Time-dependent or state-dependent pricing? Evidence from a large devaluation episode*

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Abstract

State-dependent and time-dependent price setting models yield distinct implications for how frequency and magnitude of price changes react to shocks. This note studies pricing behavior in Brazil following the large devaluation of the Brazilian *Real* in 1999 to distinguish between models. The results are consistent with state-dependent pricing.

KEYWORDS: state-dependent pricing, time-dependent pricing, currency devaluation, frequency of price changes.

JEL CLASSIFICATION: E31, E32.

1 Introduction

The real effects of monetary policy depend on the reasons behind price stickiness. In models with time-dependent pricing, firms readjust prices at previously (and possibly endogenously) determined times. In constrast, with state-dependent price setting, prices are readjusted whenever they are far enough from their desired levels, so a monetary shock leads firms to adjust their prices, which dampens the real effects of monetary policy.

This paper explores the distinct predictions of price-setting models on how the frequency and magnitude of price adjustment react to shocks in order to distinguish between models. Consider a positive shock to the desired prices of goods (the prices that would be charged in the absence of frictions). In the simplest state-dependent models (e.g., Caplin and Spulber (1987)), a firm raises the price of its good whenever the difference between the desired and current price hits a constant threshold. Hence a positive shock to desired prices raises the frequency of price changes but leaves the magnitude of price changes unaffected. In recent models of state-dependent price setting, shocks might have some effect on the magnitude of price changes, but the response of the frequency of price adjustment to shocks is a key feature of all these models.[1]

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[1]See, e.g., Golosov and Lucas (2007) and Gertler and Leahy (2008)

Time-dependent price setting yields the opposite predictions. In models that follow Calvo (1983), the frequency of price changes is exogenously given. In models with endogenous time-dependent pricing (e.g., Bonomo and Carvalho (2004)), firms optimally choose the time of the next price change when they adjust prices. In both cases, a shock that raises desired prices does not affect how long it will take for the next price change, but raises the magnitude of the price increase when it happens.

A simple correlation between inflation and frequency of price adjustment is not enough to test these predictions. Models of state-dependent pricing imply a positive correlation between inflation and frequency of adjustment, but so do models with endogenous time-dependent pricing. That is why a large shock is needed for this prediction to be explored.

The Brazilian devaluation of 1999 allows us to distinguish between time-dependent and state-dependent models. Between 1995 and January 1999, Brazil had a pegged regime: the currency was depreciating at an approximately constant rate of 0.6% a month. The peg was abandoned on January 13th. The Brazilian government then tried to keep the devaluation at a level close to 10%, but that did not last more than 2 days. In the following weeks, it gradually became clear the government had given up intervening in the foreign exchange market and a major devaluation took place. Between January 12th and the end of February 1999, the price of 1 dollar increased from 1.2 to more than 2 Reais.

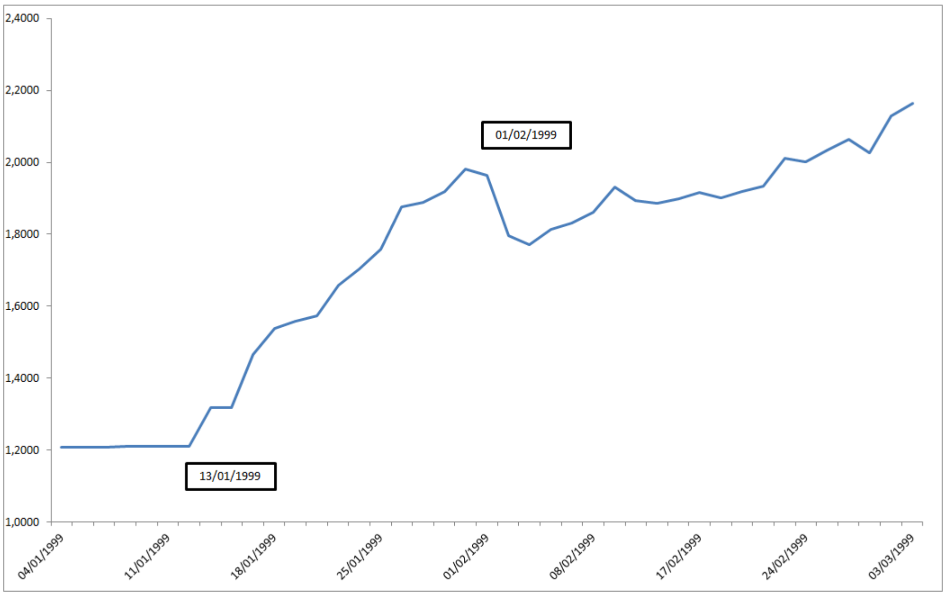

Figure 1: Exchange Rate: Beginning of 1999

Firms in the tradable sector thus experienced large shocks to their desired prices in this period.[2] In a world with state-dependent pricing, we would observe an increase in the frequency of price changes for these firms. In contrast, in a world with time-dependent

[2]Burstein, Eichenbaum and Rebelo (2007) highlight the importance of the non-tradable component of cost of 'tradable' goods when accounting for the low exchange rate pass-through after large devaluations. One implication is that the shock to costs of industrialized goods is much smaller than the actual currency depreciation, but that is still a large shock.

pricing, the frequency of price changes would not react to these shocks, but the magnitude of price changes would be affected. Non-tradable goods (services) can be used as a control group.

The difference in how the probability and expected magnitude of price changes react to shocks reflects the fundamental distinction between time-dependent and state-dependent models. For the larger real effects of time-dependent models, it is important that firms do not respond to shocks by adjusting their prices – which implies that the fraction of price changes should not be affected by the devaluation. In constrant, the crucial feature of state-dependent pricing is that shocks lead more firms to adjust their prices.

Using a large data set on consumer prices in Brazil from 1997 and 2000, we estimate patterns of pricing behavior for different groups of items. For the group of tradable goods, the devaluation pushes up the probability of a price change but has no effect on the magnitude of price increases. No significant effect is observed in the group of non-tradable goods. The results thus corroborate the strong predictions of state-dependent models.

The results of this paper speak to the debate between time-dependent and state-dependent pricing more broadly and to the discussion about price-setting in the aftermath of large currency devaluations. Time-dependent nominal rigidity is a common assumption in the literature focused on understanding how an economy reacts to large exchange rate fluctuations (see, e.g., Aghion, Bacchetta and Banerjee (2001), Cook and Devereux (2006) and Gertler, Gilchrist and Natalucci (2007)). One implication of this paper is that models with time-dependent pricing are not appropriate to describe the response of an economy to large currency devaluations. Grinberg (2015) shows this assumption is important: in his model with state-dependent pricing, when the economy is hit by a large currency depreciation, nominal rigidity in retail prices is not quantitatively important.

This paper complements previous empirical work on this topic. Klenow and Kryvtsov (2008) contrast the implications of different models to the data on hazard rates and sizes of price changes. Gagnon (2009) shows that when inflation is above a certain threshold, higher inflation corresponds to shorter price spells. Midrigan (2010) notes that in models with state-dependent pricing, firms are more likely to change prices if idiosyncratic and aggregate shocks are positively correlated, and explores the sectoral variation in the correlation between idiosyncratic and aggregate shocks. Guimaraes, Mazini and Mendonça (2014) also study how the frequency and magnitude of price adjustments react to inflation shocks, but their identification relies of differences between expected and observed inflation.

The main distinguishing feature of this paper is the use of a large shock to desired prices of a group of goods, which allows for a clean identification and enables us to distinguish between state-dependent and endogenous time-dependent models. One caveat is that it is not clear whether the patterns of price adjustment in scenarios of large devaluations can be generalized to normal times. A large currency devaluation is perhaps a situation where state-dependent models seem to be particularly appropriate. State dependent models are related to menu costs, while time dependent models might be seen as capturing informational frictions. In case of an exchange rate devaluation, it is reasonable to expect the informational cost to be low.

The structure of this paper is the following. Section 2 describes the data, Section 3 presents the methodology and Section 4 presents the results.

2 Data

We use data collected by IBRE-FGV to compute the consumer price index.[3] Products are divided in seven major expenditure classes (food, housing, clothing, health and personal care, education, reading and recreation, transport and miscellaneous expenditure). Prices are collected in 12 Brazilian cities and prices of different goods are collected in different days of a month. An *item* refers to a particular product sold in a specific reseller. An observation is the price of an item at a given date – we have accurate information on the date the price was collected.

Items were classified as *commodities*, *industrialized goods* and *non-tradables*. The non-tradable category is mostly comprised by services, which are not significantly affected by exchange rate fluctuations.[4] In contrast, desired prices of industrialized goods are significantly influenced by shocks to the exchange rate.[5] The group of commodities is composed mostly by food – and prices in this category are quite flexible.

Since our objective is to understand the impact of the large exchange rate devaluation of January 1999, we use data from july 1997 to June 2000 (from one and a half year before to one and a half year after the shock). As usual in this literature, items with regulated prices were excluded from the sample – there is a relatively large number of items whose prices are controlled by the Brazilian government. A few outliers were also excluded. Outliers were defined as prices increases greater then 700% and price decreases greater than 87.5% or more, which are likely to be typing mistakes that multiply or divide a price by 10 or 100 coupled with regular price changes.

There are 7771 items and around 251 thousand observations in the group of industrialized goods and 4505 items and around 115 thousand observations in the group of non-tradables. Items differ regarding the frequency of price collection. Most items have their prices collected about once a month, but some have their prices collected around three times a month.

[3] Using this data set, Gouvea (2007) shows the main stylized facts about price setting in Brazil.

[4] More specifically, the group of non-tradables comprises: food away from home; housing (rents); domestic services; recreation and culture; education, health care, medical and laboratory expenses; communication services; and public transportation

[5] The group of industrialized goods comprises: cleaning, hygiene and beauty products; furniture and decoration; housing appliances; petrol; vehicles; home textiles; telephone and electronic goods; tobacco and beverages; clothing; pharmacy.

3 Methodology

In order to distinguish between models, we estimated (a) the frequency; and (b) the average magnitude of (i) all price changes; (ii) positive changes; and (iii) negative changes. We then checked how they were affected by the large exchange rate devaluation of January 1999. We will show results for non-tradables and industrialized goods, as prices in the group of commodities are close to flexible.

A time series of observations was created for each item in the sample. There is a lot of variation in the number of observations for each of these individual time series. For example, an item may have its price collected every 10 days, while another will have prices collected every 30 days and only in 1997. Some items cover only a small part of the sample, but excluding items with less than 10 or 15 observation did not affect the results.

A *data spell* is defined by two consecutive collection dates and the price of the item at those dates. So the number of data spells for a specific item is the number of observations for that item minus one.

The probability (or frequency) of a price change was estimated by maximum likelihood. Let λ_t by the probability of a price change at date t and λ the vector of λ_t for all t. Then the probability function of a price change for each data spell can then be written as:

$$f(y_k, \lambda) = (1 - y_k)\pi_n + y_k\pi_c \tag{1}$$

where y_k is a binary variable equat to 1 when there is a price change in the k^{th} data spell of a particular item and equal to 0 otherwise, π_c is the probability of observing a price change in a data spell between τ and T,

$$\pi_c = 1 - \prod_{t=\tau}^{T}(1 - \lambda_t)$$

and $\pi_n = 1 - \pi_c$ is the probability of no price change in this period.

The likelihood function for one item is given by:

$$\mathcal{L}(\lambda, y_k) = \prod_{k=1}^{m} f(\lambda, y_k) \tag{2}$$

where m is the total number of data spells for an item. In practice, it is simpler to work with the log-likelihood function. Adding up the log-likelihood function values for all items in a group, we have the final value of the log-likelihood function. The objective is then to find the vector of probabilities of price changes (λ) that maximizes the log-likelihood function.

In principle, we could estimate the probability of a price change for each day in the sample. However, given the large size of the data set and the large number of parameters to be estimated, that would be computationally very costly. We thus restricted λ_t to be the same for all t in a given month. Hence, for an observation between price collections in April 26$^{\text{th}}$ and May 21$^{\text{th}}$, the probability of a price change considers 5 days in April and 20 days in May. Estimations in the first and last months are likely to be affected by censoring problems (there are very few data spells covering the beginning and the end of the period), so estimates for the first and last two months of the sample were discarded. We thus ended up with a total of 32 estimates.

If daily data were available, it would be possible to calculate the daily average magnitude of price changes by simply taking the mean of price changes for each day of the sample. The available dataset does not allow us to know when exactly a price change took place. Hence we estimated the average magnitude of price changes in a given month by taking the average of price changes of all data spells that (i) presented a price change and (ii) included that first day of the month.

4 Results

We start by showing results for non-tradable goods. They are expected to show little (or no) reaction to the currency devaluation shock and thus can be seen as a control group for this experiment. Figure 2 shows the probability of a price change and the average magnitude of a positive price change in the period around the currency devaluation of January 1999. The dotted lines are confidence intevals (estimates plus and minus 1.96 estimated standard errors), corresponding to a 5% confidence level. Results are presented in Table 1 in Appendix A.

The pricing pattern of non-tradable goods seems to be unaffected by the currency devaluation. The probability of price changes in February and March following the devaluation is similar to the observed in previous months. A similar pattern is observed for the average magnitude of price changes. No change is observed after the devaluation.

There is a small increase in the probability of a price change in January 1999, but this increase is very similar to those observed in January 1998 and January 2000 – as shown in Table 1 in Appendix A. That is likely to reflect seasonal price changes of items such as school fees (in Brazil, the academic year and the calendar year coincide).

Figure 3 shows the probability of a price change and the average magnitude of price increases for industrialized goods. Results are presented in Table 2 in Appendix A. There is a clear spike following the devaluation shock, showing a significant impact of the devaluation on the frequency of price changes for industrialized goods.

The estimate for the probability of a price change in a given day in the second half of 1998 oscilates between 2.7% and 2.86% – which means it is basically constant.[6] In January 1999, this number goes to 3.03%, but this increase is similar to those in January 1998 and January 2000. A large difference appears in February and March 1999: the estimates for the probability of a price change in a given day in those months go up to 3.47% and 3.55%,

[6]Those numbers correspond to a probability of a price change of 56% and 58% in a 30-day period. In the group of commodities, prices are even more flexible.

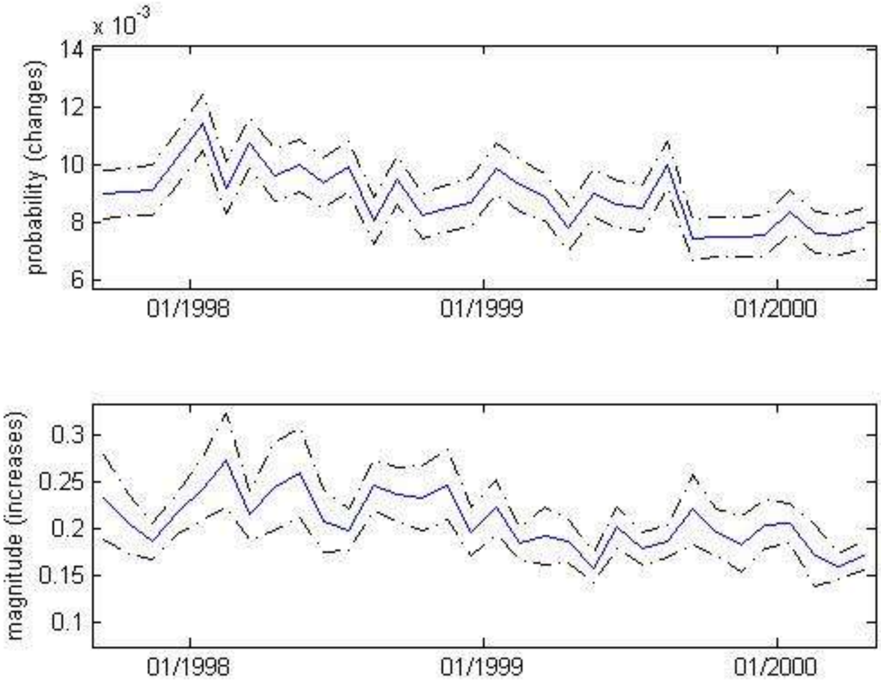

Figure 2: Pricing patterns for non-tradable goods

respectively. This number then decreases to around 3% in the following months.

Figure 3 also shows that the devaluation episode had no effect on the magnitude of price increases.[7] Differently from what time-dependent pricing models would predict, and in accordance to the predictions of state-dependent pricing models, the frequency of positive price changes was strongly affected by the devaluation shock of January 1999, while the magnitude of a devaluation was not significantly affected. Results thus match the strong predictions of a simple Ss model along the lines of Caplin and Spulber (1987).

A time dependent model would predict the opposite pattern: there should be no effect on the frequency of price adjustment and, owing to the larger than expected increase in the desired price, larger price adjustments should be observed in the months right after the devaluation. The point estimate for the average size of price increases in February 1999 is actually lower than in any other month in 1998 and 1999.

Figure 4 shows the behavior of the probability of positive and negative price changes. There is not much action in price decreases (perhaps a small effect in February 1999), but a large increase in the frequency of price increases. The evidence supports the view that firms react to large shocks by changing their prices.[8]

[7] There is an increase in the average magnitude of price changes but that is due to a composition effect: the fraction of positive price changes is larger in the months following the currency devaluation.

[8] The estimates for the probability of a price change in a given day are larger than the sum of estimates for positive and

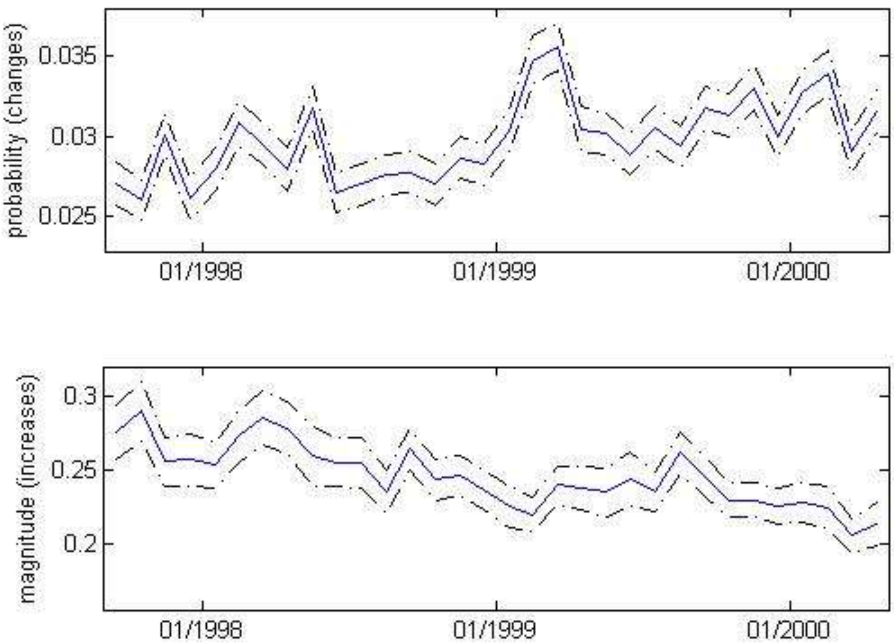

Figure 3: Pricing patterns for industrialized goods

5 Final remarks

A large currency devaluation works as a natural experiment for macroeconomists interested in firms' pricing patterns. In case of tradable goods, costs and prices of imported competitors are affected, which in turn raises the desired consumer prices. We can thus study whether the strong predictions of state-dependent pricing models are observed in the data. The test proposed in this paper could be applied in many other countries that have experienced large currency devaluations in the last decades.

The results in the paper provide evidence in favor of state-dependent pricing models. Firms' reaction to shocks in normal times could be different from their reaction to an exchange rate devaluation, so the results should be interpreted with caution. Nevertheless, the paper provides evidence against models that emphasize the role to price rigidity in the wake of a devaluation.

negative changes. That is probably because the hazard rate of price changes is not constant: very few firms will change prices in two consecutive days. Once the estimates for the daily probability of changes are converted into probabilities of price changes in a month, this discrepancy vanishes.

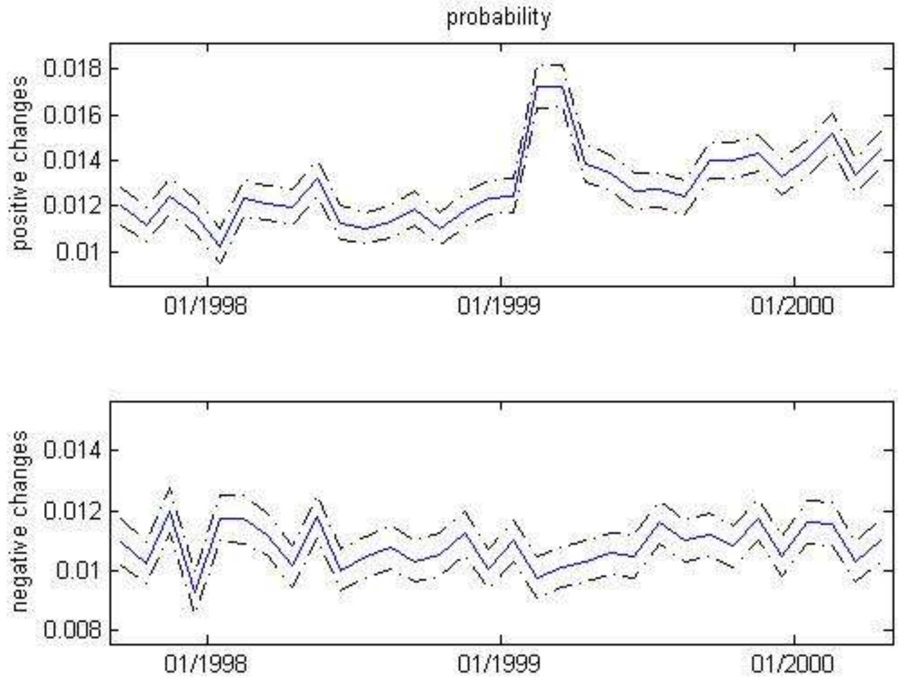

Figure 4: Price increases and decreases for industrialized goods

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A Tables

Table 1: Non-tradable goods

Month	Prob change		Size change		Prob increase		Prob decrease	
Sep-97	0.0090	(0.0004)	0.2333	(0.0229)	0.0049	(0.0003)	0.0036	(0.0003)
Oct-97	0.0091	(0.0004)	0.2052	(0.0159)	0.0047	(0.0003)	0.0038	(0.0003)
Nov-97	0.0091	(0.0004)	0.1865	(0.0097)	0.0049	(0.0003)	0.0038	(0.0003)
Dec-97	0.0103	(0.0005)	0.2168	(0.0109)	0.0051	(0.0003)	0.0045	(0.0003)
Jan-98	0.0115	(0.0005)	0.2429	(0.0170)	0.0069	(0.0004)	0.0038	(0.0003)
Feb-98	0.0092	(0.0005)	0.2732	(0.0257)	0.0038	(0.0003)	0.0048	(0.0003)
Mar-98	0.0108	(0.0005)	0.2153	(0.0134)	0.0053	(0.0003)	0.0048	(0.0003)
Apr-98	0.0097	(0.0005)	0.2449	(0.0238)	0.0043	(0.0003)	0.0047	(0.0003)
May-98	0.0100	(0.0005)	0.2598	(0.0241)	0.0044	(0.0003)	0.0049	(0.0003)
Jun-98	0.0094	(0.0004)	0.2087	(0.0174)	0.0041	(0.0003)	0.0048	(0.0003)
Jul-98	0.0100	(0.0004)	0.1992	(0.0109)	0.0049	(0.0003)	0.0044	(0.0003)
Aug-98	0.0081	(0.0004)	0.2459	(0.0135)	0.0040	(0.0003)	0.0037	(0.0003)
Sep-98	0.0095	(0.0004)	0.2371	(0.0146)	0.0041	(0.0003)	0.0048	(0.0003)
Oct-98	0.0082	(0.0004)	0.2324	(0.0176)	0.0043	(0.0003)	0.0036	(0.0003)
Nov-98	0.0085	(0.0004)	0.2471	(0.0194)	0.0042	(0.0003)	0.0039	(0.0003)
Dec-98	0.0087	(0.0004)	0.1968	(0.0132)	0.0042	(0.0003)	0.0039	(0.0003)
Jan-99	0.0099	(0.0005)	0.2239	(0.0147)	0.0058	(0.0003)	0.0035	(0.0003)
Feb-99	0.0093	(0.0005)	0.1847	(0.0089)	0.0054	(0.0003)	0.0033	(0.0003)
Mar-99	0.0089	(0.0004)	0.1934	(0.0156)	0.0048	(0.0003)	0.0036	(0.0003)
Apr-99	0.0078	(0.0004)	0.1869	(0.0114)	0.0042	(0.0003)	0.0032	(0.0003)
May-99	0.0090	(0.0004)	0.1584	(0.0082)	0.0041	(0.0003)	0.0043	(0.0003)
Jun-99	0.0086	(0.0004)	0.2016	(0.0113)	0.0052	(0.0003)	0.0030	(0.0002)
Jul-99	0.0085	(0.0004)	0.1791	(0.0084)	0.0043	(0.0003)	0.0036	(0.0003)
Aug-99	0.0100	(0.0004)	0.1874	(0.0086)	0.0053	(0.0003)	0.0040	(0.0003)
Sep-99	0.0074	(0.0004)	0.2207	(0.0189)	0.0037	(0.0003)	0.0033	(0.0002)
Oct-99	0.0075	(0.0004)	0.1962	(0.0125)	0.0039	(0.0003)	0.0032	(0.0002)
Nov-99	0.0075	(0.0004)	0.1834	(0.0151)	0.0040	(0.0003)	0.0031	(0.0002)
Dec-99	0.0075	(0.0004)	0.2051	(0.0133)	0.0042	(0.0003)	0.0029	(0.0002)
Jan-99	0.0084	(0.0004)	0.2056	(0.0106)	0.0048	(0.0003)	0.0031	(0.0002)
Feb-99	0.0076	(0.0004)	0.1718	(0.0168)	0.0038	(0.0003)	0.0034	(0.0002)
Mar-99	0.0076	(0.0004)	0.1600	(0.0066)	0.0040	(0.0003)	0.0032	(0.0002)
Apr-99	0.0078	(0.0004)	0.1719	(0.0078)	0.0041	(0.0003)	0.0033	(0.0002)

Standard errors in parentheses.

Table 2: Industrialized goods

Month	Prob change		Size change		Prob increase		Prob decrease	
Sep-97	0.0271	(0.0007)	0.2758	(0.0094)	0.0120	(0.0004)	0.0110	(0.0004)
Oct-97	0.0260	(0.0006)	0.2903	(0.0102)	0.0112	(0.0004)	0.0103	(0.0004)
Nov-97	0.0301	(0.0007)	0.2561	(0.0083)	0.0124	(0.0004)	0.0120	(0.0004)
Dec-97	0.0261	(0.0007)	0.2571	(0.0090)	0.0116	(0.0004)	0.0092	(0.0004)
Jan-98	0.0279	(0.0007)	0.2536	(0.0078)	0.0102	(0.0004)	0.0118	(0.0004)
Feb-98	0.0308	(0.0007)	0.2728	(0.0089)	0.0123	(0.0004)	0.0117	(0.0004)
Mar-98	0.0295	(0.0007)	0.2854	(0.0095)	0.0121	(0.0004)	0.0112	(0.0004)
Apr-98	0.0279	(0.0007)	0.2783	(0.0090)	0.0119	(0.0004)	0.0101	(0.0004)
May-98	0.0318	(0.0007)	0.2594	(0.0100)	0.0132	(0.0004)	0.0118	(0.0004)
Jun-98	0.0265	(0.0006)	0.2555	(0.0085)	0.0113	(0.0004)	0.0100	(0.0004)
Jul-98	0.0270	(0.0006)	0.2552	(0.0086)	0.0110	(0.0004)	0.0105	(0.0004)
Aug-98	0.0276	(0.0006)	0.2361	(0.0075)	0.0113	(0.0004)	0.0108	(0.0004)
Sep-98	0.0277	(0.0006)	0.2643	(0.0070)	0.0119	(0.0004)	0.0103	(0.0004)
Oct-98	0.0270	(0.0006)	0.2440	(0.0072)	0.0110	(0.0004)	0.0105	(0.0004)
Nov-98	0.0286	(0.0007)	0.2463	(0.0068)	0.0118	(0.0004)	0.0112	(0.0004)
Dec-98	0.0282	(0.0007)	0.2371	(0.0066)	0.0124	(0.0004)	0.0100	(0.0003)
Jan-99	0.0303	(0.0007)	0.2254	(0.0071)	0.0125	(0.0004)	0.0110	(0.0004)
Feb-99	0.0347	(0.0008)	0.2202	(0.0059)	0.0172	(0.0005)	0.0098	(0.0004)
Mar-99	0.0355	(0.0007)	0.2400	(0.0068)	0.0173	(0.0004)	0.0101	(0.0003)
Apr-99	0.0304	(0.0007)	0.2381	(0.0072)	0.0139	(0.0004)	0.0103	(0.0004)
May-99	0.0301	(0.0007)	0.2351	(0.0081)	0.0135	(0.0004)	0.0106	(0.0003)
Jun-99	0.0289	(0.0007)	0.2446	(0.0094)	0.0126	(0.0004)	0.0105	(0.0004)
Jul-99	0.0305	(0.0007)	0.2352	(0.0068)	0.0127	(0.0004)	0.0116	(0.0004)
Aug-99	0.0294	(0.0007)	0.2619	(0.0071)	0.0124	(0.0004)	0.0110	(0.0004)
Sep-99	0.0317	(0.0007)	0.2453	(0.0067)	0.0140	(0.0004)	0.0112	(0.0004)
Oct-99	0.0313	(0.0007)	0.2298	(0.0059)	0.0140	(0.0004)	0.0108	(0.0004)
Nov-99	0.0330	(0.0007)	0.2302	(0.0061)	0.0143	(0.0004)	0.0117	(0.0004)
Dec-99	0.0300	(0.0007)	0.2257	(0.0061)	0.0133	(0.0004)	0.0105	(0.0003)
Jan-99	0.0328	(0.0007)	0.2288	(0.0068)	0.0141	(0.0004)	0.0116	(0.0004)
Feb-99	0.0339	(0.0007)	0.2252	(0.0074)	0.0152	(0.0004)	0.0116	(0.0004)
Mar-99	0.0290	(0.0006)	0.2062	(0.0058)	0.0133	(0.0004)	0.0103	(0.0003)
Apr-99	0.0315	(0.0007)	0.2137	(0.0074)	0.0145	(0.0004)	0.0110	(0.0004)

Standard errors in parentheses.