Working Paper

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Author(s):
Müller, Christian; Köberl, Eva M.

Publication Date:
2007-06

Permanent Link:
https://doi.org/10.3929/ethz-a-010805525

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KOF Working Papers

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Christian Müller and Eva Köberl

No. 170
June 2007

ETH
Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

KOF

ETH Zurich
KOF Swiss Economic Institute
WEH D 4
Weinbergstrasse 35
8092 Zurich
Switzerland

Phone +41 44 632 42 39
Fax +41 44 632 12 18
www.kof.ethz.ch
kof@kof.ethz.ch

The speed of adjustment to demand shocks: A Markov-chain measurement using micro panel data

Christian Müller* and Eva Köberl†

28th June 2007

*ETH Zurich, KOF Swiss Economic Institute, E-mail: mueller@kof.ethz.ch
†ETH Zurich, KOF Swiss Economic Institute, E-mail: koeberl@kof.ethz.ch

Abstract

In this paper we measure the speed at which firms adjust to demand shocks using individual firm data. Identification of shocks is achieved by a combination of quantitative and qualitative judgments on capacity utilisation in micro survey data. A novel feature of our approach is the distinction between positive and negative shocks that allows us to also discriminate between the speed of adjustment following either kind of shock. Furthermore, there is no need for using previous data filtering to extract business cycles or equilibrium definitions but only to observe the states of the firms that define their economic situation. One main result is that the firms' adjustment to these two shocks is varying in speed. It should therefore be paid regard to the separation of positive and negative shocks in empirical and theoretical models. The findings of this paper bear implications for monetary policy making and model building alike.

JEL classification: E32, C4, C5

Keywords: demand shock, Markov-chain, microfoundation

1 Introduction

Economic theory is very often based on concepts of equilibrium. Market solutions are derived from the idea of intersection of demand and supply, markets are cleared when the right price is quoted. Likewise, individual decisions such as the choice of optimal inputs in terms of quantity and prices can be modelled by equilibrium approaches where a solution obtains given market structure, profit maximisation objectives and certain state variables. A regular observation is however, that equilibrium is too often not achieved. For example, unemployment and business cycle fluctuations should not arise under perfect equilibrium conditions. Both phenomena do, however, occur regularly in most economies (Kydland and Prescott, 1982; Stadler, 1994, among others). Therefore, economists such as Mankiw (1985) and Clarida, Galí and Gertler (1999), for example, have suggested to augment economic models by considering imperfectness such as costly and time consuming adjustments to shocks that distort equilibrium.

Delayed adjustment can have many sources, among them shortage of differentiated production factors like skilled labour, legal obstacles to layoff employees, transport costs and time for delivering intermediate goods and so on. With respect to the effects of adjustment lags it seems plausible to assume that single delays may easily accumulate and finally deliver measurable effects on the aggregate economy level. In short, the speed at which economic agents are able to adjust to shocks is of great importance for economic modelling and policy making alike.

Furthermore, while it is straightforward to imagine an economy in which adjustment takes time (Calvo, 1983), it is far less easy to confirm the claims empirically. For example, researchers have become aware of the fact that the standard approach of learning from aggregate data readily leads to severe overestimation of the time needed for adjustment (Caballero and Engel, 2003). Hence, the request to focus on firm behaviour in the first place (Clower, 1998) before drawing conclusions for the whole of the economy finds even more support. One of the first contributions that actually investigated individual firm's reaction to shocks to labour demand is Hamermesh (1989). He points to the fact that at the firm level the decision to augment the labour force is a discrete decision while in macroeconomic models the augmentation process appears to be continuous.

Subsequent research (Khan and Thomas, 2003; King and Thomas, 2006, for example) has consequently tried to recover the determinants of the discrete choice, mainly by explaining the decision process as an evaluation of costs and benefits of adjustment.

Regarding the different components of adjustment an individual firm has to face, there has been fundamental research on most of them, even on micro level. Caballero, Engel and Haltiwanger (1997) analyze employment adjustments by measuring the discrepancy between desired and actual employment of U.S. manufacturing establishments. The adjustment pattern of capital and investment on firm level is analyzed by Doms and Dunne (1998). Analyses of price changes as an option for the adaptation to shocks can be found in Nakamura and Steinsson (2007) and Rupprecht (2007). The latter finds a robust relationship between price increases and capacity constraints at micro level. Rupprecht (2007) suggests that firms use increases in capacity utilization as an alternative to raising prices.

Surprisingly, analyses of quantity adjustments in business cycle, unlike price adjustments, lack such a broad empirical micro-foundation. First results of quantity adjustments based on survey data stem from Bhaskar, Machin and Reid (1993). In their evaluation of a questionnaire from a sample of small firms in the UK, they find that quantity adjustments are much more important than price adjustments when firms are faced with demand shocks. Another study by Copeland and Hall (2006) focuses on micro data of automakers in the US to analyse the impulse response functions of a demand shock. They find that, for adequately large shocks, the cumulative production response is significantly larger than the cumulative price response. Hence, there is a lack of micro-founded analyses of quantity adjustments to demand shocks on a broader and more general data base.

In this paper we aim at filling this gap. The backbone of the analysis is a panel data set that combines both qualitative and quantitative information on a firm level basis. Our data set comprises several hundred firms observed quarterly which provides us with a rich information set on how firms behave. The aim of this study is to uncover a *typical* reaction pattern following a demand shock. It is thus meant to equip theorists with a good guess of how to match theory and empirics. A further value added of our approach is the possibility to distinguish between positive and negative shocks and the time it takes for each of them to be digested by firms.

The remainder of the paper is structured as follows. In section 2 the empirical methodology is described and section 3 presents the results. Section 4 gives an outlook on further research based on recent findings.

2 The empirical methodology

2.1 The data

The speed of adjustment of an economy to shocks is usually measured by means of economy wide aggregates such as industrial production indexes or Gross domestic product (GDP). A standard procedure would be to adjust a possibly multivariate autoregressive model to the data and then to estimate the impact a shock has by, for example, impulse-response analysis. This procedure invokes a series of approximations and assumptions that have to be made. Shocks are broadly speaking derived by formulating a data generating process and by using the unexplained variables, ie the residuals as the shocks that drive the dependent variable. Obviously, the thereby calculated shocks are contingent on the model used and the information set considered. If it was possible to observe shocks more directly macroceconomic analysis would certainly benefit.

Further issues that are used to refine the identification of shocks are, for example, the distinction between shocks which have a long-run and those which have a short-run impact only. A common and also – in general – necessary assumption is that negative and positive shocks have the same impact on the economy such that it is sufficient to measure the net effect that then shows up as a positive or negative value for the residual and hence the shock.

2.2 The definition of a demand shock

Quite contrary to the usual aggregated analysis we use micro data on the firm level. The data source is the Swiss Economic Institute's (KOF) business tendency survey in the Swiss manufacturing industry. The data is available from 1989 to 2006 on a quarterly basis. As there was a reclassification of industry branch codes in 1998, we split our sample into two parts. The first subsample covers the period from 1989 to 1998 third quarter with 57160 observations. The second subsample contains the time span from 1999 first quarter to 2006 third quarter and consists of 22122 observations. Relating to capacity utilisation, there are two questions. It is asked whether the technical capacities are currently too high, just right or too low. Simultaneously, the firms are asked to quantify the capacity utilisation within the past three months in percentage points, where the firms can choose from a range of 50% to 110% in five percent steps. From the latter we can calculate the percentage change in production capacity from t to $t+1$ and compare this to the judgment about capacity utilisation given by the firm in t.

The key to answer the research question is our ability to match the qualitative answer which tells whether or not firms are in need of more capacity and the change in their actual capacity utilisation. For example, if firms indicate that their technical capacities are too low and we observe that their use of capacity utilisation increases it is safe to say that this particular firm has been hit by a shock. Before turning to the systematic analysis we establish that this shock can be best interpreted as a demand shock.

The argument is fairly simple. An optimising firm does all that it can to produce the profit maximising amount of output and to choose the appropriate output price if possible. In particular, any issue that is related to production and hence supply of the output is considered to be effectively under the control of the firm. A typical supply side shock that is discussed in the literature is technological progress. At a firm level, however, an increase in the productivity of the means of productions would have to be implemented by buying and installing a new machine, for example. Likewise, intermediate goods and other factors of production are ordered well in advance of actual production. Therefore, if there is a shock to the supply of those goods, the firm can be assumed to adjust prior to producing its output. In additions, these kind of disruptions should not (directly) impact *technical* capacities, the issue that is the subject of the survey question. In sum, the firm will work with the capacities it considers optimal. If nevertheless a firm reports too high or too few capacities without actually adjusting immediately it must be due to a demand shock that by definition could not be foreseen by the firm. From now on we

Table 1: The principle structure of the contingency table

		realisation		
		-	=	+
judgment	-	mm	me	mp
	=	em	ee	ep
	+	pm	pe	pp

therefore use shock and demand shock as interchangeable expressions.

2.3 Contingency tables

The next step of the analysis gives an overview of the data properties. We will first examine the data by means of contingency tables suggested by Ivaldi (1992). They are constructed as follows (see table 1).

The rows describe the judgment of the firms in t about their current technical capacity; '+' stands for 'too high', '=' for just right, '-' for too low. In the columns, the possible outcomes in capacity utilisation changes are listed. A '+' means that the level of capacity utilisation has been augmented between t and $t+1$, a '=' stands for an unchanged level and '-' means a lower level. On the basis of this classification of nine different states of the firms, we are able to identify states that can be associated with either positive or negative demand shocks. The remaining states will be considered equilibrium situations, or states during which adjustment takes place.

When looking at state pm, for example, firms positioned in this field consider their capacities in t as 'too high', but from t to $t+1$ their degree of capacity utilisation still declines. Using the previous arguments we can classify this state as a situation of a negative demand shock to the particular firm. The argumentation for state mp is similar. As capacities in t are stated as 'too low' and the capacity utilisation rises anyway in the next quarter, we can classify pm as a state of a positive demand shock. The equilibrium derived from this observations is the state ee, where capacity is 'just right' in t and hence there follows no change in capacity utilisation in $t+1$.

For the two subsamples in our study, the repartition of percentage shares to the different states of the 3×3 matrix is composed as summarised in table 2.

Table 2: Contingency tables

Subsample 1 (1989 – 1998)		realisation -	realisation =	realisation +
judgment	-	2.7	3.7	2.1
judgment	=	23.5	34.2	21.6
judgment	+	3.1	4.6	4.5

Subsample 2 (1999 – 2006)		realisation -	realisation =	realisation +
judgment	-	2.5	2.7	2.4
judgment	=	25.6	29.9	25.5
judgment	+	3.0	3.7	4.7

The table entries report the shares of firms who judge their capacities according to the row labels and likewise experience a change in capacity utilisation as indicated by the column headers.

Apart from simply summarising the data properties, the table shows a few interesting features. For example, the majority of firms find itself in a situation where capacities are sufficient. Approximately as many of these firms who experience an increase in capacity utilisation report a decrease afterward. Hence, it seems that on average the firms have now better information on what is going to happen to them than what they actually fill in the questionnaires. Similarly, firms who have too much capacities will most likely increase their level of capacity utilisation in the following period. In contrast, respondents with too few capacities will report an unchanged level afterward most often. However, for the second subsample the difference between the '=' and the '-' share is just one tenth of percentage point. All in all the contingency tables point to a rather reliable answering pattern where the sequence of responses is overall consistent with rational expectations on part of the surveyed firms.

2.4 Transition probabilities and Markov-chain

Having established the states a firm can find itself in, it remains to identify the path and speed of adjustment a firm follows once it has been hit by a demand shock. We suggest to regard the move from state $s_{j,t}$ to $s_{k,t+1}$, $j,k \leq 9$ to be ruled by an ergodic 9-dimensional Markov-chain. We thus define the probabilities

$$p_{j,k} = Prob(s_{k,t+1}|s_{j,t}),\ j,k \leq 9 \tag{2.1}$$

$$\sum_{k=1}^{9} p_{j,k} = 1\, \forall j = 1, \ldots 9 \tag{2.2}$$

where j and k denote either of the 9 states defined before. In order to find the adjustment paths of the firms, we have to estimate the implied 9×9 matrix of transition probabilities. To facilitate estimation we need to calculate the repartition of firms to the different states of the contingency table both for t to $t+1$ and $t+1$ to $t+2$. Matching these two dates leaves us 48103 observations for the first and 17526 observations for the second subsample. In this very first analysis we also assume that all firms are homogeneous in $p_{j,k}$. Then it is checked in which state the firms are in t and where they are in $t+1$. As an intermediate result we obtain a 9×9 matrix, whose elements show the frequency by which firms move from a state given by the row number to

Table 3: One-step-transition frequencies in subsample 2

t / $t+1$	pp	pe	pm	ep	ee	em	mp	me	mm	sum
pp	105	95	158	124	134	187	6	6	8	823
pe	158	219	89	79	71	35	5	4	1	661
pm	198	108	57	80	36	24	11	4	2	520
ep	27	41	68	883	1303	1853	50	120	156	4501
ee	56	69	71	1222	2458	1251	41	90	42	5300
em	235	126	86	1874	1115	833	93	52	29	4443
mp	2	3	5	44	43	110	41	43	93	384
me	7	4	2	34	104	65	55	133	71	475
mm	13	4	2	115	63	77	72	43	30	419

the state given by the column number. Table 3 above illustrates this step for subsample 2.

For example, table 3 implies that of all 823 firms that take position pp at time t 105 will be found in state pp at time $t + 1$ too, while 134 move to ee, the equilibrium state. Table 3 tells a number of interesting stories about the economy. First of all, the most prominent position for a firm is equilibrium (ee). Once being there it is most likely that it will stay there. This is only true also for positions pe and me. On the other hand, more than one half of the firms in ee move out of there the following period. This can be taken as an indication that demand shocks occur rather frequent and hence firms are constantly forced to adjust in one way or another. Thus, measuring the time it takes before a firm gets active may not be an appropriate measure of the actual speed of adjustment since during that time span additional shocks hit the firm making it impossible to relate the eventual action to a particular point in time. This said, the approach followed here accounts for the fact that shocks and adjustment to shocks happen simultaneously. The adjustment measured should thus be regarded as the typical adjustment process in an environment that is characterised by both frequent shocks and the permanent struggle for coping with them.

Conditioning on the respective initial state the one-step transition probabilities can be defined. The one-step probability of moving from state pp to state pp again will be denoted p_{11}. The estimated one-step-transition probabilities are collected in the matrix $A_{i=1}$ whose 81 elements $a_{j,k}$, $j,k = 1,\ldots,9$ correspond to the p_{jk}. For the two subsamples we obtain the following estimates:

$$\hat{A}(1)_1 = \begin{bmatrix} 0.1523 & 0.1519 & 0.1709 & 0.1305 & 0.1590 & 0.2150 & 0.0043 & 0.0062 & 0.0100 \\ 0.1934 & 0.3937 & 0.1457 & 0.1013 & 0.1104 & 0.0500 & 0.0023 & 0.0018 & 0.0014 \\ 0.3558 & 0.2458 & 0.1492 & 0.1276 & 0.0608 & 0.0398 & 0.0149 & 0.0034 & 0.0027 \\ 0.0063 & 0.0079 & 0.0151 & 0.1661 & 0.3141 & 0.4172 & 0.0095 & 0.0244 & 0.0393 \\ 0.0091 & 0.0152 & 0.0093 & 0.1768 & 0.5374 & 0.2178 & 0.0066 & 0.0199 & 0.0079 \\ 0.0540 & 0.0282 & 0.0216 & 0.3929 & 0.2796 & 0.1877 & 0.0189 & 0.0105 & 0.0066 \\ 0.0031 & 0.0010 & 0.0083 & 0.0896 & 0.1146 & 0.2260 & 0.1063 & 0.2135 & 0.2375 \\ 0.0023 & 0.0051 & 0.0028 & 0.0568 & 0.1863 & 0.1002 & 0.0979 & 0.3872 & 0.1615 \\ 0.0313 & 0.0094 & 0.0086 & 0.2383 & 0.1711 & 0.1750 & 0.1484 & 0.1320 & 0.0859 \end{bmatrix}$$

and

$$\hat{A}(2)_1 = \begin{bmatrix} 0.1276 & 0.1154 & 0.1920 & 0.1507 & 0.1628 & 0.2272 & 0.0073 & 0.0073 & 0.0097 \\ 0.2390 & 0.3313 & 0.1346 & 0.1195 & 0.1074 & 0.0530 & 0.0076 & 0.0061 & 0.0015 \\ 0.3808 & 0.2077 & 0.1096 & 0.1538 & 0.0692 & 0.0462 & 0.0212 & 0.0077 & 0.0038 \\ 0.0060 & 0.0091 & 0.0151 & 0.1962 & 0.2895 & 0.4117 & 0.0111 & 0.0267 & 0.0347 \\ 0.0106 & 0.0130 & 0.0134 & 0.2306 & 0.4638 & 0.2360 & 0.0077 & 0.0170 & 0.0079 \\ 0.0529 & 0.0284 & 0.0194 & 0.4218 & 0.2510 & 0.1875 & 0.0209 & 0.0117 & 0.0065 \\ 0.0052 & 0.0078 & 0.0130 & 0.1146 & 0.1120 & 0.2865 & 0.1068 & 0.1120 & 0.2422 \\ 0.0147 & 0.0084 & 0.0042 & 0.0716 & 0.2189 & 0.1368 & 0.1158 & 0.2800 & 0.1495 \\ 0.0310 & 0.0095 & 0.0048 & 0.2745 & 0.1504 & 0.1838 & 0.1718 & 0.1026 & 0.0716 \end{bmatrix}$$

where each row sums up to one and the number in brackets indicates the subsample.

It is interesting to note that the typical adjustment path of, say a negative shock (initial position pm), is pm→pp→em→ep→em.... This implies that after being hit firms most often indeed start to adjust immediately with the majority of them reducing their capacities in the following period. The adjustment closes with a sustained switching between the two near equilibrium states em and ep.

Furthermore, the probability of jumping from a state of a positive shock to a state being regarded a negative shock (from pm to mp) and vice versa is comparably low. In general, a move from one of the more extreme situations which are given in the lower left and top right 3×3 sub matrices to the other extreme positions appears very unlikely. This can be inferred from the low values in these parts of the matrices. This also is reassuring in the sense that the data under investigation has properties that comply with straightforward economic reasoning.

The final state of the system is given by the marginal distribution of the Markov chain. This state exists if the Markov chain is regular (Hamilton, 1994). Regularity follows when there exists an m for which all elements of the m-step transition matrix $A(\cdot)_m$ are positive. Then all $A(\cdot)_m^t$ are regular for all $t \geq m$. The marginal distribution $\tilde{\pi}$ is stationary if

$$\tilde{\pi} A(\cdot)_m = \tilde{\pi}. \tag{2.3}$$

It can be shown that this condition holds for the two matrices of the subsamples. Then the limit $\lim_{t\to\infty} A(\cdot)_i^t = A(\cdot)_\infty$ exists and the matrix $A(\cdot)_\infty$ has identical cells:

$$A(\cdot)_{\infty} \quad = \quad \begin{bmatrix} p_1 & p_2 \dots & p_9 \\ p_1 & p_2 \dots & p_9 \\ \dots & \dots & \dots \\ p_1 & p_2 \dots & p_9 \end{bmatrix} \tag{2.4}$$

For the two subsamples, we get the following marginal distributions:

$$\hat{A}(1)_{\infty} \quad = \quad 1_{(9,1)} \otimes \begin{bmatrix} .045 & .047 & .031 & .214 & .347 & .234 & .019 & .037 & .026 \end{bmatrix}$$

and

$$\hat{A}(2)_{\infty} \quad = \quad 1_{(9,1)} \otimes \begin{bmatrix} .046 & .039 & .031 & .254 & .304 & .252 & .022 & .029 & .025 \end{bmatrix}$$

where $1_{(9,1)}$ signifies a column of nine ones.

We find that the fifth column, which represents state ee, shows the highest marginal probability. Consequently, following the Markov-chain, the firms will end up in the equilibrium state with highest probability. Of course, this should not come as a surprise, since this is also the state in which firms find themselves in on average (see table 2).

Here again it is interesting to observe that the final state is characterised by a non-zero proportion of firms off the equilibrium position (ee). The implicit conclusion would be that the economy does not move towards equilibrium as a whole but rather to a steady state with a certain ratio of firms being on and off equilibrium.

2.5 Simulation of demand shocks

To measure the effect of positive and negative demand shocks, we impose an extreme initial position of the system by assuming that all firms have simultaneously been hit by a negative or positive shock pushing all of them to either the pm or the mp position. Then we quantify the adjustment by observing the movement of the firms along the Markov-chain until convergence to the marginal distribution is achieved. In so doing we can measure the time span until the marginal probability is reached. During the adjustment process we can also assess the extent to which the gap between the actual and the final state of the whole systems are bridged.

The two 9×9 initial value matrices for a demand shock will be called N for the negative, and P for the positive shock. Both matrices have zero elements except for the elements in the third column in matrix N and in the seventh column in matrix P which represent jumps to positions pm and mp respectively. In essence, this is equivalent to saying that *all* firms are initially hit by a positive or negative demand shock. The shocks are then fed into the system by post multiplying N and P by $A(\cdot)_1$. The product reports the situation of the whole system after one period. This operation is then repeated further $h_N - 1$ ($h_P - 1$) times until the marginal distribution is achieved. The value of h_N and h_P will inform us how long it typically takes until firms completely adjust to demand shocks.

3 Results

Applying the procedure described before enables us to observe the reduction in the distance between the initial position and the final state. Since by definition all states will achieve their final values at the same time, it is convenient to

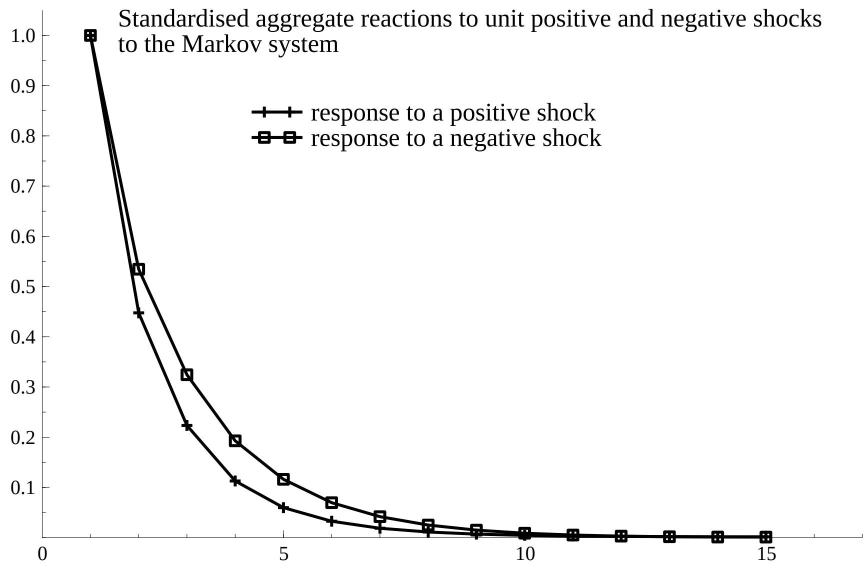

Figure 1: Adjustment to demand shock in the subsample 1989–1998.

summarize the adjustment of the system by considering the squared distance of each position to its asymptotic value. These squared differences are then added up and the square root is taken. Finally, the adjustment path is standardised. More formally, the aggregated state of the economy, $S(\cdot)_i$, i periods after shock is calculated as

$$S(N)_i = \sqrt{tr\left((N * A(\cdot)_i) - A(\cdot)_\infty\right)\left(N * A(\cdot)_i - A(\cdot)_\infty)'\right)}$$

and the normalisation of the sequence $S(N) = \{S(N)_1, S(N)_2, \ldots, S(N)_{h_P}\}$ is obtained by dividing all elements of the sequence by $S(N)_1$. Values for $S(P)$ are obtained along similar lines.

The following graphs depict the adjustment process from the first to the fifteenth period after the shock. For simplicity, both shocks share a common sign. Looking at the graphs it turns out that the bulk of the adjustment occurs within two quarters, or half a year. During that time approximately two thirds of the time distance to the equilibrium situation passes, and after one year about 90 percent of the shock has died out.

Two more aspects can be inferred from the results. First, it turns out that the reaction to the shock is consistently asymmetric for both subsamples. In each experiment the adjustment to the positive shock is faster than the adjustment to the negative shock. In the first subsample firms have closed the gap to the final marginal distribution by 55% after one and almost 80% after two quarters when they were hit by a positive demand shock while these numbers amount to 45% and 65% after a negative shock. Likewise, it takes two more quarters in case of a negative shock until the distance to the marginal distribution is effectively zero in the case of a negative shock. This phenomenon is the more remarkable since the marginal distribution features a larger probability to be subjected to a negative shock than to be subject to a positive shock. Therefore, assuming that all firms are hit by a negative shock is a situation which is closer to the final state than the assumption of a positive shock. The reason for this asymmetry is not easy to identify. One could have expected that a negative shock would trigger a faster reaction on part of the firms since losses are often more heavily felt than profits. On the other hand, firms may have difficulties to realise losses in comparison to profits and hence may turn a blind eye on them more readily. Finally, it might be simply less trivial to adjust downward than upward due to fixed contract periods and sunk costs.

The same asymmetry can also be observed in the second subsample. The difference remains the same although the speed of adjustment is now higher for both shocks. After one period 65% (positive shock) and 55% (negative shock) of the initial distance to the marginal distribution are covered while it still takes two more periods for a negative shock to be properly digested. If

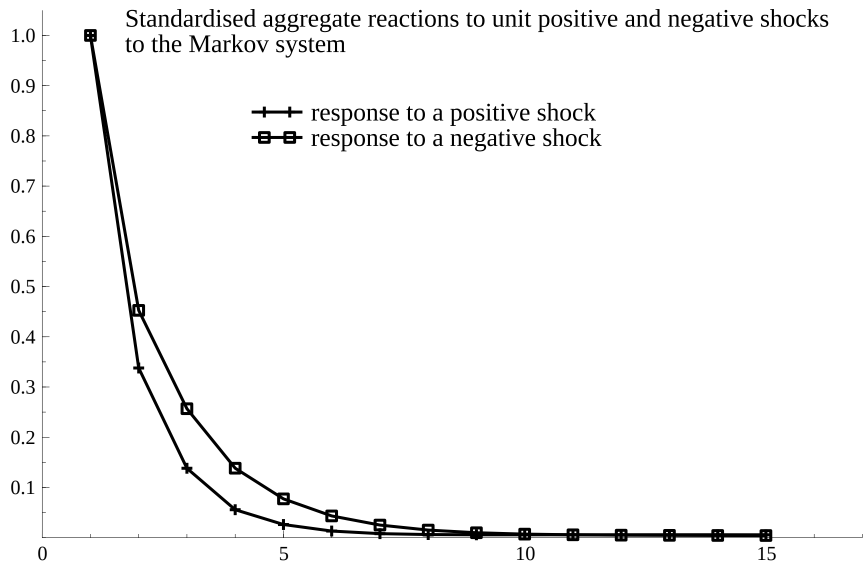

Figure 2: Adjustment to demand shock in the subsample 1999–2006.

this reduction in the adjustment time was genuine, this could be an indication of increased competition and flexibility on the part of the firms. It is yet too early, however, to conclude whether or not this result is owed to the different sample sizes, or to a more fundamental change in the structure of the economy as a whole.

4 Summary and conclusion

This paper models the adjustment of a firm to a demand shock as a series of states of a Markov-chain. The basis for our analysis is a micro data set of firms in the manufacturing industry that allows us to combine qualitative and quantitative information on an individual basis. We interpret the judgment of a firm about its technical capacities in combination with the effective change in capacity utilisation as positive, negative, or no demand shock depending on whether or not the implicit expectations is met.

The outcome of the investigation indicates that firms do react differently depending on whether or not the experienced shock was a negative, or positive one. The difference amounts to half a year. After two and a half years the typical firm will have adjusted completely. Further, preliminary, evidence also shows that the speed of adjustment has increased in the economy after 1998. It has yet to be seen whether or not this result will find additional support in the future.

In the aftermath of a demand shock firms can react by adjusting prices or output, or both. The more readily output is adjusted the lower should be the impact on prices. Hence, our findings suggest that prices face an upward pressure for about one year after a positive shock. This observation should be interesting to policy makers and model builders alike. A natural extension of our analysis is therefore to test whether or not those periods of a strong indication of either shock has a corresponding price effect.

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