensive margin, average 0.83 per cent. With 27.8 of prices changing and the magnitude of price changes of 0.83 per cent, monthly goods inflation increases by 0.25 per cent, or 3.0 per cent annualised from 2009 to 2015; i.e. 0.83×0.278. Third, the variance in monthly inflation is mainly explained by the extensive margin, or the fraction of prices changing. This suggests that inflation in South Africa is state-dependent, driven by outcomes such as changes in input costs, rather than time-dependent. Fourth, the variance in inflation is dominated by price increases which explain 70 per cent. Fifth, sales prices only account for around four per cent of prices and do not materially change our assessment of the role of the intensive and extensive margin in explaining inflation.

When it comes to the role of sales in the South African consumer goods basket, the results show that on average four per cent of products are on sale. The incidence of sales has risen since 2009, from around two per cent in January 2009 to over six per cent in December 2014, and to an average five per cent for the first five months of 2015. Sales are most common in the sub-categories of "Furniture and furnishings" (18 per cent of products in this category were on sale), "Household appliances" (11.9 per cent), "Audiovisual and photographic equipment" (9.6 per cent), and "household textiles" (7.1 per cent), while they are least common in "Vehicles" (0 per cent), "Telephone equipment" (0 per cent) and "Tobacco" (0.2 per cent). Despite the relatively small number of sales that occur in South Africa, they remain an important contributor to price decreases and, hence, keeping goods inflation lower. From 2009 to 2015, inflation based on product-level data weighted using expenditure weights would have been 3 per cent instead of the actual 4.8 per cent that it was, excluding all items on sales.

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1 Introduction

Inflation, or the general increase in prices, is the result of many unobserved adjustments. Only a fraction of prices change in a month. Some of those prices will not have changed for over a year, while others will have changed last month. Some rise and fall faster than others. Some goods are on sale, while others are not. These dynamics matter a lot in themselves, as they describe pricing behaviour. But they also matter for the economic theory forming the foundation of how these prices, and hence inflation, are predicted and forecast.

To address these underlying dynamics, this paper introduces a decomposition of South African goods inflation into its extensive margin[1] – (the fraction of prices changing in a specific month) – and its intensive margin – (the magnitude of price changes). These are further decomposed into the magnitude and fraction of prices that are increasing and decreasing. Decompositions of this nature provide economists with the underlying price dynamics needed to both replicate the empirical properties found in consumer prices and to make choices about which models better fit this data. Models of micro-founded pricing dynamics generally fall into two categories: time-dependent or state-dependent, each having significantly different implications for pricing behaviour. Time-dependent models rely on firms setting prices every n^{th} period (as in Taylor, 1999) or randomly (as in Calvo, 1983), while state-dependent models are based on firms that face a cost to change prices and hence only change prices once the change is larger than a 'menu cost' (as in Mankiw, 1985). The role and incidence of sales can also have important implications for the decomposition of inflation, as sales can be a vital source of price flexibility.

The contribution of this paper is fourfold. First, we analysed a previously not available dataset of product-level data for the goods component of the consumer price index (CPI) from 2009 to 2015. Second, we have extended the analysis of the frequency of price changes by Creamer et al. (2012), looking at the distribution of frequencies by product over time. This analysis reveals that the distribution of frequencies changes significantly over time and by product. Third, we decomposed South African inflation into its extensive and intensive margins to provide a more in-depth analysis of inflation dynamics. Fourth, we looked at the role sales have on price dynamics in the South African economy. The classification of prices as 'regular' or 'sale' only started to become available in the latter part of the dataset used by Creamer et al. (2012), and it was only in 2011 that all observations in the underlying product data was classified.

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[1]This paper refers to inflation as goods inflation unless specified otherwise.

inflation increases by 0.25 per cent, or 3.0 per cent annualised, from 2009 to 2015, i.e. 0.83×0.278. Third, the variance of monthly inflation is mainly explained by the extensive margin, or the fraction of prices changing. This suggests that inflation in South Africa is state-dependent, driven by shocks to the economy and changes in input costs, rather than time-dependent. Fourth, the variance in inflation is dominated by price increases, which explains 70 per cent. Fifth, sales prices account for only around four per cent of prices and do not materially change our assessment of the role of the intensive and extensive margins in explaining inflation.

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The paper proceeds are follows: In section two we provide a brief literature review and contextualise our work within the existing literature. Section three provides details on the dataset used. Section four looks at the initial properties of the intensive and extensive margin, including extending the analysis of the fraction of prices by describing its distributional properties. Section five provides an analysis of the factors that explain the extensive margin. Section six uses the information in section four to decompose goods inflation and explain its level and variation. Section seven looks at how sales affect this decomposition. Section eight considers the impact of outliers on the main results of this paper, and section nine concludes.

2 Literature review

There are two common approaches to the study of price behavior: surveys and micro-data analyses[2]. Survey approaches started with the seminal work of Blinder (1991) and Blinder et al. (1998), who recognised that many theories of nominal price rigidity exist but that methods to censor the correct theories were proving inconclusive. The reason is that most theories "involve unobservable variables in an essential way, or they carry no real implications other than that prices are 'sluggish' in some unmeasurable sense, or both" (Blinder, 1991, :3). Blinder asserts that if theories state that price-setters operate in a specific way, then you can just ask them whether this is true or not. This led to similar survey-based studies in countries including Germany (for example Kohler, 1996), the United Kingdom (Hall et al., 1997), Canada (Amirault et al., 2006), Turkey (Şahinöz and Saraçoğlu, 2008) and the euro area as a whole (Fabiani et al., 2005). Govender (2013) is the only South African study to use survey-based techniques to determine the pricing behavior of manufacturing firms.

Govender (2013) found that the median adjustment of prices by firms was once a year, while 32 per cent of firms adjusted prices twice yearly. Over half of firms used current trading conditions to determine prices, while 24 per cent of firms took a view of the near future. Close to 70 per cent of firms used time-dependent instead of state-dependent pricing rules. Also, the most common pricing strategy was a mark-up (mainly a variable percentage but also a fixed percentage) above cost. Finally, in general, manufacturing firms in South Africa follow a barometric price leadership strategy. In this situation some firms have more and better information than others and act as a type of 'barometer' for less informed firms on price changes. Therefore, less informed firms wait for a pricing signal from the more informed firms.

The second approach uses micro-data analyses to understand the extent of price stickiness, and started with Stigler and Kindahl (1970), who collected individual transaction prices for intermediate products used in manufacturing (other notable examples in the early literature include Carlton, 1986; Cecchetti, 1986; and Kashyap, 1995). The datasets used in these studies were generally narrow. More contemporary work on micro-datasets that started looking at large datasets includes Chevalier et al. (2003) on supermarket scanner data and Bils and Klenow (2004) on data collected by the Bureau of Labour Statistics (BLS) for the US consumer price index. It was with this work that the full extent of pricing dynamics could be understood and models of prices tested. Other studies using micro-data include Baharad and Eden (2004); Álvarez et al. (2010); Dias et al. (2007); and Castellet and González (2004).

Work that uses micro-price data in South Africa is limited and includes Creamer and Rankin (2008), Creamer et al. (2012) and Aron et al. (2014). These papers' focus is limited to the behaviour of prices (as in Creamer and Rankin, 2008 and Creamer et al., 2012) and exchange rate passthrough to disaggregated consumer prices (Aron et al., 2014).

Creamer et al. (2012) found that prices change on average every five months, that there is substantial variation in price changes among goods, that price changes tend to be big on average but still a high frequency of small changes occur, that goods prices change more frequently than services prices, that the frequency of price changes increase with inflation, and that studying pricing behaviour at a micro level provides important information for econometricians with which to calibrate models. Aron et al. (2014) exploit the granularity of micro-price data to study the behaviour of individual prices to exchange rate changes.

Once micro-price data studies had provided the underlying pricing dynamics, it became possible to assess models of inflation to determine which actually fit the data and accurately characterise price persistence. There are two types of models of micro-founded pricing behaviour: time-dependent and state-dependent. Time-dependent models rely on firms setting prices every n^{th} period (as in Taylor, 1999) or randomly (as in Calvo, 1983) and treat the determinant of price rigidity as exogenous. State-dependent models are based on firms that face a cost to changing prices and hence only change prices once the change is larger than a 'menu cost' (See for example Sheshinski and Weiss, 1977; Mankiw,

[2] A third approach is studying aggregate price indices to determine the behaviour of prices, including in the early work by Millard and O'Grady (2012) and Means (1935)

1985; and Caplin and Spulber, 1987). The treatment of inflation based on time- or state-dependence leads to different dynamics of prices. For example, from a monetary policy perspective, time-dependent models lead to more persistent impacts of monetary shocks to the real economy. Also, inflation responds more rapidly in menu cost models. Models of inflation also make predictions about whether the extensive (fraction of prices changing) or intensive (size of price changes) margin dominates inflation outcomes when faced with a monetary shock. In Dotsey et al. (1999), the model predicts that the majority of the response comes from a change in the fraction of price changes, while in Golosov and Lucas Jr (2007) it is the size of price changes and the incidence of price increases and decreases.

Bils and Klenow (2004) show that underlying price dynamics are at odds with conventional time-dependent models of price stickiness (as in Calvo, 1983 and Taylor, 1999). The durations of price changes for the majority of the 123 categories of products were significantly more 'volatile and transient' than implied by these models. Also, inflation was less related to the frequency of price changes suggested in these models. Klenow and Kryvtsov (2008) show that most models of inflation could not replicate all the stylised facts discovered using micro-price data. They found similarly that the Taylor and Calvo models do not support empirical facts, including predicting large price changes for older prices, which does not occur. In the state-dependence domain, they found that the Dotsey et al. (1999) model does not produce significantly large price changes and allows the extensive margin too much importance when compared with the empirical data. Similarly, the Golosov and Lucas Jr (2007) model cannot replicate enough small price changes. Álvarez (2008) takes this analysis one step further by surveying the existing literature on micro-price data and then applying these facts to 25 pricing models including sticky information, menu costs, time-dependent, costs of adjustment and customer anger models[3]. He similarly concludes that no model can replicate all the empirical findings from micro-price data.

The variable and often poor performance of pricing models against the empirical data led to a re-formulation of these models in order to address shortcomings (see for example Midrigan, 2011; Nakamura et al., 2010; Gertler and Leahy, 2008; Costain and Nakov, 2011a; Costain and Nakov, 2011b; and Dotsey et al., 2013). Midrigan (2011) focused on two empirical facts that models were unable to replicate – the large number of small price changes and the distribution of prices exhibiting excess kurtosis – formulating a menu-cost model that addressed these findings and therefore better replicated the large-aggregate business cycle fluctuations that were the success of time-dependent models. Costain and Nakov (2011a,b) developed a general model of state-dependent pricing that nests a continuum of models between two extremes: Calvo (1983) and fixed menu-costs. Dotsey et al. (2013) extended their earlier model to include "stochastic variation in productivity at the firm level" to address the outsized importance of the extensive margin.

Our contribution to this literature is as follows. First, we used a previously unavailable dataset of product-level data for the goods component of the CPI and updated the micro-price information provided in Creamer et al. (2012) for 2009 to 2015. Second, we extended the analysis of the frequency of price changes by Creamer et al. (2012), looking at the distribution of frequencies by product over time. Third, we decomposed South African goods inflation into its extensive and intensive margins to provide a more

[3]See table 11 in Álvarez (2008) for a summary of the ability of models to replicate empirical findings.

in-depth analysis of inflation dynamics. This analysis reveals that state-dependent modelling strategies of pricing better replicate pricing dynamics in SA. Fourth, we looked at the role sales have on the price dynamics in the South African economy. The classification of prices as 'regular' or 'sale' only started to become available in the latter part of the dataset used by Creamer et al. (2012) and it was only in 2011 that all observations in the underlying product data were classified.

3 The dataset

The micro-dataset used in this study is based on the underlying product data provided by Statistics South Africa (StatsSA) and used to produce CPI. It covers the period January 2009 to May 2015 and is an extension of the dataset used by Creamer and Rankin (2008), which included data up to December 2007. We started in 2009 to ensure a compatible dataset with no structural breaks. In January 2009, StatsSA introduced a new CPI basket based on the Classification of Individual Consumption by Purpose (COICOP). This included dropping over 600 goods and services that were collected under the old methodology – products dropped included items such as bath salts, guitar, white bread rolls, and snoek (type of fish) – while 72 were added – including CDs and DVDs, sporting tickets, and teddy bears. Our dataset includes only goods and does not provide any information on services. This is different to the dataset used in Creamer and Rankin (2008) and Creamer et al. (2012) because although that dataset comprised predominantly goods products it also included services. There were $5,200,466$ individual price quotes in the period under review. Appendix A provides detail on the categories provided as well as a snapshot of what the dataset looks like.

In order to prepare the dataset for analysis, we include only data with an acceptable status code. This means that prices collected which were indicated as "Wrong item collected", "Item available but not comparable", "Extreme values not verified", "Quality adjustment" and "Available shelf price wrongly collected" were excluded. This left $4,986,454$ individual price quotes, a drop of $214,006$. Despite a robust approach to processing this information at StatsSA, it is possible that due to the size of the dataset mistakes in price collection still exist after this censoring. Generally, in a dataset of this size, extreme outliers – assuming a normally distributed sample – should account for less than 1000 price quotes. To address this problem, we checked the robustness of our results to outliers. We also looked at the role of product substitutions, given the relative importance this can have on price dynamics (see Klenow and Malin, 2010); however, the dataset includes only 30 examples of this, and therefore, it was ignored. Finally, we removed all prices recorded as zero to ensure accurate frequency and magnitude calculations.

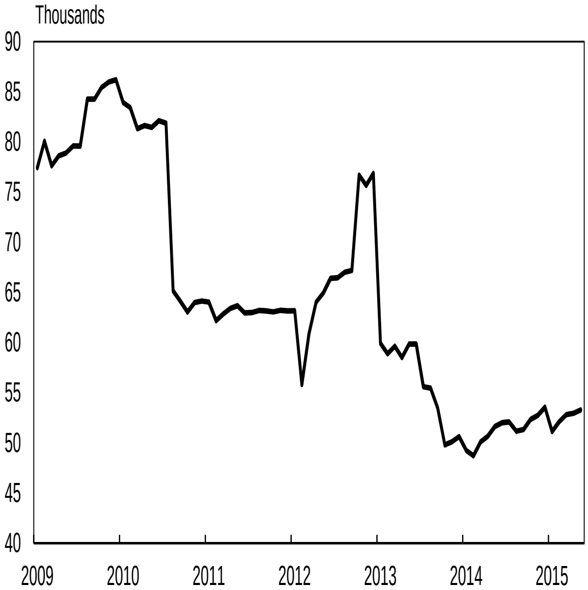
The dataset includes multiple observations of individual products from all over the country, including both rural and urban areas[4]. For example, in the entire dataset, there are over $72,000$ individual price observations for a loaf of brown bread. No single product dominates the dataset, with the maximum contribution of a single product at 1.5 per cent. Products were also collected from $3,497$ outlets nationwide.

[4]Although we compared the results to the goods CPI for all urban areas from StatsSA, we did not feel the need to drop price data from rural areas in this study, as the objective was not to replicate the CPI but to uncover the behaviour of prices in the economy.

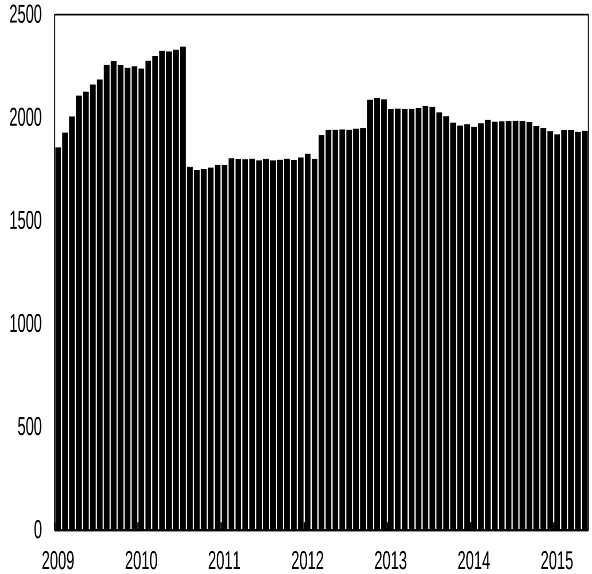
Figure 1 shows the number of individual price records (1a), the number of outlets (1b), the number of products (1c), and the number of product varieties (1d) over time. The number of product varieties distinguishes between product brands, and their type; i.e. one-ply versus two-ply toilet paper. Initially, the number of observations per month was over $75,000$ but this drops over time to around $52,000$ in 2014-15. A significant drop occurs in August 2010. The number of outlets at which prices were collected and available each month varies between $1,745$ and $2,344$. The data sample has on average 415 unique products per month. There is quite a lot of variation in the number of goods included in the dataset over time, initially around 347 in January 2009, before rising to 568 in March 2012, and again declining towards the end of the sample. Each product however has different types and brands with the number of varieties averaging 5836 per month. There is also significant variation is the number of product varieties over months, between $5,136$ and $7,422$.

Figure 1: Basic properties of the data

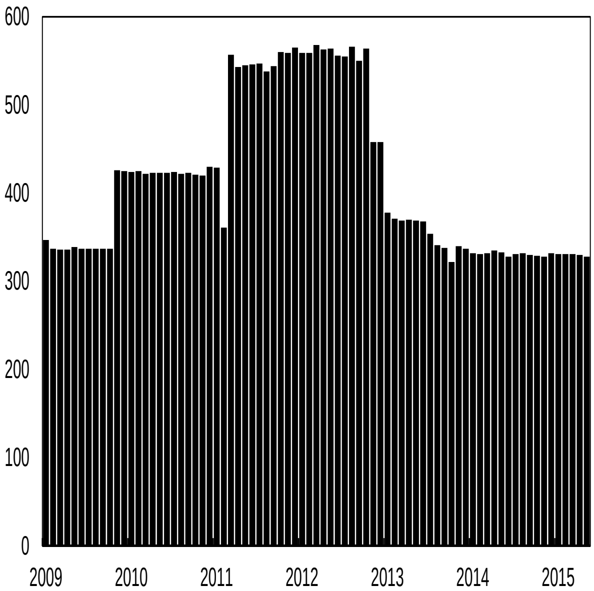
(a) Total observations per month



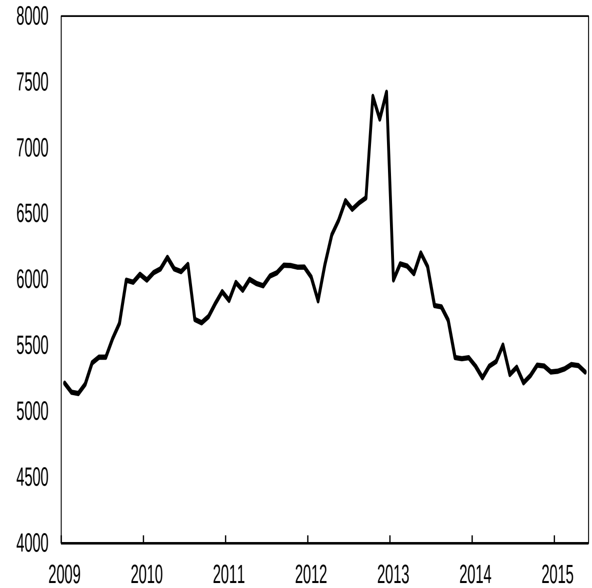
(b) Total outlets per month



(c) Total products per month



(d) Total product varieties per month



4 Properties of price dynamics

In this section we present an update to the frequency and size of price changes in South Africa for the period January 2009 to May 2015. We also extend the analysis of frequency in Creamer et al. (2012) by providing a discussion of the distribution of the frequency of products over time. Creamer et al. (2012) provides initial estimates of the frequency of price changes from 2001 to 2007. The authors show that prices changed once every five months, that the frequency of price changes was heterogeneous, and that price changes were large on average, but that many small price changes also occur [5].

4.1 Size of price changes

We define a price change in this paper as:

$$dp_{j,k,t} = (p_{j,k,t} - p_{j,k,t-1}) \cdot 100 \tag{1}$$

where $p_{j,k,t}$ is the log price of a specific variety of product j at retailer k in time t. A variety of product refers to a unique brand or type of product. For example comparing one- and two-ply toilet paper from a number of different brands at a specific retailer or firm. To ensure that we compared price changes of identical products over time we created a unique identification number for each product, in a specific region, at a specific outlet, for a specific month, and of a specific type.

The price changes $dp_{j,k,t}$ are then aggregated using either the mean or median to the product level i, representing the consumption products collected using the COICOP methodology. Therefore the mean price change at product level i is:

$$dp_{i,t} = \frac{\sum_{j=1}^{J} \sum_{k=1}^{K} dp_{j,k,t}}{J + K} \tag{2}$$

Using the earlier example this would be the aggregation of all varieties of toilet paper as an individual product. Other examples of products in our dataset are loaf of brown bread, beef – rump steak fresh, feta cheese, sport shoes (for women), firewood, cough syrup, and printer.

We also normalised price changes by its mean, $\mu_{dp_{i,t}}$, and standard deviation, $\sigma_{dp_{i,t}}$ such that:

$$z_{i,t} = \frac{dp_{i,t} - \mu_{dp_{i,t}}}{\sigma_{dp_{i,t}}} \tag{3}$$

Figure 2 plots the distribution of $dp_{i,t}$ (2a) and $z_{i,t}$ (2b). It is clear from figure 2a that actual monthly price changes are dominated by no change (0), which accounts for 74.3 per cent of $dp_{i,t}$. Prices that do change are generally large in absolute terms. Of the number of price changes, 11.5 per cent are larger than 5 per cent while 8.7 per cent are smaller than -5 per cent. When comparing these results to Creamer et al. (2012), we see that the sample from 2009 to 2015 is comparable with regard to the number of 0 observations, as well as the number of large positive price changes, those above 5 per cent.

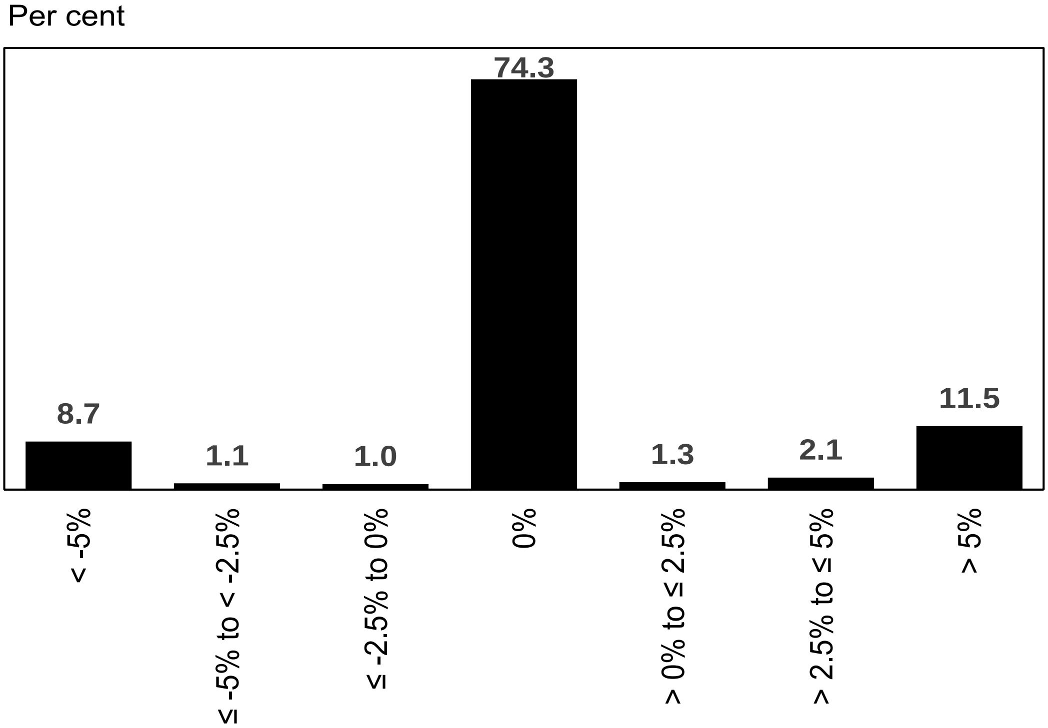
[5] Creamer et al. (2012) highlighted a number of other important properties of prices in SA, including that price changes are not synchronised to the business cycle, and that neither size nor frequency increase in the age of prices, but these are not of interest in this paper.

However, our sample has a substantially higher proportion of negative price changes compared with the 3.89 per cent found in the CPI micro-price data from 2001 to 2007.

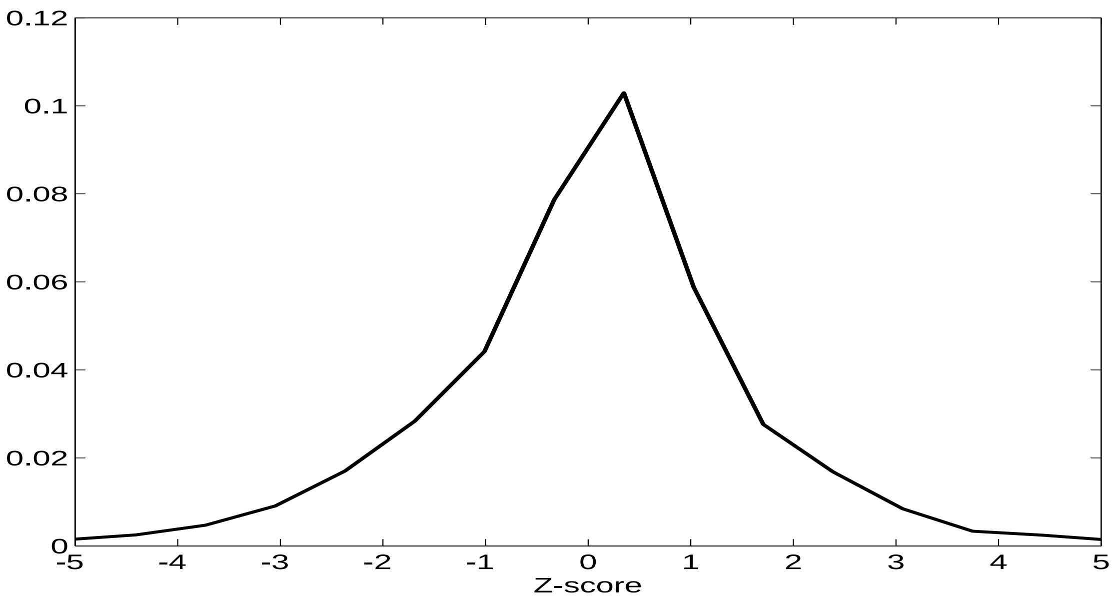
Figure 2b plots an estimated kernel density function of $z_{i,t}$. Of the distribution of $z_{i,t}$, 87.6 per cent is within one standard deviation, 94.8 per cent is within two standard deviations, and 97.8 per cent is within three standard deviations. The standard deviation of $dp_{i,t}$ is equal to 11.4 per cent.

Figure 2: Distribution of price changes

(a) Distribution of dp_{it}



(b) Kernel density estimate of z_{it}



4.2 Frequency of price changes

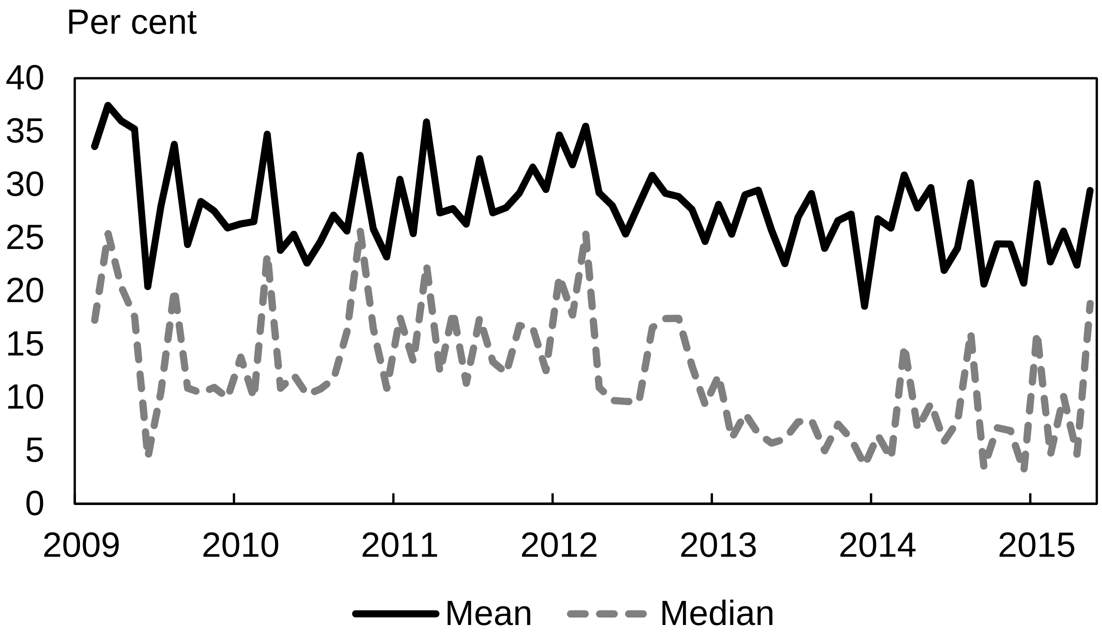
To calculate the frequency of price changes on a monthly basis, we created an indicator variable $I_{i,t}$ that is equal to 1 if there was a price change and 0 otherwise. This is aggregated up to the product level from varieties j and firms k as above. For price increases, $I^{+}_{i,t} = 1$ for $dp_{i,t} > 0$ and 0 otherwise, and similarly for price decreases, $I^{-}_{i,t} = 1$ for $dp_{i,t} < 0$ and 0 otherwise. This was then aggregated to the product level using both the mean and median. We then applied the CPI weights, dynamically, to get weighted frequency changes, i.e. we used the same weights as were used to calculate the overall CPI. Since we did not have full coverage such that the weights added up to 1, we normalised the frequency calculations.

Over the sample period, the weighted mean frequency of price change is 27.8 per cent while the median is significantly lower, at 12.5 per cent. This was calculated at the individual product level. In order to get an approximation of the duration in months between price changes we took the inverse of the frequency measure. This implies that the prices of goods changed on average every 3.6 months, while only every 8.0 months at the median. The approximate estimate of duration requires that all prices have the same expected duration, an assumption that is unlikely to hold given the heterogeneity in price changes. Another method of calculating the average duration involves taking the inverse of the frequency at the product level and aggregating that back to an overall value, as is done in Dhyne et al. (2006). Using this method we calculated that the weighted average duration of price changes is 6.5 months.

The frequency of goods price changes in SA increased in the sample period of 2009 to 2015 compared with the findings of Creamer et al. (2012). They found that on average the frequency of price changes in goods was 17 per cent from 2001 to 2007 compared with 27.8 per cent in our sample. Cross-country comparisons show that SA is now more similar to the US than Europe. In the US there is evidence that the mean frequency of prices changes is diverse but converges in the upper 20s. Bils and Klenow (2004) found an average frequency of 26.1 per cent. Klenow and Kryvtsov (2008) found that for regular prices the frequency is 30 per cent and 36 per cent for posted prices. Finally, Nakamura and Steinsson (2008) found that the frequency of price changes including sales was between 26 and 28 per cent. In Europe, Dhyne et al. (2006) found that over the period 1996 to 2001, prices changes occur 15.1 per cent of the time for all euro area countries, excluding Ireland and Greece. An important cross-country finding in Klenow and Malin (2010) is that prices in Europe tend to change the least frequenctly, followed by the US, and then high inflation developing countries such as Brazil, Mexico and Sierra Leone.

Figure 3 plots the weighted mean and median frequency of price changes per month from 2009 to 2015. The frequency of price changes has a slight downward slope, falling from an average 37.4 per cent in March 2009 to 29.4 per cent in May 2015. The decline in the frequency is more clear when looking at the median, with a significant break occuring in the second half of 2012 and early 2013.

Figure 3: Mean and median frequency of monthly price changes over time



An important distinction worth highlighting is the difference between mean and median frequencies. In SA, we found that the median frequency change was significantly lower than the mean. This implies that the distribution of frequency of price changes are skewed to the left or has a positive skew. When looking at frequency by product over time, we note that skewness averages 1.36. In the US, Bils and Klenow (2004) found that the mean frequency is also higher than the median, but the spread is not as large: 20.9 per cent compared to 26.1 per cent. This empirical fact highlights important heterogeniety in the frequency of price changes by product.

4.3 Heterogeneity in the frequency of price changes

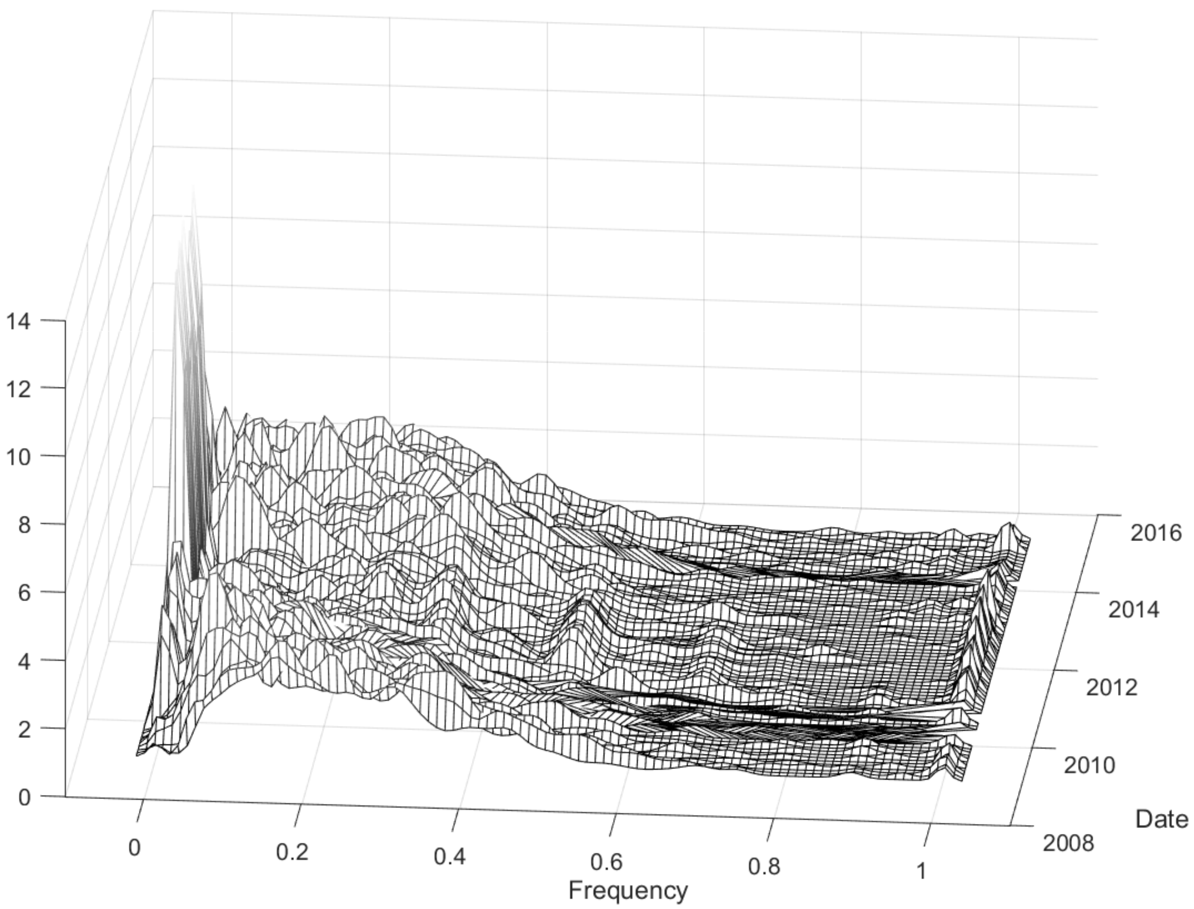
Another way to look at the heterogeniety in the frequency of price changes is to look at the unweighted distribution of this frequency by product over time. Figure 4 provides a 3-D kernel density estimate of the frequency of CPI products from 2009 to 2015[6]. The x-axis is the frequency estimate by products, the y-axis is the date, and the z-axis is the density function.

Figure 4 shows that the underlying distribution of frequencies changes over time and is multi-modal. Generally there is clustering around 0 and 1 with products that do not change and those that always change price in a specific month. There is also clustering around the median, which averages 19 per cent over the sample (this is unweighted). Between March 2011 and May 2012 there was a significant rise in the number of products that do not change price and, similarly, those that do. This means that although the proportion of products at the mode was higher during this period (around 26 per cent compared with

[6]The bandwidth for kernel smoothing was set to 0.05. The estimate was also generated with supports at -0.2 and 1.2 such that the function used the transformation $Log(\frac{x-(-0.2)}{1.2-x})$.

11 per cent for the entire sample), there was also more dispersion in the frequencies of products. There is nothing necessarily significant during that period from a macroeconomic perspective that may shed light on this phenomenon.

Figure 4: Distribution of frequency of monthly price changes by product over time



Three measures can help highlight important heterogeneity over time in the underlying distribution of price changes. First, the distribution is always positively skewed with an average skewness of 1.36. This, however, moves in the range of a moderate positive skew, 0.59, in March 2014, to a maximum value of 2.08 in December 2013. The distributions are also always heavy-tailed, with an average kurtosis of 5.8. Again this varies significantly, from a distribution that is almost normal in December 2013, with a kurtosis of 3.16 (remember this is the same date as the lowest positive skew) and a maximum of 10.2. Finally, the coefficient of variation averages 0.84 over time, with a minimum value of 0.59 and a maximum of 1.15. The coefficient of variation is higher during March 2011 and May 2012, when we observe significantly more 0 and 1 observations.

Further heterogeneity occurs at the category level. Table 1 provides information on the frequency of price changes in aggregate as well as increases and decreases, and the weight coverage, for 23 sub-groups of the CPI. Only goods are included in this analysis, and therefore, categories such as "operation of vehicles" do not include the price of a major or minor service, for example.

The subcategory with the most frequent price changes is "Vehicles" (39.7 per cent) followed by "miscellaneous goods" (39.4 per cent) and, unsurprisingly, "Food" (34.1 per cent). This implies that Vehicle prices changed once every 2.5 months. The categories with the least frequent price changes are "Footwear" (7.0 per cent), "Clothing" (7.4 per cent), and "Hotel and restaurant goods" (9.0 per cent). This implies that the category with the least frequent price changes occur once every 14.4 months. These results are generally consistent with the findings in Creamer et al. (2012), who also found that "Other goods and services", "Food" and "Transport" experienced the most frequent price changes, while "Communication", "Footwear", and "Clothing" experienced the least frequent price changes. The categories are generally the same, but the ordering does differ slightly between periods.

All sub-categories, except three, experienced a higher frequency of price increases versus decreases. The three exceptions are "Furniture and furnishings", "Vehicles" and "Telephone equipment". The incidence of price decreases was highest in "Vehicles" where 25.5 percentage points of the 39.7 per cent price changes were decreases. One explanation for the higher incidence of price decreases in these categories could be sales. However, this is true for "Furniture and furnishings" in which goods were on sale 18 per cent of the time in this dataset. The "Vehicles" and "Telephone equipment" sub-categories did not have any recorded sales items. The high incidence of price changes in "Vehicles" is due to used vehicle prices declining over time. The fraction of used vehicle prices changing was 88 per cent, dominated by price decreases, while new car prices changed 21 per cent of the time, dominated by price increases. "Telephone equipment" was likely to have a higher incidence of price decreases, since this is an area where technological gain has rapidly decreased prices over time. In Creamer et al. (2012) only one category experienced a higher frequency of price decreases, which was "Footwear".

5 What factors explain the frequency of price changes?

What explains frequency over time? We used the determinants of a simple micro-founded mark-up model of prices, as in Campa and Goldberg (2005), and extended it to CPI as in Aron et al. (2014) to build an equation of frequency. The regression model we estimated is:

$$\begin{aligned} fr_t = c + \beta_\pi \sum_{i=1}^{6} \Delta log(cpi_{t-i}) + \beta_{er} \sum_{i=1}^{6} \Delta log(er_{t-i}) + \beta_{ulc} \sum_{i=1}^{6} \Delta log(ulc_{t-i}) \\ + \beta_y \sum_{i=1}^{6} \Delta log(y_{t-i}) + \beta_{\pi^*} \sum_{i=1}^{6} \Delta log(cpi^*_{t-i}) + \gamma X_t \end{aligned} \tag{4}$$

where fr_t is the frequency of price change, cpi_t is an index of seasonally adjusted monthly domestic consumer goods prices multiplied by 100, cpi^*_t is foreign prices proxied by foreign wholesale prices weighted according to export and import weights, er_t is the spot rate of the rand against the US dollar, y_t is domestic demand proxied by the volume of manufacturing production, ulc_t is unit labour cost proxied by an interpolated manufacturing ULC, and X_t are other variables of interest, including the

Table 1: Average weighted frequency of price changes by CPI category

	Frequency of price changes (%)	Frequency of price increases (%)	Frequency of price decreases (%)	2013 CPI weight
Food	34.1	19.9	14.1	12.3
Non-alcoholic beverages	26.1	15.7	10.4	1.2
Alcoholic beverages	18.1	13.1	5.0	4.0
Tobacco	20.3	17.1	3.2	1.5
Clothing	7.4	4.0	3.4	2.8
Footwear	7.0	3.8	3.2	1.3
Maintenance and repair of dwelling	16.7	10.6	6.1	1.0
Other fuels	25.1	15.1	10.0	0.0
Furniture and furnishings, carpets and other	25.8	12.9	13.0	0.5
Household textiles	16.7	8.7	8.0	0.6
Household appliances	25.8	13.8	12.0	0.6
Glasswear, tableware and household utensils	13.9	7.5	6.5	0.1
Tools and equipment for house and garden	17.0	9.8	7.2	0.1
Goods for routine household maintenance	28.2	16.3	11.9	0.5
Medical products, appliances and equipment	20.3	13.4	6.9	0.4
Vehicles	39.7	14.1	25.5	6.0
Operation of vehicles	27.5	17.7	9.9	0.6
Telephone equipment	27.9	8.0	19.8	0.1
Audiovisual and photographic equipment	23.1	9.9	13.2	0.7
Other recreation equipment	17.8	10.8	7.0	0.8
Newspapers, books and stationery	14.9	9.5	5.4	0.0
Hotel and restaurant	9.0	7.1	1.9	2.5
Miscellaneous goods	39.4	21.6	17.8	1.9

number of observations each month and seasonality. Since the factors that explain frequency are unlikely to have strong contemporaneous relationships, we implemented lags of order six. To overcome any problems with degrees of freedom, we followed Aron et al. (2014) and use ‘parsimonious longer lags’ (PLL)[7]. In the equation above, we used $\Delta_3 log(cpi_{t-3})$ and $\Delta_6 log(cpi_{t-6})$ to replace lags from three to six. $\Delta_3 log(cpi_{t-3})$ is the three-monthly change in cpi, lagged three periods.

Table 2 presents the long-run coefficient results of an ordinary least squares (OLS) regression of equation 4 with heteroskedastic and autocorrelation consistent (HAC) standard errors. All coefficients that are significant at a 5 per cent level of significance are in bold. The long-run coefficient values (6-months) and their significance are based on a Wald test for all the variables of interest. The overall adjusted R^2 is 0.7, with an F-statistic of 5.76. The errors are serially uncorrelated, with no evidence of heteroscedasticity according to the Breusch-Pagan-Godfrey test. The errors are also normally distributed according to the Jarque-Bera test.

Table 2: Regression results of frequency: long-run coefficients

	Coefficient	Std. error	t-statistic
$\Delta log(cpi)$	1.44	1.80	0.80
$\Delta log(er)$	**0.65**	**0.20**	**3.26**
$\Delta log(ulc)$	**3.65**	**1.31**	**2.79**
$\Delta log(cpi^*)$	**4.00**	**1.24**	**3.22**
$\Delta log(y)$	**-1.40**	**0.71**	**-1.98**
Adjusted R^2	0.70		
F-statistic	5.76		
DW-stat	2.37		
JB-stat	0.61		

The regression results show that the exchange rate, unit labour cost, foreign inflation and demand all have a significant relationship with frequency, at a 5 per cent level of significance. The significance of these variables suggests that both domestic and imported pricing pressures increase the frequency of price changes. On the domestic side, a 1 per cent increase in the exchange rate leads to a 0.65 per cent increase in frequency. A 1 per cent increase in domestic unit labour costs increases the extensive margin by 3.65 per cent. On the foreign side, a 1 per cent increase in foreign inflation increases the extensive margin by 4.0 per cent. Domestic demand is also significant but has the opposite sign to what is expected, suggesting an increase in production lowers the frequency of price changes.

There is some evidence of seasonality in price changes, with January, February, March, April, May, August, September, October and November all being significant at a 5 per cent level of significance. January and March are by far the most significant seasonal dummies, with the highest t-statistic values. January is likely to be a month during which most firms following a time-dependent pricing strategy

[7] See the online Appendix 3 from Aron et al. (2014) for more information.

would consider changing prices. March is likely significant from a frequency perspective, since taxes for certain items, especially alcoholic beverages and tobacco, rise during this month. The results are not affected by the number of observations since it is not a significant predictor of frequency.

6 Decomposing inflation

6.1 The intensive and extensive margins

Having the underlying price data used to construct CPI inflation allowed us to decompose inflation into an extensive margin (EM), or the fraction of items that change price in a particular month, and an intensive margin (IM), or the average magnitude of price changes, as in Klenow and Kryvtsov (2008). The advantage of this decomposition is threefold. First, this allows us to determine whether inflation is driven by the actual average size of changes or how often prices change. Second, and related to the first, is the ability to determine what drives the variance in inflation. Third, inflation is the outcome of many different price increases and decreases as well as changing and unchanging prices all occuring in a particular month. This decomposition can aid in understanding these dynamics over time and enriching the picture we have of aggregate consumer goods inflation.

Inflation can be decomposed into IM ($dp_{i,t}$) and EM ($fr_{i,t}$) such that:

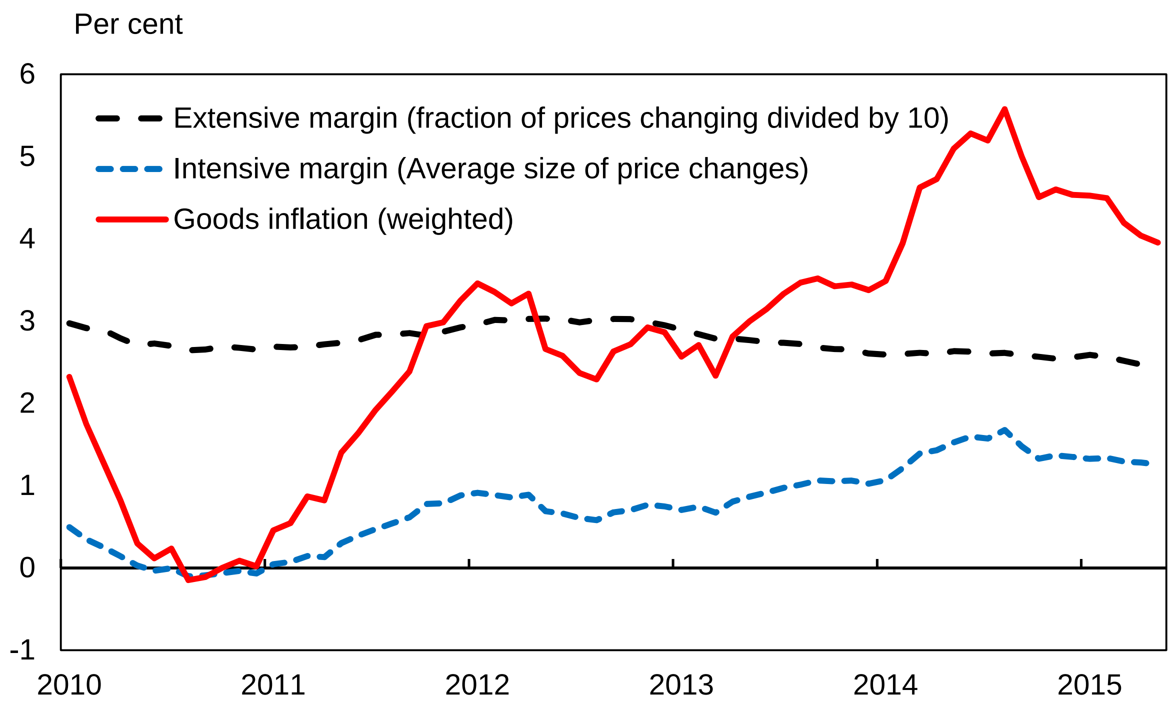
$$\begin{aligned}
\pi_t &= \sum_{i=1}^{n} \omega_{i,t}(p_{i,t} - p_{i,t-1}) \\
&= fr_t \cdot dp_t \\
&= \sum_{i=1}^{n}\sum_{t=1}^{T} \omega_{i,t} I_{i,t} \cdot \frac{\sum_{i=1}^{n}\sum_{t=1}^{T} \omega_{i,t}(p_{i,t} - p_{i,t-1})}{\sum_{i=1}^{n}\sum_{t=1}^{T} \omega_{i,t} I_{i,t}},
\end{aligned} \tag{5}$$

where $p_{i,t}$ is the log price of product i at time t, π_t is monthly inflation, $I_{i,t}$ is an indicator that is equal to 1 if there was a price change and 0 otherwise, and $\omega_{i,t}$ is the CPI weights. In this dataset there are up to 568 individual products ($n = 568$). Equation 5 decomposes inflation into the fraction of items changing price in month t, $fr_t = \sum_{i=1}^{n}\sum_{t=1}^{T} \omega_{i,t} I_{i,t}$, and the weighted average magnitude of price changes, $dp_t = \frac{\sum_{i=1}^{n}\sum_{t=1}^{T} \omega_{i,t}(p_{i,t} - p_{i,t-1})}{\sum_{i=1}^{n}\sum_{t=1}^{T} \omega_{i,t} I_{i,t}}$.

Table 3 reports the results for the components of inflation, showing the mean and standard deviation for each component, as well as their correlation to inflation, and the results of a regression analysis. We regressed each component successively on monthly inflation and report the coefficient value, its significance and the R^2. The standard errors are HAC.

Figure 5 replicates Figure 9 in Klenow and Kryvtsov (2008) and shows the 12-month moving average for the extensive margin (fr_t), scaled for ease of reference, the intensive margin (dp_t) as well as the annual inflation rate weighted using CPI weights provided by StatsSA. Monthly goods inflation over the sample period from February 2009 to May 2015 averages 0.25 per cent (or 3.0 per cent on an annual basis) with a standard deviation of 0.32 per cent (see Table 3). This is due to an average 27.8 per cent fraction of prices changing every month (EM), and a 0.83 per cent average monthly increase in prices (IM). The fraction of prices changing (fr_t) varies between 18 and 37 per cent. The correlation between fr_t and inflation is 0.53. Regressing fr_t on inflation shows that a 1 per cent increase in the frequency of price changes increases the monthly inflation rate by 0.04 per cent, with an R^2 of 0.28. The coefficient of variation of fr_t is 0.14. Average monthly increases in prices (dp_t) is a significantly more important driver of inflation. Regressing dp_t on inflation indicates that a 1 per cent increase in the extensive margin increases inflation by 0.29 per cent and explains 97 per cent of the variation in inflation according to the R^2. Over the sample period, it was twice as likely for the fr_t to change by 1 per cent (85.5 per cent of the time) as it was for dp_t to change by 1 per cent. Also, dp_t was much more strongly correlated with inflation at 0.98. Over the period under study monthly inflation increased by as much as 3.2 per cent and declined by a maximum of -1.3 per cent. The coefficient of variation is significantly larger for dp_t, at 1.3.

Figure 5: Intensive and extensive margins



6.2 Price increases and decreases

A fraction of prices are changing, and aggregate prices are rising each month on average, but this is due to an interplay of goods price increases and decreases. An important finding in the literature on pricing behaviour is that a distinction between price increases and decreases matters for the dynamics of inflation. Nakamura and Steinsson (2008) show that inflation outcomes are driven by price increases (pos_t) and not decreases (neg_t). This is contradicted in Klenow and Kryvtsov (2008), who found that not only do price decreases matter but they tend to explain $40-50$ per cent of inflation variance. Gagnon (2009) takes this analysis further, by showing that price decreases, rather than the magnitude of price increases was a key driver of dynamics between high- and low-inflation environments, based on Mexican micro-price data.

In order to determine the contribution of price decreases and increases, we decomposed inflation further into the frequency of price increases and decreases, combined with the size of those increases and decreases. Hence, inflation in equation 5 can also be represented as:

$$\begin{aligned}\pi_t &= fr_t^+ \cdot dp_t^+ + fr_t^- \cdot dp_t^- \\ &= pos_t + neg_t,\end{aligned} \tag{6}$$

This is based on the decomposition of fr_t into those prices that are increasing and decreasing:

$$fr_t = fr_t^+ + fr_t^- = \sum_{i=1}^{n}\sum_{t=1}^{T} \omega_{i,t} I_{i,t}^+ + \sum_{i=1}^{n}\sum_{t=1}^{T} \omega_{i,t} I_{i,t}^- \tag{7}$$

where $I_{i,t}^+ = 1$ if $p_{i,t} > p_{i,t-1}$ and $I_{i,t}^- = 1$ if $p_{i,t} < p_{it-1}$, else it is equal to 0. A similar decomposition for dp_t can be calculated where $dp_t^+ = \frac{\sum_{i=1}^{n}\sum_{t=1}^{T}\omega_{i,t}I_{i,t}^+(p_{i,t}-p_{i,t-1})}{\sum_{i=1}^{n}\sum_{t=1}^{T}\omega_{i,t}I_{i,t}^+}$. Finally, we can define the positive part of inflation as $pos_t = fr_t^+ \cdot dp_t^+$ and the negative component as $neg_t = fr_t^- \cdot dp_t^-$.

Table 3 shows the contribution of the decomposition of the intensive and extensive margins into its positive and negative components. Both price increases and decreases occur each month, but price decreases are less frequent than price increases. Over the sample, 14.8 per cent of price changes were due to price increases (fr_t^+) compared with 12.9 per cent due to price decreases. The standard deviation of the frequency of price increases is also larger at 3.8 per cent compared with 2.9 for price decreases. As expected, price increases are also more strongly correlated with inflation at 0.8, while price decreases are weakly and negatively correlated at -0.3. The opposite signs of correlation between price increases and decreases lower the overall correlation of fr_t to inflation. The regression results support the relative importance of the frequency of price increases to decreases, with a 1 per cent increase in $fr_t^+ (fr_t^-)$, leading a 0.069 per cent increase (-0.037 per cent decrease) in monthly inflation. The R^2 for frequency of price increases is also 0.64 compared with 0.1 for the frequency of price decreases.

Table 3: Decomposing inflation into intensive and extensive margin

Variable	Mean, %	Standard deviation, %	Correlation with π_t	Regression on π_t Coefficient	S.E	R^2
π_t	0.25	0.32				
fr_t	27.8	4.01	0.53	0.043	0.006	0.28
dp_t	0.83	1.12	0.98	0.285	0.009	0.97
fr_t^+	14.81	3.77	0.81	0.069	0.004	0.64
fr_t^-	12.89	2.85	-0.32	-0.037	0.014	0.1
dp_t^+	4.18	0.98	0.75	0.248	0.022	0.56
dp_t^-	-2.98	0.75	0.65	0.284	0.043	0.43
pos_t	0.63	0.25	0.95	1.223	0.061	0.9
neg_t	-0.38	0.12	0.73	2.031	0.167	0.54

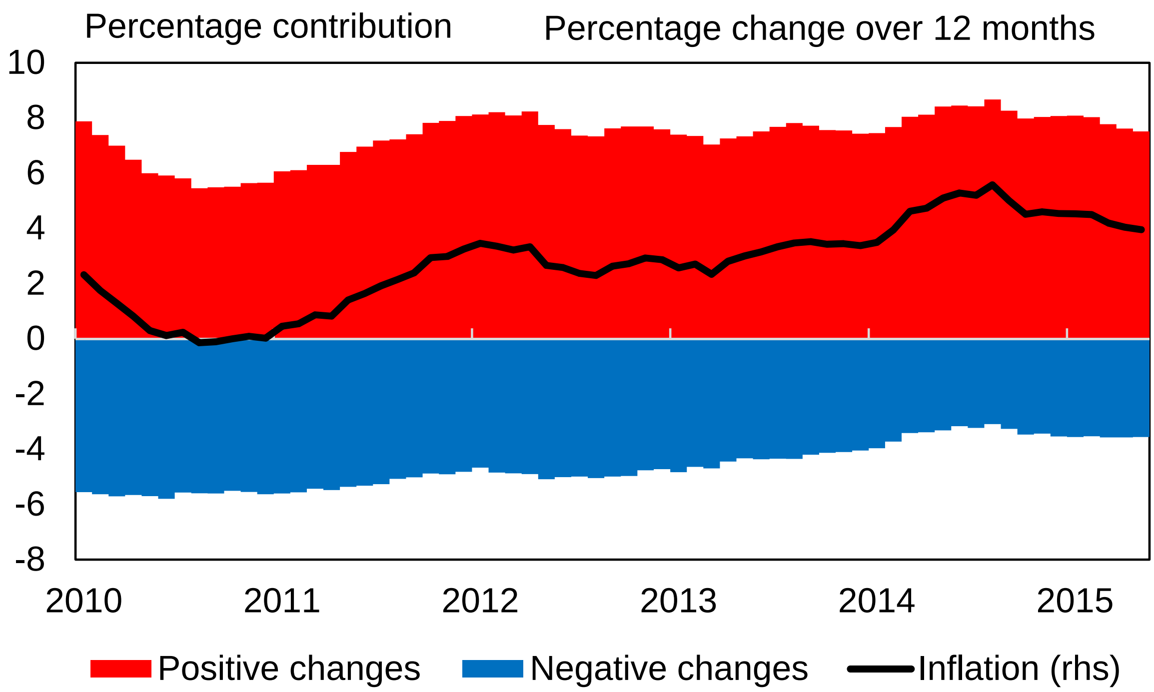
The frequency of price changes has increased in SA compared with the results found in Creamer et al. (2012) for the period 2001 to 2007, but price increases remain more prevalent than decreases. They found that for goods, the mean frequency of price increases was 10.8 per cent and for price decreases 6.1 per cent. Our results are similar to what Klenow and Kryvtsov (2008) found for the US. Over the period 1988 to 2004, the mean frequency of price increases was 15 per cent compared with 11.5 per cent for decreases.

Moving to the intensive margin, the average magnitude of price increases was 4.2 per cent, and price decreases -3.0 per cent. dp_t^+ is more correlated with inflation than dp_t^-, and similarly more volatile. dp_t^+ and dp_t^- are also less correlated to monthly inflation than dp_t. Regression results suggest that a 1 per cent increase in dp_t^+ (dp_t^-) increases inflation by about 0.25 (0.28) per cent, with dp_t^+ having a higher R^2 at 0.56 compared with 0.43.

An analysis of pos_t and neg_t supports the finding that price increases mattered more than price decreases to the dynamics of inflation during this period. Figure 6 plots the marginal impact of pos_t and neg_t to inflation on an annual basis from 2010 to 2015. The graph indicates that there were both large increases and decreases that combined to form aggregate inflation movements. Over this period, as inflation rose, the magnitude of price increases rose and the magnitude of price decreases fell. According to Table 3, pos_t is significantly more strongly correlated to inflation at 0.95 compared with neg_t at 0.73. The impact, however, of a 1 per cent rise in pos_t tends to be smaller, leading to a 1.2 per cent increase in monthly inflation compared with a 2.0 per cent increase due to neg_t. Pos_t nevertheless explains more of the variation in inflation according to the R^2.

The decomposition above of inflation into its intensive and extensive margins provides information on the level of inflation but does not explain its variation. The drivers of the variation in inflation are vital to determining which models of micro-founded pricing behaviour best replicate the properties of price dynamics in SA – time-dependent or state-dependent models.

Figure 6: Annual inflation decomposed into price increases and price decreases



6.3 Decomposing the variation in inflation

In this section we look at the importance of IM and EM as drivers of the variance of inflation. In order to do this we followed Klenow and Kryvtsov (2008) and used a first-order Taylor expansion of $\pi_t = fr_t \cdot dp_t$ around the sample means $\overline{fr}$ and $\overline{dp}$ such that:

$$var(\pi_t) = var(dp_t) \cdot \overline{fr}^2 + var(fr_t) \cdot \overline{dp}^2 + 2 \cdot \overline{fr} \cdot \overline{dp} \cdot cov(fr_t, dp_t) + O_t \tag{8}$$

The higher-order terms are expressed as O_t and are functions of fr_t. The advantage of this variance decomposition is that it allows us to determine whether inflation is driven by the intensive margin (IM term $= var(dp_t) \cdot \overline{fr}^2$), and hence inflation is time-dependent, or the extensive margin (EM term $=$ $var(fr_t) \cdot \overline{dp}^2 + 2 \cdot \overline{fr} \cdot \overline{dp} \cdot cov(fr_t, dp_t) + O_t$), and state-dependent. Over the full sample available, the intensive margin accounts for only 26.5 per cent of the variance in monthly inflation, while 73.5 per cent is due to the extensive margin. When we exclude sales from the sample, the intensive margin accounts for only 21.9 per cent of the variation in inflation. The importance of the extensive margin in explaining inflation variance in SA suggests that prices are state-dependent. This contrasts with the survey results of Govender (2013) who found that 70 per cent of manufacturing firms in SA use time-dependent pricing strategies (of course this was only for manufacturing firms, whereas our sample covers many firms including wholesalers and retailers).

These results also contrast with the results of Klenow and Kryvtsov (2008) who found that the intensive margin explains the majority of inflation variance, between 86 and 113 per cent for different samples, for the United States between 1988 and 2004. Gagnon (2009) found that in Mexico from 1994 to 2004, the extensive margin (or frequency of price changes) explains the majority, close to 60 per cent, of the variance of inflation. This is particularly acute during periods of high inflation, in the specific case of rates above 10-15 per cent, the extensive margin explains over 60 per cent of the variation in inflation. This suggests that countries that have higher inflation rates would tend to be better described by state-dependent models of price rigidities.

How much do price decreases and increases contribute to the variance of inflation? In order to calculate this, we decomposed the variance of inflation such that:

$$var(\pi_t) = var(pos_t) - cov(pos_t, neg_t) + var(neg_t) - cov(pos_t, neg_t) \tag{9}$$

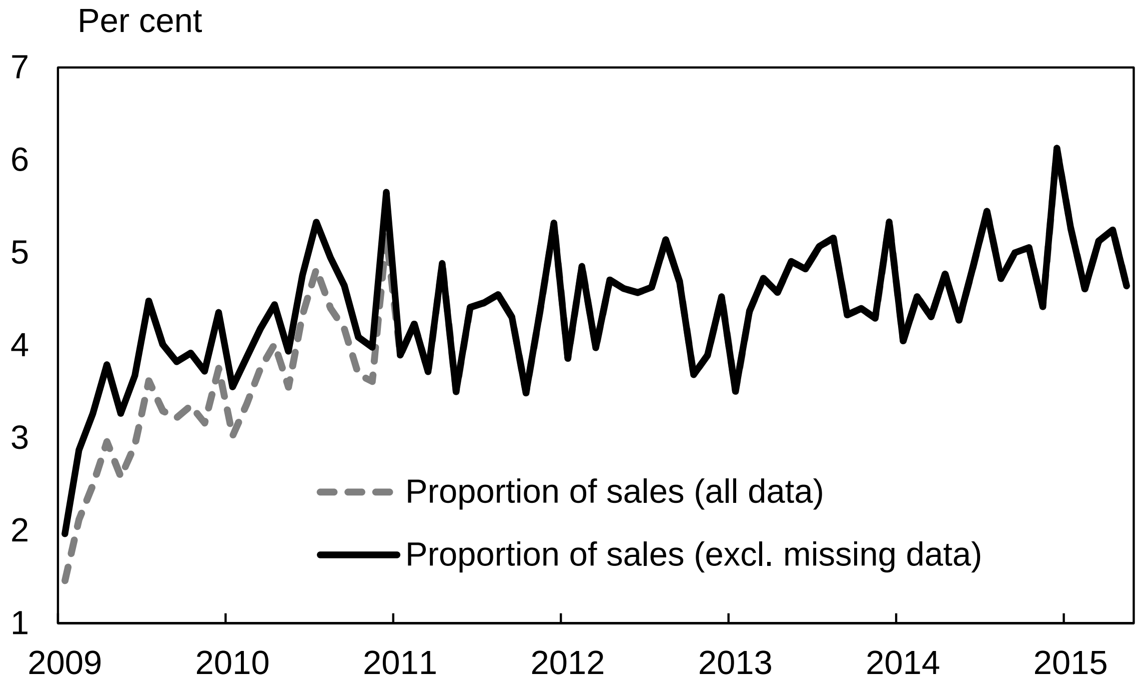
where the contribution of positive price changes is $var(pos_t) - cov(pos_t, neg_t)$ and negative price changes is $var(neg_t) - cov(pos_t, neg_t)$. According to this decomposition, the majority of the variance of inflation is explained by positive price movements. Of the variance in overall inflation, pos_t explains 69.7 per cent of it, while neg_t explains 30.3 per cent. This result is confirmed by the regression analysis in Table 3, where pos_t has an R^2 of 0.95 compared with neg_t of 0.54. When we exclude sales items from the analysis, the results tend to increase the importance of price increases, with pos_t explaining 75.4 per cent of the inflation variance.

7 How important are sales in pricing conduct and flexibility?

A question that remains unanswered in South Africa is the role of sales in pricing conduct and flexibility. This question was impossible to answer from a consumer prices perspective prior to 2006, as the statistical authorities did not provide information on whether an item was on sale or not. From March 2006 onwards, this information is available, but the dataset does suffer from missing data values, making it difficult to determine whether products were indeed on sale. For example, in 2008, of the $1,248,255$ individual observations, $410,741$ observations or 32.9 per cent did not indicate whether a product was on sale or not. This gradually improved to 18.6 per cent for 2009 and 10 per cent for 2010. By 2011 all observations indicated whether or not a product was on sale. Creamer et al. (2012) do provide some evidence for the role of sales in price frequency changes, highlighting that since sales information started being provided, the frequency of price changes has risen. The causal link to sales remains elusive given the short sample period available. This section looks at the role of sales in pricing conduct. It is important to note that sales usually last for a much shorter period than a month, the period of time we have between observations. This discrepancy means that we are likely to understate the true frequency of price changes.

Figure 7 plots the proportion of items classified as sales in the dataset. There are two lines: the proportion including all data where a large subset of items is not classified, and the proportion that include only data points that are classified either 'sale' or 'regular'. The total number of items that are classified under 'sales' according to the 'Price type' code averages between 4.2 and 4.4 per cent from January 2009 to May 2015, depending on the treatment of unclassified items. However, the actual proportion of items on sale has increased gradually over time. In January 2009, the proportion of items on sale was 2 (1.5) per cent based on only those items classified (the entire dataset), rising gradually to 4.4 (4) per cent in 2010, before peaking at 6.1 per cent in December 2014.

Figure 7: Proportion of sales



The proportion of sales is low compared with Klenow and Kryvtsov (2008) who showed that about 11 per cent of prices in the US BLS data for the CPI was for items on sale. In Norway, Wulfsberg and Ballangrud (2009) showed that sales account for only three per cent of observations in the Norwegian CPI. Dhyne et al. (2006) do not report the incidence of sales, but showed that frequency results were not that sensitive to these changes. These findings are of course not directly comparable, as they include both goods and services, whereas we have only goods data. However, analysis shows that goods, especially food, dominate sales items. Including services is likely to lead to a downward shift in the proportion of sales, suggesting that these numbers would be higher if they excluded services. It is also important to highlight the challenge in doing cross-country comparisons. Statistical agencies' modus operandi differ by country in the reporting of sales[8].

Table 4 shows the impact of sales on the frequency of aggregate price changes, price increases and price decreases in the columns labelled 'Freq'. Next to these in columns labelled 'Change' is the

[8]One way research has resolved this is to introduce filters. Nakamura and Steinsson (2008) use a V-shaped sales indicator to identify products on sale.

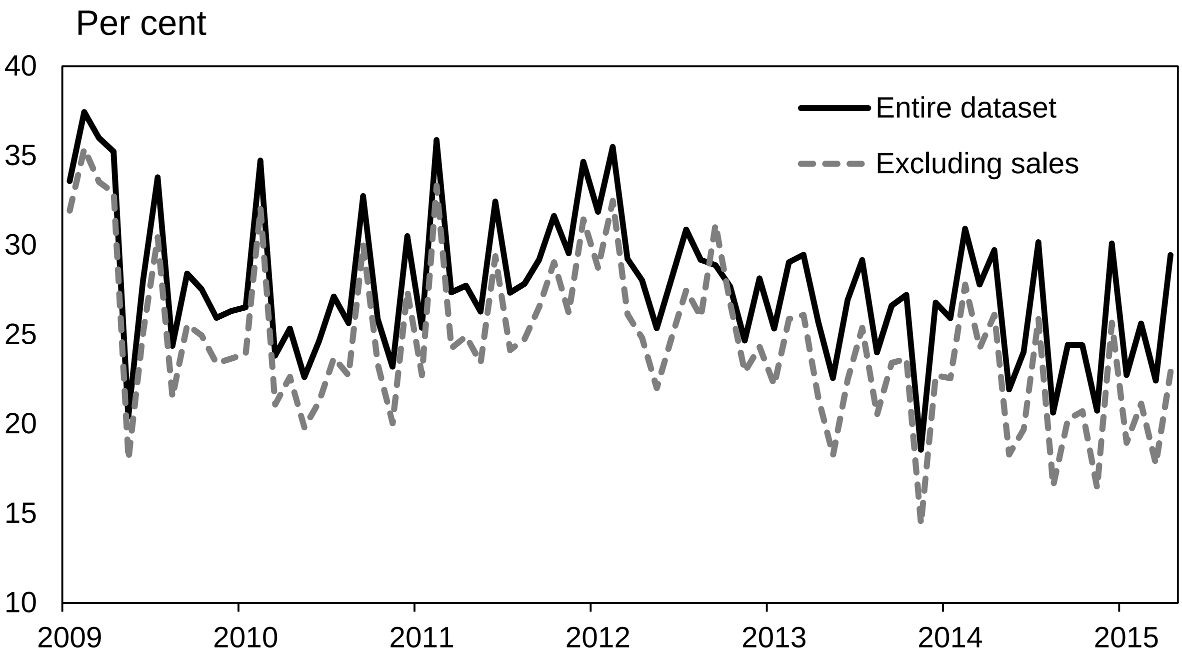
difference between the frequency including and excluding sales, i.e. a positive number indicates a drop in the frequency. The last two columns show the proportion of sales to total sales and the proportion of sales within each category.

The distribution of sales among commodities is dominated by 'food goods' (second last column in Table 4), which account for 47.4 per cent of all classified sales in the dataset. Despite this dominance, excluding sales does not decrease the frequency of price changes, nor increase the magnitude of price changes, mostly in the food category. The next categories with the most number of sales in order are "Furniture and furnishings" (8.3 per cent), "Miscellaneous goods" (7.5 per cent), "Household appliances" (6.3 per cent), "Audiovisual and photographic equipment" (5.5 per cent), and "Non-alcoholic beverages" (4.3 per cent).

Next we look at the proportion of sales within each CPI category. "Furniture and furnishings" has the highest rate of sales, with goods on sale 18 per cent of the time. This category is also most affected by sales, with the frequency of price changes dropping by 11.5 percentage points, to 14.4 per cent, of which 7 percentage points are due to price decreases. The next few categories also experiencing higher proportions of within-category sales are "Household appliance" (11.9 per cent), "Audiovisual and photographic equipment" (9.6 per cent), "Household textiles" (7.1 per cent), "Goods for routine household maintenance" (5.7 per cent), and "Miscellaneous goods" (5.1 per cent). Categories that have little to no sales items include "Vehicles" (0 per cent), "Telephone equipment" (0 per cent), "Tobacco" (0.2 per cent), and "Hotel and restaurant goods" (0.2 per cent).

Sales impact on the frequency of price changes. In the full sample, the frequency of price changes is 27.8 per cent but declines to 24.5 per cent when sales are excluded. The implied duration of price changes therefore rises from 3.6 months to 4.1 months when excluding sales. The median frequency drops from 12.5 to 10.6 per cent. Using an alternative method to calculate the average duration by taking the inverse of the frequency at the product level and aggregating that back to an overall value as in Dhyne et al. (2006), yields an average duration of 7.9 months, compared with 6.5 months when including sales products. The impact of sales on frequency is low compared with US data, where Nakamura and Steinsson (2008) found that excluding sales decreases the frequency of price changes by roughly half. Figure 8 shows the evolution of frequencies over time with sales included and excluded.

Figure 8: Weighted average frequency of price changes: impact of sales



The conventional way of thinking about the impact of monetary policy is through using models where the frequency of price changes plays a central role, such as in Calvo (1983). If prices are relatively inflexible, then a monetary policy shock has large real effects, and if these prices are flexible, then the real effects of a monetary policy shock are small. Creamer et al. (2012) have already showed that the microdata contradicts the Calvo assumption of price changes and that the frequency of price changes occur more often than what was estimated in models of monetary policy, such as in Steinbach et al. (2009). As a consequence, they found that monetary policy should be more aggressive but less persistent.

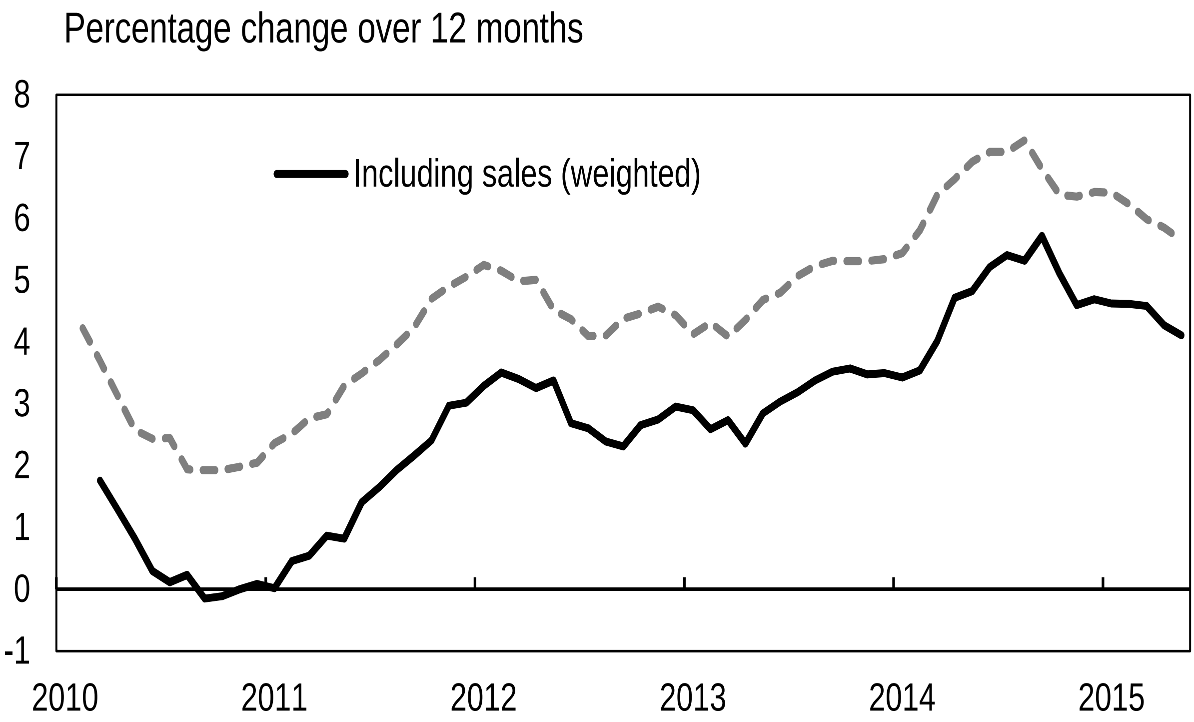
The incidence and impact of sales on the frequency of price changes may also have important monetary policy implications. Kehoe and Midrigan (2008) show that the treatment of temporary versus permanent price changes can make a big difference to whether prices are considered flexible or inflexible and modelling choices about this. Our contribution is to show that in SA the role of sales, which are temporary price changes, does not substantially change the frequency of price changes in the aggregate. This means that more simple menu-cost models, which do not include an extension, as in Kehoe and Midrigan (2008), can more adequately replicate the properties of pricing conduct in SA compared with countries where sales have a larger impact. We also found that the frequency of price changes among goods has risen compared with the findings in Creamer and Rankin (2008), suggesting that prices may be even more flexible from a modelling perspective. Two issues complicate this analysis. First, services have become more important in the overall CPI basket over time, with a weighting of 50.14 per cent currently compared with 45.8 per cent in 2011. Second, the proportion of sales has been increasing over time (only gradually) but if this continues, the role of temporary price changes may need to be reassessed.

Table 4: Average weighted frequency of price changes by CPI category excluding sales

	Frequency of price changes (%)		Frequency of price increases (%)		Frequency of price decreases (%)		Proportion of sales to total (%)	Proportion of sales in each category (%)
	Freq	Change	Freq	Change	Freq	Change		
Food	29.3	4.8	18.1	1.9	11.2	2.9	47.4	4.6
Non-alcoholic beverages	20.2	5.8	13.2	2.4	7.0	3.4	4.3	4.6
Alcoholic beverages	16.2	1.8	12.4	0.7	3.9	1.1	2.2	2.0
Tobacco	20.1	0.2	17.0	0.0	3.0	0.1	0.1	0.2
Clothing	5.6	1.8	4.0	0.0	1.6	1.8	3.0	1.3
Footwear	5.4	1.6	3.8	0.0	1.6	1.6	1.4	1.4
Maintenance and repair of dwelling	15.4	1.3	10.1	0.4	5.3	0.8	1.0	1.5
Other fuels	24.7	0.4	15.1	0.1	9.7	0.3	0.1	0.6
Furniture and furnishings, carpets and other	14.4	11.5	8.4	4.5	6.0	7.0	8.3	18.0
Household textiles	10.4	6.4	6.2	2.5	4.1	3.9	3.0	7.3
Household appliances	15.9	9.9	9.8	4.0	6.1	5.8	6.3	11.9
Glasswear, tableware and household utensils	10.2	3.7	6.1	1.4	4.1	2.3	1.2	3.0
Tools and equipment for house and garden	13.9	3.2	8.7	1.1	5.2	2.0	0.6	2.6
Goods for routine household maintenance	21.5	6.6	13.5	2.8	8.0	3.9	2.7	5.7
Medical products, appliances and equipment	16.4	3.9	11.8	1.7	4.6	2.3	1.3	2.6
Vehicles	39.6	0.0	14.1	0.0	25.5	0.0	0.0	0.0
Operation of vehicles	26.2	1.4	17.2	0.5	9.0	0.9	0.7	1.9
Telephone equipment	25.3	2.5	7.4	0.6	17.9	1.9	0.8	0.0
Audiovisual and photographic equipment	16.0	7.1	7.4	2.6	8.7	4.5	5.5	9.6
Other recreation equipment	14.4	3.4	9.5	1.3	4.9	2.1	2.3	2.9
Newspapers, books and stationery	12.9	2.0	8.6	0.9	4.3	1.1	0.3	1.9
Hotel and restaurant	8.8	0.2	7.0	0.1	1.8	0.1	0.1	0.2
Miscellaneous goods	33.3	6.0	19.1	2.4	14.2	3.6	7.5	5.1

Despite the small proportion of sales in the overall dataset, its impact on the level of inflation seems outsized. Figure 9 plots annual inflation weighted using dynamic expenditure weights from StatsSA. It is clear that there is a significant divergence between inflation that does and does not account for the role of sales. Monthly inflation including sales data averages 0.25 per cent compared with 0.4 per cent excluding sales. On an annualised basis, the average difference is 1.8 percentage points from 3.0 to 4.8 per cent.

Figure 9: Goods inflation including and excluding sales



Sales also impact on the decomposition of inflation variance. Excluding sales tends to predictably magnify the role of price increases, raising their importance to 75.4 per cent compared with 69.7 per cent in the entire dataset. Similarly, excluding sales lowers the variance of the intensive margin more than that of the extensive margin, increasing the variation explained by the extensive margin to 78.1 per cent compared with 73.5 per cent.

8 Sensitivity to outliers

Outliers can occur due to very large price changes or due to mistakes in the dataset. This section looks at the possible impact of outliers on the main results of this paper. Caution is needed in this section, as the price data is complicated by two regularities that are defining characteristics. First, there are sales that can substantially change the price of an item. Second, the distribution of price changes has excess kurtosis, which we wish to maintain as a property.

We define outliers as any price change that is greater than four standard deviations away from the mean[9]. This equates to $43,676$ observations or 0.88 per cent of the sample. Removing outliers had a small impact on the extensive margin, decreasing the average frequency of price changes by only 0.5 percentage points, to 27.2 per cent. It similarly did not significantly change the incidence of price increases or decreases, taking away an equal amount from the frequency of both. The exclusion of outliers did have a variable impact on the categories of CPI, with the largest impact being on "Miscellaneous goods", where the frequency of price changes declined by 4.1 percentage points to 35.3 per cent. The next most affected category was "Furniture and furnishings" with a decline of 1.3 percentage points; thereafter all categories change by less than 1 percentage point. The categories least affected were "Vehicles" (0 per cent change), "Alcoholic beverages" (-0.1 per cent change), and "Tobacco" (-0.1 per cent change).

Removing outliers also had a small effect on the intensive margin. The average price change (dp_t) was 0.1 percentage points higher, at 0.92 per cent, with both increases and decreases being moderated to leave the aggregate change small. The average price increase was 3.8 per cent, compared with 4.2 per cent, while the average price decrease was -2.4 per cent compared with -3.

Moving to the variance of inflation, excluding outliers increased the variation explained by the extensive margin slightly more to 74.2 per cent compared with 73.5 per cent while the variation explained by price increases rose to 70.8 per cent, less than 1 percentage point higher.

9 Policy implications

This paper has a number of policy implications. First, and most prominently, goods inflation in SA is best represented by state-dependent pricing models, rather than time-dependent models. Generally This means that models used in a policy setting, such as Steinbach et al. (2009), that are based on time-dependent pricing rules, may not accurately capture the type of pricing dynamics in South African consumer prices. With the micro-price-level data, we are now able to choose and calibrate models of pricing behaviour that align to these micro-price outcomes. This is left to future research. Second, the prominence of time-dependent models suggest that even if these models may not capture all the price dynamics occurring at the micro-level, they can still be calibrated based on this micro-price data. This is done in Creamer et al. (2012) for example. However, an important outcome in this paper is that the frequency of price changes is not constant over time. Therefore the parameter calibration in Creamer et al. (2012) is no longer appropriate as the frequency of price changes has risen. In practice, models can be calibrated more frequently based on the results of the micro-price data of the time. Third, sales can have important impacts on the flexibility of prices in an economy. Hence, the modeling choices surrounding the inclusion of sales can lead to significantly different outcomes for pricing behaviour. We have shown, however, that sales do not have a large impact on the frequency of price changes in the South African context. Fourth, uncovering the granularity of pricing behaviour at a micro-price-level widens the SARBs understanding of pricing dynamics and hence its ability to implement policy in

[9]Results for this section are available on request.

future. Finally, the results of this paper show that prices are sticky or downwardly rigid.

10 Conclusion

The underlying dynamics of prices matter for how we choose to model inflation, think about price stickiness, contextualise inflation outcomes, and conduct monetary policy. To these ends this paper provides a decomposition of inflation into its extensive and intensive margins. We show that the extensive margin in South Africa from 2009 to 2015 averaged 27.8 (median is 12.5) per cent, but this can vary anywhere between 37 (25.6) and 18 (3.1) per cent in any particular month. The magnitude of price changes, or the intensive margin, in a particular month averages 0.83 per cent. Multiplying the extensive and intensive margins meant that monthly inflation averaged 0.25 per cent, or 3.0 per cent annualised. The variance of monthly inflation is explained mainly by the extensive margin, or the fraction of prices changing, which accounts for 73.5 per cent of the variance. This suggests that inflation in South Africa is state-dependent rather than time-dependent. Inflation is also dominated by price increases, which explains 70 per cent of the variation in inflation.

We also found that sales do not substantially change the frequency of price changes but do have an important impact on their level. On average, four per cent of products were on sale. The incidence of sales has risen since 2009, from around two per cent in January 2009 to over six per cent in December 2014, and an average five per cent for the first five months of 2015. Sales were most common in the sub-categories of "Furniture and furnishings" (18 per cent of products in this category were on sale), "Household appliances" (11.9 per cent), "Audiovisual and photographic equipment" (9.6 per cent), "Household textiles" (7.1 per cent) and were least common in "Vehicles" (0 per cent), "Telephone equipment" (0 per cent), "Tobacco" (0.2 per cent). Despite the relatively small number of sales that occur in South Africa, they remain an important contributor to price decreases, and hence keeping inflation lower. Over the period from 2009 to 2015, goods inflation based on the product level would have been 3.0 per cent instead of the actual 4.8 per cent it excluded all sales items.

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Appendices

A Representation of dataset

Table 5 provides an example of what the micro-price dataset looks like. These are fictitious to ensure the confidentiality of the data is maintained. It includes the following information: the outlet a product was collected at; the province and region; a unique commodity code for each product; the price of the product; an item status code describing the status of the product (for example if it is out of season or substituted); an item unit code describing its attribute such as weight, size, or unit number; a commodity sub-code describing brands; and the price type code indicating whether the product is on “sale” or “regular” price.

For example, in the fourth row of table 5 we have a box of 38 painkillers collected in the city of Polokwane in Limpopo province which is on sale at R17.50 in January 2015. In order to ensure that we compare this specific product over time we create a unique identification (ID) code which is a function of the outlet, commodity, item unit and commodity sub-codes. So for this product the unique ID would be 139061110111652. The data is then sorted and price changes are calculated.

Table 5: Micro-price dataset

Outlet	Survey Period	Province Code	Region Code	Commodity Description	Commodity Code	Commodity SubCode	Item Status Code	Item Status Description	Current Price	Item Unit Code	Item Unit Description	Price Type Code	Price Type Description
130	201207	7	10	SHIRT - BUSINESS - MEN	3121004	1	25	Item available	350	651	Each	R	Regular
130	201405	7	10	SHIRT - BUSINESS - MEN	3121004	1	25	Item available	450	651	Each	R	Regular
1390	201501	9	1	PAIN KILLERS	6111001	1	23	Item available	21.99	167	Box Of 38	S	Sale
1390	201501	9	1	PAIN KILLERS	6111001	2	23	Item available	17.5	165	Bag Of 24	R	Regular
1	201308	6	10	TOOTH BRUSH	12131007	1	20	Item available	13.95	651	Each	R	Regular
59	201103	1	2	SLEEPWEAR - GIRLS	3123023	1	20	Item available	99.99	651	Each	R	Regular