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Huw D. Dixon, Christian Grimme

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State-Dependent or Time-Dependent Pricing? New Evidence from a Monthly Firm-Level Survey: 1980-2017

Abstract

We take a monthly panel of German firms over the period 1980–2017 to examine the relative importance of time and state dependence in the decisions of firms to raise, lower or leave their price constant. In addition, we seek to estimate the relative importance of macroeconomic factors and firm-specific factors within state dependence. While price decreases can be well explained by time dependence alone, price increases are best predicted by the interaction of time-dependent and firm-specific state factors. Whilst on their own macroeconomic variables might seem important, once we add firm-specific variables the effects of macroeconomic variables become much smaller in magnitude. Our empirical results suggest that theoretical models should integrate both time and state dependence rather than developing the approaches separately. We also show that time dependence is better captured if we allow for different hazard functions for price increases and decreases.

JEL-Codes: E300, E310, E320.

Keywords: survey data, price setting, extensive margin, state-dependent pricing, time-dependent pricing.

Huw D. Dixon
Cardiff Business School
Cardiff / United Kingdom
dixonh@cardiff.ac.uk

Christian Grimme
ifo Institute – Leibniz Institute for Economic Research at the University of Munich / Germany
grimme@ifo.de

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1 Introduction

Theoretical models of price adjustment divide into two broad classes: time-dependent and state-dependent models. In time-dependent models (Taylor, 1980, Calvo, 1983 and their generalizations Sheedy, 2010, Dixon and Le Bihan, 2012, Taylor, 2016), the probability of price-change depends on the time elapsed since the previous change. In state-dependent models, the decision to change price depends on the cost and demand conditions facing the firm now and in the future relative to the lump-sum cost of changing price (Sheshinski and Weiss, 1977, Alvarez and Lippi, 2014, Alvarez et al., 2016a). Furthermore, within the class of state-dependent models, we can ask to what extent common macroeconomic variables such as inflation and growth matter relative to firm-specific factors.[1] The relative importance of time-dependence, macroeconomic factors and firm-specific state variables in influencing the decision to change price can only be determined empirically, which is what this paper does.

We use the micro data of the monthly ifo Business Climate Survey which covers on average 3,500 German manufacturing firms over the long period 1980 to 2017. The survey includes information on whether firms have changed their price since the previous month and whether it was an increase or a decrease in price. The survey also includes qualitative firm-specific information about each firm relevant to their pricing decisions. Germany makes an interesting case study in price flexibility. The German economy is the fourth largest economy in the World and has a large weight within the Eurozone both politically and economically. When we combine this data with macroeconomic data on inflation and output growth, we are able to determine the relative importance of macroeconomic versus firm-specific factors alongside time-dependence.

Our conclusion is that both time dependence and firm-specific state effects are essential for a full explanation of price changes. We measure how successful the different factors are in explaining the price changes that occur at the firm level. Price increases are best predicted by the interaction of firm-specific state and time-dependent factors. For price-cuts, time dependence is much more important than state dependence, possibly capturing the importance of time dependence in the product cycle. It should be stressed that the time-dependency captured by the hazard dummies is over and above seasonal effects captured by monthly dummies. We find that although macroeconomic variables have a statistically significant effect on pricing, they are much less important than both the firm-specific and the time-dependent effects. In fact, macroeconomic factors explain only a very small percentage of price changes.

Our first step is to use only the aggregated data, the monthly proportion of firms changing price, and to see if there is a time-series relationship with aggregate inflation and output

[1] This is another case of the wide-ranging discussion of the importance of aggregate versus idiosyncratic shocks, including investment (Schankerman, 2002) and labour supply (Storesletten et al., 2001) among others.

growth.[2] Even if macroeconomic variables have only a small effect on each firm, they can be important because they affect all firms. Theory would suggest that inflation and output growth would both have a positive effect on the frequency of price change, although the impact of output might be weak if there is "real rigidity" (Ball and Romer, 1990).[3] We find that there is a positive relationship between inflation and output growth on the proportion of firms changing price upwards and a negative relationship with respect to price decreases. This is in line with similar approaches using UK data (Dixon et al., 2014) and US data (Vavra, 2014).

The second step is to go to the firm level and combine the macroeconomic variables with firm-specific and time-dependent variables using the Multinomial Logit (MLogit) model. The Mlogit model allows us to model both price increases and decreases at the same time. For comparison with other studies, we also consider probit and ordered-probit models as a robustness check. We propose a refined version of time-dependence by introducing hazard dummies, which allow the probability of price changes (differentiating up and down) to vary with the duration since the previous price change (again differentiating up and down). Our use of multiple sets of hazard dummies allows us to capture time-dependency in a more detailed manner. The conventional approach bundles price increases and decreases together into "price changes". In contrast, we allow for the probability of a price increase or decrease to differ and for both to depend on how long it has been since the previous price increase and decrease. We find that the hazard function for a price increase following an increase to look completely different to the probability of a decrease following a decrease. The former has the familiar 12-month spike, whereas the latter falls away monotonically. We show that modeling hazards the conventional way greatly reduces the importance of time dependence for price setting. Therefore, our results challenge the conventional approach of bundling together price increases and decreases.

We contribute to two strands of the literature on price-setting behavior that are closely linked: (i) studies of firms using survey data and (ii) studies using CPI micro price-quote data. Turning first to firm survey data, Lein (2010) undertakes a similar exercise to ours with a quarterly survey of Swiss firms over the period 1984 to 2007 using logit models. Her results show that state-dependent factors are more important in the decision to change prices than time-dependence. However, Lein only allows for a restrictive form of time-dependence in the form of hazard dummies that bundle together price increases and decreases. Her study shows that "Macroeconomic factors are significant, but add little in terms of goodness of fit" and

[2] A good survey about the impact of aggregate inflation on the price change frequency is Dhyne et al. (2006), page 25.

[3] Real rigidity in this context means that marginal cost is flat and does not increase much with output and employment.

that firm-specific factors are more important than macroeconomic factors. However, Lein does not model specific macroeconomic variables as we do, but rather general time-specific dummies, giving rise to the possibility that the effects of different macroeconomic factors cancel each other out. Carlsson and Skans (2012) use an annual survey of Swedish firms over the period 1990–2002 which is used to link specific product prices to unit labour costs at the plant level. They find that a time-dependent Calvo model (without indexation) outperforms alternative models of sticky information (Mankiw and Reis, 2002) and rational inattention (Mackowiak and Wiederholt, 2009). Carlson and Skans focus on the link between changes in marginal costs and the pass through to prices rather than analyzing the frequency of price adjustments as we do. Bachmann et al. (2019) focus on the effect of firm-level volatility on price setting using the same German dataset as this study. They find that firm-level volatility has a positive effect on the frequency of price change. Loupias and Sevestre (2013) use a French business survey conducted by the Banque de France over the period 1996–2005. Using an ordered probit model, they find that firm-specific cost effects and sectoral inflation influence price changes, but they do not allow for time dependence. Other studies include Schenkelberg (2013) and Stahl (2010).[4]

We next turn to studies using CPI price-quote data (and hence without firm-specific data). Gagnon (2009) looks at the Mexican experience using CPI price-quote data from 1994–2002, and finds that "When the annual rate of inflation is low (below 10%–15%), the frequency of price changes comoves weakly with inflation because movements in the frequency of price decreases and increases partly offset each other". Gagnon finds that inflation affects the frequency of prices increases positively and decreases negatively. The two effects almost cancel each other out when combined into the overall frequency. However, Gagnon is unable to link the pricing behaviour to firm-specific effects because he lacks the data. Berardi et al. (2015) use French CPI price-quote data over the period 2003–2011 to explore the effect of macroeconomic variables on the frequency and size of price change. Using a Tobit model, they find that the probability of a price increase (decrease) is increased (decreased) by the cumulative aggregate inflation since the last price change. Neither of these papers allows for a general form of time-dependence. Dixon and Le Bihan (2012) use French CPI data to model

[4] Schenkelberg (2013) employs German survey data for retailers over the period 1991–2005. Stahl (2010) uses just the year 2004 of the same ifo survey employed in this paper, but where an additional questionnaire was sent to each firm from the Bundesbank as part of the Eurosystem Inflation persistence network (IPN) project. Stahl's study focuses mostly on the decision process of firms rather than the effects of inflation on price behaviour.

the hazard rate for all price changes, but leave out all state-dependent effects and follow a purely descriptive approach.[5]

2 The Data

In this section we briefly outline the data used. Then we describe the construction of the additional state variables and the hazard dummies. Finally, we discuss the data properties and the censoring procedure.

2.1 Description of the Data

The ifo Business Climate Survey is a monthly business survey for Germany. From this survey the ifo Business Climate Index is computed, which is a much-followed leading indicator for economic activity in Germany. The ifo survey is part of the EU-harmonized business surveys commissioned by the Directorate General for Economic and Financial Affairs of the European Commission. In this paper, we use the data from the manufacturing sector from January 1980 until December 2017; before 1991 the data only contains West-German firms. At the beginning of our sample, the average number of participants is approximately 5,400; at the end the number declines to 2,200.[6] Participation in the survey is voluntarily; 12% of all firms are one-time respondents. On average, firms participate 89 months. The survey covers all relevant sectors of German manufacturing as well as all types of firm sizes. Further details are in Appendix D.1.

The ifo survey asks each firm whether it has increased or decreased its price or left it unchanged compared to the month before (see Table 1). In addition, the survey contains other firm-specific variables that help us to control for first-moment effects. The variables *Business Situation*, *Business Expectations*, *Orders*, and *Expected Prices* have three possible response categories like our price variable; e.g., a firm can assess its current state of business as being good, satisfactory, or unsatisfactory. To account for possible asymmetric effects, we include these variables with both positive and negative values separately (see Table 2). For example, the variable *Business Expectation* is divided into two sub-variables *Expbus Up* and *Expbus Down*. If firm i at time t expects its situation to improve, the variable *Expbus Up* is equal to one, and the variable *Expbus Down* is equal to zero. If the firm expects its state to

[5]Dixon and Tian (2017) do the same for UK CPI data. The descriptive approach means using the Kaplan-Meier non-parametric method to estimate the survivor function for price-spells, from which the hazard function is derived.

[6]The survey is conducted at the product level, so that firms operating in different product groups are asked to fill out different questionnaires. However, only 0.7% of the responses are multiple products (Link, 2018). Therefore, we use the terms “firm” and “product” interchangeably.

become unfavorable, *Expbus Up* is equal to zero, and *Expbus Down* is equal to one. If the firm expects its state to remain about the same, both *Expbus Up* and *Expbus Down* are equal to zero, which is the baseline. We proceed analogously with *Business Situation*, *Orders*, and *Expected Prices*. Price expectations are lagged by one month.

Table 1: Questionnaire

Number	Label	Question	Response categories		
Q1	*Price*	Our net domestic sales prices for product XY have ...	increased	remained about the same	decreased
Q2	*E*(*Price*)	Expectations for the next 3 months: Our net domestic sales prices for XY will ...	increase	remain about the same	decrease
Q3	*Business Situation*	We evaluate our business situation with respect to XY as ...	good	satisfactory	unsatisfactory
Q4	*Business Expectations*	Expectations for the next 6 months: Our business situation with respect to XY will in a cyclical view ...	improve	remain about the same	develop unfavourably
Q5	*Orders*	Our orders with respect to product XY have ...	increased	roughly stayed the same	decreased
Q6	*Production*	Our domestic production activity with respect to product XY have ...	increased	roughly stayed the same	decreased
Q7	*E*(*Production*)	Expectations for the next 3 months: Our domestic production activity with respect to product XY will probably ...	increase	remain virtually the same	decrease

Notes: The table provides the translated questions and response possibilities of the ifo Business Climate Survey for manufacturing. For the production questions Q6 and Q7 firms are explicitly asked to ignore differences in the length of months or seasonal fluctuations.

2.2 Further State Variables

To capture supply shocks, we include changes in input costs. Intermediate good costs play an important role as a determinant of a firm's price setting (Lein, 2010). The ifo survey does not contain any information about input costs, therefore, we construct a variable that proxies the change in input costs for each sector k for each time period following Schenkelberg (2013). This variable is computed as the weighted average of net price changes of input goods from all sectors. The weights reflect the relative importance of the sectors in the production of goods in sector k. A detailed description of the construction of the variable can be found in Schenkelberg (2013) and Bachmann et al. (2019).

Bachmann et al. (2019) show that firm-level volatility is a statistically significant determinant for a firm's decision to reset its price. We follow their approach and construct production expectation errors at the firm level from the survey questions regarding expected and realized production changes (Questions 6 and 7 in Table 1). Volatility is proxied by the rolling window standard deviation of the expectation errors of a firm across several consecutive time periods; details on its construction can be found in Bachmann et al. (2019).

Table 2: Description of Variables in the Model

Variable	Description	Response	Scale
Price Change	Price change	change	Binary
Price	Price change	increase / decrease	Nominal
Input Costs	Cost of input goods		Interval
Expprice Up	Expected price	increase	Binary
Expprice Down	Expected price	decrease	Binary
Statebus Up	Business situation	good	Binary
Statebus Down	Business situation	unsatisfactory	Binary
Expbus Up	Business expectation	increase	Binary
Expbus Down	Business expectation	decrease	Binary
Order Up	Orders	increase	Binary
Order Down	Orders	decrease	Binary
$Uncertainty$	Dispersion of intra-firm forecast errors		Interval
Hazard Change	Hazard dummies for price change for 36 months		Binary
Hazard Up-Up	Hazard dummies for price increase after a price increase for 36 months		Binary
Hazard Down-Down	Hazard dummies for price decrease after a price decrease for 36 months		Binary
Hazard Up-Down	Hazard dummies for price increase after a price decrease for 36 months		Binary
Hazard Down-Up	Hazard dummies for price decrease after a price increase for 36 months		Binary
Sector Dummy	Sector dummies for 14 sectors		Binary
Seasonal Dummy	Seasonal dummies for each month		Binary
$Unific$	Unification dummy		Binary
Euro	Dummy for introduction of Euro		Binary
Fin Crisis	Dummy for Financial Crisis 2008/09		Binary
Other Crises	Dummy for other crises		Binary
$Inflm$	Producer price inflation, month-over-month rate, annualized		Interval
$Infly$	Producer price inflation, year-over-year rate		Interval
Mpm	Manufacturing production growth, month-over-month rates, annualized		Interval
Mpy	Manufacturing production growth, year-over-year rates		Interval

Notes: $Inflm$, $Infly$, Mpm, and Mpy are computed from official data by the German Statistical Office.

We include several sets of dummies in addition to the hazard dummies, which are described in Section 2.3. Sector-specific dummies take into account unobserved heterogeneity between manufacturing sectors. Since there are seasonal fluctuations in price setting, we include monthly time dummies. We also control for important institutional events like the reunification of Germany in October 1990 and the introduction of the Euro in January 2002. In addition, we have two crises dummies for economic crises periods as dated by the German Council of

Economic Experts for Germany. One dummy is for the financial crisis in 2008/2009 (January 2008 to April 2009), the other dummy for all the other crises (January 1980 to November 1982, February 1992 to July 1993, and February 2001 to June 2003).

We are interested to what degree firms react to information about aggregate inflation and aggregate output growth. For inflation we look at both month-on-month changes (annualized) and annual changes in producer prices; for output we use month-over-month changes (annualized) and annual changes in manufacturing production. The underlying data come from the German Statistical Office. The combination of month-on-month and annual changes is a parsimonious version of a more general 12-month lag structure. The general lag structure suffers from collinearity issues and performs little better than our two-parameter version. Also, the annual inflation rate is what is reported by the media and well known as is the annual output growth. We also use an output gap measure, but in Robustness Section 4 we show that this does not make any substantive difference. The four aggregate variables are lagged to take into account that firms observe aggregate information only with some lag. Considering the publication lag, inflation is lagged for two months and output for three months. Lagging these variables also avoids potential endogeneity issues.

2.3 Construction of the Hazard Dummies

In order to capture time dependence at the firm level, the literature uses a single set of dummies that treats all price changes as the same and gives the probability of a price change (either up or down) t periods after the previous price change (up or down). This corresponds to the standard approach to estimating the survival function.[7] This formulation obviously leaves out a lot of information and does not allow the hazard to be different for prices up and down or to depend on whether the price-spell started with a price cut or price increase. Instead, we suggest employing up to four hazard dummies.

$H1(t)$: The probability of a price increase t periods after the previous price increase.

$H2(t)$: The probability of a price increase t periods after the previous price decrease.

$H3(t)$: The probability of a price decrease t periods after the previous price decrease.

$H4(t)$: The probability of a price decrease t periods after the previous price increase.

The best way to interpret the multiple hazard probabilities are as transition probabilities. A price spell can be thought of belonging to one of two categories: a price spell that starts with a price increase and one that begins with a price decrease. $H1(t)$ and $H3(t)$ are the

[7]See, e.g., Klenow and Kryvtsov (2008), Dixon and Le Bihan (2012), and Dixon and Tian (2017).

probabilities that the price spell ends and transitions to a new price spell in the same category. $H2(t)$ and $H4(t)$ are the probabilities that the spell ends and transitions to the other category. The probability that a current price spell continues is 1 minus the sum of probabilities that it ends and starts as a new spell in the same or in the other category. Thus, the probability that a price spell that started with an increase (decrease) continues is $1 - H1(t) - H4(t)$ $(1 - H2(t) - H3(t))$. The four transition probabilities are conditional on the duration since the price spell began. In contrast, the standard approach has only one category: price spells that begin with a price change.

In our data, 49.8% of all changes are increases following a previous increase, 37.5% are decreases following a previous decrease, and only 6.1% are a decrease following an increase and 6.7% are an increase following a decrease. In effect, the two hazards $H1(t)$ and $H3(t)$ capture more than 87% of all the changes. We therefore use the two-dummy case as our baseline.[8]

Hazard dummies can allow for very general patterns of time dependence.[9] Lein (2010) uses a single set of hazard dummies for price increases and decreases up to eight quarters since the last price change. This restricted form is not supported by our results. Carlsson and Skans (2012) only consider time dependence in the Calvo model in which there is a constant hazard, which is also at odds with our results. We believe that our approach is a significant advance on the existing literature in that it can better capture the way prices respond very differently for increases and decreases.

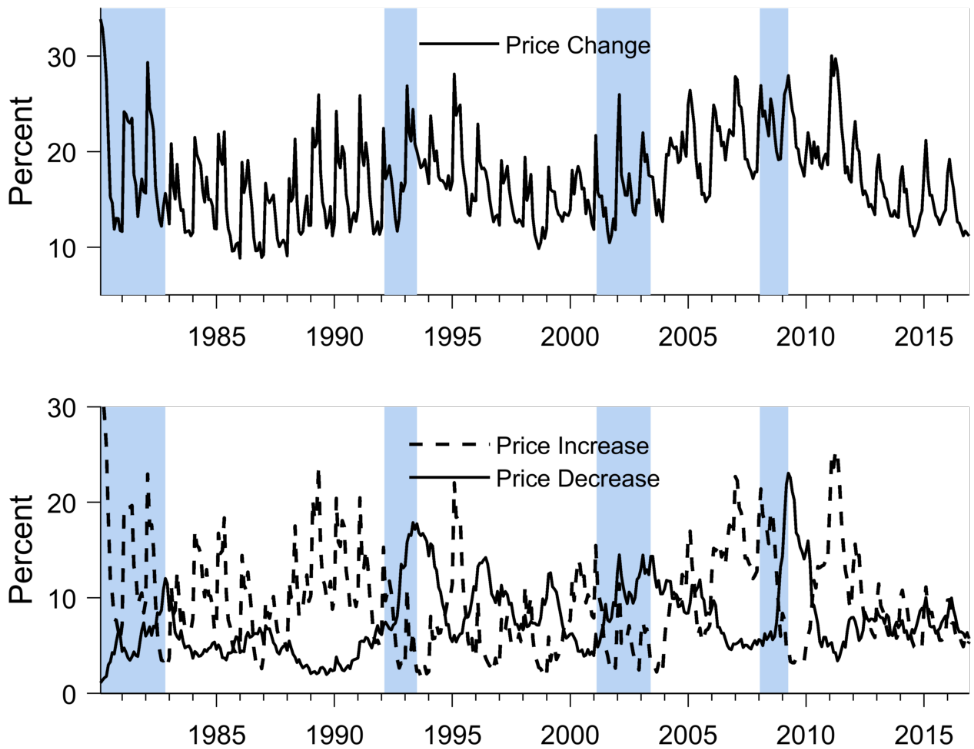
2.4 Discussion of the Data

We now look at some of the key data. Figure 1 presents the fraction of price changes and of price increases and decreases in our data. The visual inspection shows that the frequency of price adjustment increases in times of recession; while the share of price increases falls, this is more than picked up by the large increase in the fraction of price decreases. Furthermore, there is considerable evidence of seasonal effects in price changes which is mostly due to price increases. In order to see how representative the ifo sample is, Figure 2 compares the price balances from the responses to the ifo survey to producer price inflation (PPI) as published by the German Statistical Office. The price balances are computed as the fraction of price increases minus the fraction of price decreases. The two series are highly correlated with a correlation coefficient of 0.65.

[8] As we show in Appendix B and in Table 7, Hazards $H2(t)$ and $H4(t)$ are small in magnitude, vary little relative to $H1(t)$ and $H3(t)$, and do not improve the power of the model to explain price increases and decreases.

[9] Special cases are when the coefficients on the hazard dummy are constant as in the Calvo model, or in the Taylor model where the hazard is zero until the predetermined end of the contract when change is certain.

Figure 1: Frequency of Price Changes

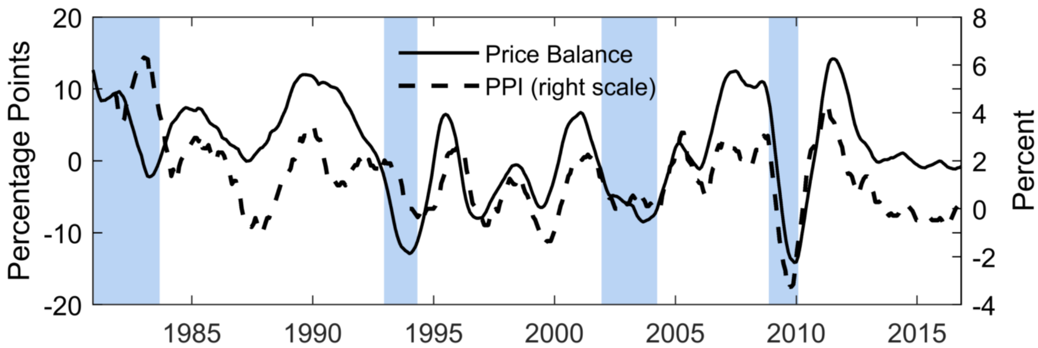


Notes: Upper panel: Frequency of price changes; lower panel: frequency of price increase and price decreases. All data is monthly. Shaded regions show recessions as dated by the German Council of Economic Experts: 1980m1–1982:m11, 1992:m2–1993:m7, 2001:m2–2003:m6, and 2008:m1–2009m4.

In Table 3, we compare the German PPI data with French and UK PPI data along with US and UK CPI data. The mean frequencies in the PPI data are not dissimilar, however, the standard deviation is much bigger in Germany than the UK. The CPI mean frequency in the UK and US are lower, with the UK standard deviation being a little higher and the US much lower.

Before we move to the firm-level estimations, we check whether the aggregate frequency of price changes is related to some key macroeconomic variables. Even if macroeconomic variables have only a small effect on a single firm, they can be important because they affect all firms (Dixon et al., 2014). The variables are monthly and annual inflation, monthly and annual output growth along with various dummies controlling for seasonal effects, German unification and the introduction of the Euro. Table 4 shows that annual and monthly inflation increase the frequency of price changes overall, higher inflation making price increases more likely and price decreases less likely. Annual output growth makes price increases more likely, decreases less likely, with the two effects canceling out when we look at all price changes. The signs of coefficients are all as expected and similar to Gagnon (2009). Whilst these simple

Figure 2: Comparision ifo-Data with Official Data



Notes: Price Balance: Balance statistics of price statements of ifo-sample of manufacturing firms; fraction of price increases minus fraction of price decreases. PPI: producer price inflation as published by Statistical Office, month-over-month rate. All data are displayed as 12-month moving averages. Shaded regions show recessions as dated by the German Council of Economic Experts: 1980m1–1982:m11, 1992:m2–1993:m7, 2001:m2–2003:m6, and 2008:m1–2009m4.

aggregate regression results are interesting, we will need to explore how these translate to the micro data.

Figure 3 depicts the development of producer price inflation and production growth in Germany over the sample period. Year-over-year (month-over-month, in annualized terms) changes in the producer price index vary from a maximum of almost 7% (13.5%) to deflation below -3% (-8.1%). Industrial production is much more volatile with peaks of more than 20% (month-over-month, in annualized terms: 71.5%) and a trough of almost -30% (month-over-month, in annualized terms: -64%).

We conclude this section with some brief remarks about the attributes of the price spells. There are 296,521 price spells in the panel. The weighted average duration of price spells is 5.7 months, with spells ranging from 1 to 323 months; less than 0.02% of the price spells last more than two years. 77% of price-spells are uncensored; there are 8% left-truncated spells, 6% right-truncated spells, and 9% truncated at both ends. For the main results, we can only use the uncensored spells, since we need to know whether the price goes up or down at the end of the spell. This introduces some bias, since longer spells are more likely to be censored. However, it is unavoidable given that we do not combine price increases and decreases.[10] In Appendix A we explore the differences between all spells and the uncensored spells.

[10]We only make one exception. If we observe a series of no price changes for a firm that is interrupted by a month that is missing, then the missing value is treated as a no price change. It is a higher probability that a missing observation is the same price than a different price.

Table 3: Summary Statistics and Comparison with French, U.K. and U.S. Data

	Germany		France		United Kingdom				United States	
	PPI data (ifo)		PPI data (BDF)		PPI data (ONS)		CPI data (ONS)		CPI data (BLS)	
	Mean	StDev	Mean	StDev	Mean	StDev	Mean	StDev	Mean	StDev
Frequ Change	0.171	0.046	0.186	NA	0.177	0.020	0.149	0.048	0.150	0.026
Frequ Up	0.095	0.054	0.109	NA	0.106	0.021	0.097	0.037	0.085	0.027
Frequ Down	0.076	0.038	0.077	NA	0.071	0.011	0.052	0.024	0.065	0.019

Notes: The statistics for Germany are based on the ifo survey of German manufacturing firms spanning the period January 1980 to December 2016. The data from France is based on a Banque de France monthly survey of producer prices taken over 1996–2005, found in Loupias and Sevestre (2013). The PPI statistics for the United Kingdom are from the micro data collected by the Office for National Statistics (ONS) and are computations from Zhou (2012) over the period 1998 to 2008. The CPI statistics for the United Kingdom collected by the ONS that underlie the Consumer Price Index (CPI) are computations from Dixon et al. (2014) for the period January 1996 to December 2014. The statistics for the United States use Bureau of Labor Statistics (BLS) micro data for the Consumer Price Index (CPI); the data spans the period January 1988 to December 2011. We thank Joseph Vavra for providing us with the US aggregate frequency data.

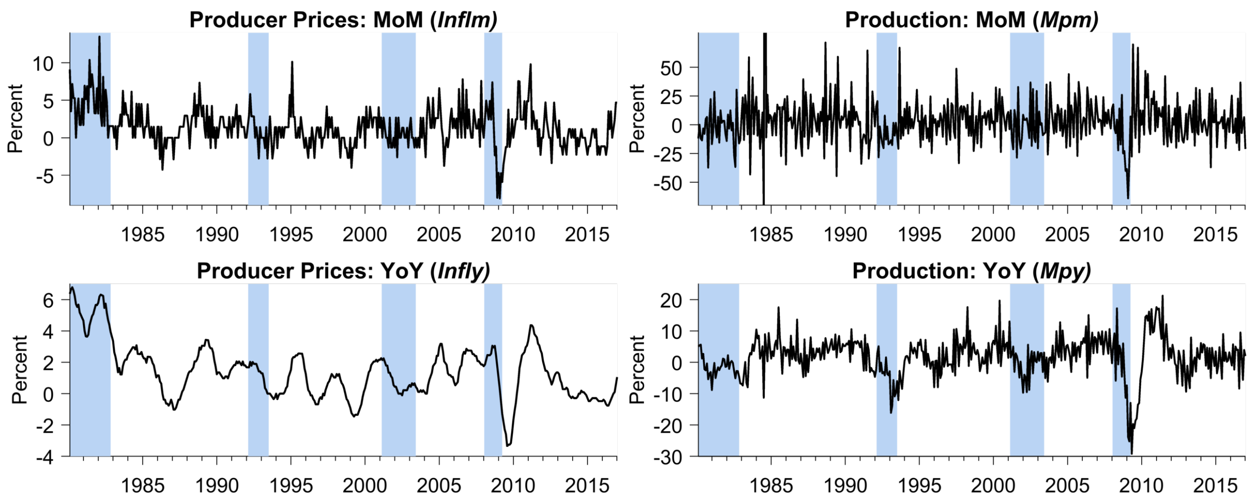
Table 4: Time Series Results for Germany

Dep. Variable	Price Change	Price Increase	Price Decrease
Inflm	0.220**	0.558***	-0.337***
	(0.070)	(0.080)	(0.059)
Infly	0.738***	1.204***	-0.467***
	(0.168)	(0.209)	(0.098)
Mpm	0.003	0.008	-0.004
	(0.004)	(0.006)	(0.005)
Mpy	-0.067	0.127**	-0.194***
	(0.056)	(0.042)	(0.024)
No. of obs.	440	440	440
R-squared	0.65	0.68	0.67

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table reports OLS coefficients. Newey-West standard errors are in parentheses. Included in the model but not shown in the table are a constant, a linear trend, seasonal dummies, and dummies for reunification, the introduction of the Euro, and economic crises. Aggregate inflation is lagged by two months and production by three months. $Inflm$ and Mpm are annualized.

Figure 3: Producer Prices and Manufacturing Production



Notes: PPI: producer price inflation as published by Statistical Office. Production: manufacturing production as published by Statistical Office. All data is monthly. The upper panels depict month-over-month rates (annualized), the lower panels year-over-year rates. Shaded regions show recessions as dated by the German Council of Economic Experts: 1980m1–1982:m11, 1992:m2–1993:m7, 2001:m2–2003:m6, and 2008:m1–2009m4.

3 Results

To get a better understanding of the price-setting decision of firms, we model the probability of three mutually exclusive and exhaustive outcomes: the firm can leave its price unchanged, increase its price, or reduce it. Since the probabilities add up to one, we treat "no change" as the default and then estimate the probabilities of a price increase or price decrease. In the baseline, we use the multinomial logit model, which provides a direct estimate of the probabilities and allows for the determinants of price increases and decreases to differ.

The multinomial logit is in effect a method of classification, which seeks to classify particular combinations of independent variables as giving rise to a particular choice. In Section 4 and in Appendix C, we will also examine some alternatives used in the literature, including separate probit models for price increases and decreases and an ordered probit model covering both increases and decreases. The ordered probit framework is natural if there is a clear ordering of the outcomes – for example, when comparing the position of the price level relative to the optimal flexible price – and they arise from the same "latent variable". Since we look at the change of the price level, a natural ordering is not so clear here. Therefore, we use the multinomial logit which allows for a more general possibility.

We estimate four specifications for our multinomial logit model, all with sectoral dummies, seasonal dummies, dummies for unification, the introduction of the Euro, and crises (the financial crisis and other recessions). Table 5 reports marginal effects of the multinomial logit model. The first model, depicted by column (1), focuses on the macroeconomic variables alone (along with industry, crises and seasonal dummies). The second model in column (2) contains, in addition, a set of hazard dummies. The third model in column (3) includes the firm-specific variables in addition to macroeconomic variables, but without hazard dummies, while column (4) also includes hazard dummies. Note that the number of observations in (3) and (4) is smaller than in models (1) and (2). This is because we can only include those observations for which there is a full set of relevant firm-specific variables, which reduces the number of observations from 1.6 million to 1 million. This could potentially lead to misleading results, so we also ran models (1) and (2) with the restricted sample and found the results were very similar.[11]

If we just include the macroeconomic variables, we find that both inflation and output growth variables matter, significant with the expected signs: inflation and output growth reduce the probability of price cuts and increase the probability of rises. However, whilst significant, the pseudo R^2 is very low.

[11] We would like to thank Rebecca Riley for suggesting this.

Table 5: Baseline Results with Multinomial Logit Model

	(1)		(2)		(3)		(4)	
Depend. Var.:	Price ↓	Price ↑	Price ↓	Price ↑	Price ↓	Price ↑	Price ↓	Price ↑
Inflm	-0.186***	0.518***	-0.082***	0.312***	-0.005	0.061***	-0.009***	0.037***
	(0.019)	(0.029)	(0.007)	(0.016)	(0.006)	(0.008)	(0.003)	(0.005)
Infly	-0.165***	1.332***	0.054***	0.607***	-0.052***	0.150***	0.012**	0.044***
	(0.027)	(0.074)	(0.009)	(0.032)	(0.014)	(0.019)	(0.004)	(0.010)
Mpm	-0.002***	0.006***	-0.002***	0.003***	0.000	0.001	-0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Mpy	-0.130***	0.184***	-0.042***	0.084***	-0.004	0.003	0.003**	-0.003
	(0.012)	(0.012)	(0.003)	(0.006)	(0.003)	(0.003)	(0.001)	(0.002)
Unific	0.029***	-0.010***	0.010***	-0.003***	0.005***	0.005***	0.001***	0.001***
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Euro	0.000	0.023***	-0.001	0.015***	0.002*	0.007***	0.000*	0.005***
	(0.001)	(0.003)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Fin Crisis	0.011***	0.015***	0.010***	0.004**	-0.003**	0.003*	0.001**	0.001
	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Other Crises	0.015***	-0.032***	0.006***	-0.017***	-0.001	-0.003***	0.000*	-0.000
	(0.002)	(0.002)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
Expprice Up					-0.013***	0.276***	-0.004***	0.159***
					(0.001)	(0.013)	(0.000)	(0.008)
Expprice Down					0.235***	-0.016***	0.022***	-0.005***
					(0.019)	(0.002)	(0.002)	(0.001)
Order Up					0.001*	0.015***	-0.001***	0.010***
					(0.001)	(0.001)	(0.000)	(0.001)
Order Down					0.014***	-0.004***	0.008***	-0.003***
					(0.002)	(0.001)	(0.001)	(0.000)
Statebus Up					-0.009***	0.012***	-0.002***	0.006***
					(0.001)	(0.001)	(0.000)	(0.000)
Statebus Down					0.023***	-0.005***	0.005***	-0.003***
					(0.002)	(0.001)	(0.000)	(0.000)
Expbus Up					0.000	0.004***	-0.000	0.003***
					(0.001)	(0.001)	(0.000)	(0.000)
Expbus Down					0.012***	-0.001	0.005***	-0.001*
					(0.001)	(0.001)	(0.000)	(0.000)
Input Costs					-0.039***	0.070***	-0.012***	0.040***
					(0.005)	(0.005)	(0.001)	(0.003)
Uncertainty					0.004***	0.002***	0.001***	0.001***
					(0.001)	(0.000)	(0.000)	(0.000)
Hazard Dummies	no	no	yes	yes	no	no	yes	yes
No. of obs.	1,613,872		1,613,872		1,015,178		1,015,178	
Pseudo R^2	0.04		0.24		0.26		0.38	

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table reports marginal effects; clustered (by firm) standard errors are in parentheses. Included in the models but not shown in the table are a constant, industry-specific dummies, hazard dummies, and seasonal dummies. Aggregate inflation is lagged by two months, aggregate production by three months, and price expectations by one month.

The next step is to introduce the two sets of hazard dummies to allow for time dependence. This leads to a huge increase in the pseudo R^2 and all the macroeconomic variables remain significant. However, the magnitude of the inflation coefficients is much smaller and the sign on the annual inflation effect on price decreases "flips" from negative to positive, whilst output growth remains significant and the coefficients only reduce by a small amount. In Column (3), we add the firm-specific effects and leave out the hazard dummies, which increases the pseudo R^2 only by a small amount. Output growth now becomes insignificant and much smaller, whilst the inflation coefficients retain their signs and significance but are also much smaller. Lastly, we include the hazard dummies along with all the state variables, which increases the pseudo R^2 by a greater amount. Output remains largely insignificant, while the signs on inflation equal those of model (2), although the coefficients are much smaller. The firm-specific variables remain all significant and retain their signs, but are smaller in size compared to model (3).

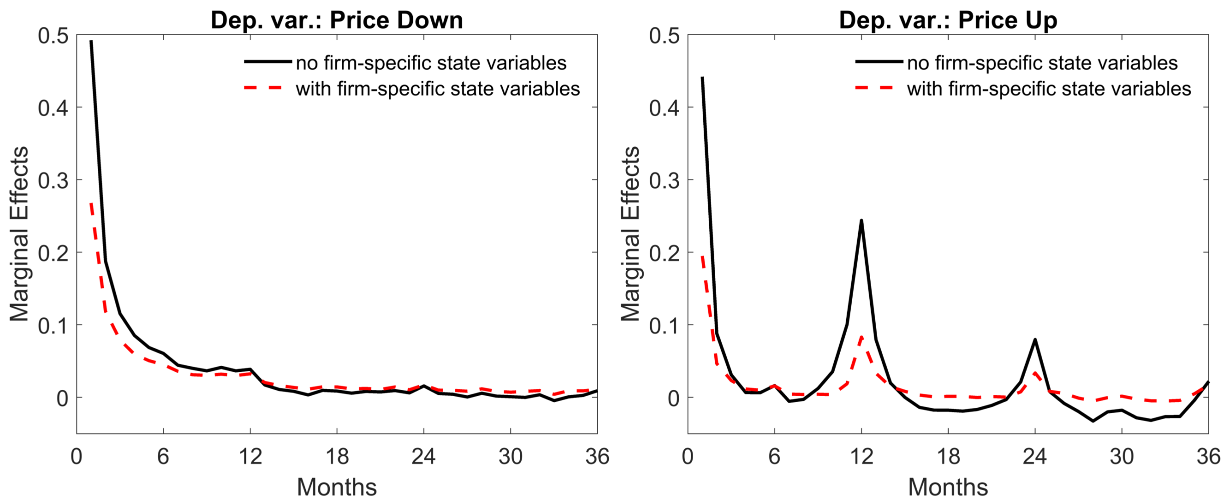
The quantitative interpretation of the coefficients is as the marginal effects of the explanatory variables. For example, in model (4) if *inflm* increases by 1 percentage point (pp) then the probability of a price rise increases by 0.037 pp; if *infly* increases by 1 pp, then the same probability increases by 0.044 pp. Hence, the coefficient on (annualized) *inflm* is of the same order as annual inflation. The only marginally significant coefficient on output *Mpy* implies that a 1 pp increase in annual output growth causes a 0.003 pp increase in the probability of a price cut. Since increases in output of 10 pp or more are not uncommon, the seemingly small marginal effect is, in effect, not so small. Overall, the quantitative effects of the macroeconomic variables greatly diminish when the model also includes hazards and firm-specific variables. Comparing model (1) to model (4), the effects of inflation and output are much larger in the smaller model, and the marginal effects for output turn all significant. For example, in model (1) a 1 pp increase in annual inflation leads to a 1.3 pp increase in the probability of a price increase; a 1 pp increase in annual growth leads to an increase of 0.2 pp.

Overall, the firm-specific variables in models (3) and (4) have the expected signs. In terms of the size, increases in price expectations, orders, and the state of business are particularly important for increasing the likelihood of price increases, while decreases in price expectations lower the probability of price increases. The likelihood of price decreases increases particularly with lower price expectations, decreasing orders, and a deterioration of the state of business. Higher input costs raise the likelihood of price increases and lower that of price decreases. Uncertainty raises both the likelihood of price increases and decreases.

The hazard dummies show the marginal effect (above or below the baseline case) in terms of time since the last price change. The hazard function in Figure 4 is simply one method of representing the distribution of durations, which we see in alternative form in Figure 6 in

Appendix A. It is the proportion of (surviving) spells that come to an end after surviving for i periods. The estimated hazard dummies show how the probability of a price increase (decrease) changes relative to the baseline probability after the last price increase (decrease). We have two sets of hazard dummies: one for price increases (following a previous increase) and one for price cuts (following a previous cut) which we depict in Figure 4, which shows the hazards estimated for both the full model (4) with firm-specific variables and model (2) without them.

Figure 4: Hazards



Notes: The figures report marginal effects. The black solid lines are derived from the estimation of the multinomial logit model with macroeconomic variables and hazard dummies as explanatory variables (model (2) in Table 5), the red dashed lines are derived from the model including macroeconomic and firm-specific state variables and hazard dummies as explanatory variables (model (4) in Table 5).

The hazard for a price increase starts from a high level, which reflects that there are many one period price-spells. The hazard decreases with a small spike at six months but with big spikes at 12 and 24 months. These peaks are very common features of micro-price CPI and PPI data (although standard approaches combine price increases and decreases). Apart from around the peaks, the price increase hazard is almost zero (the baseline) after seven months. The hazard for a price decrease following a previous price cut is decreasing: it starts high and falls off to almost zero from 13 months on.

The hazard almost equal to zero means that the probability equals the baseline probability.[12] The value of the estimated hazard dummy gives the change in probability of a price change relative to the baseline. For example, the probability of a price increase one month

[12] The baseline probability is computed when all dummy variables are zero and the aggregate variables, equal their respective sample mean. The probability for a price decrease is 2.6%, for a price increase it is 7.3%.

after a previous increase is 44 pp higher, after 12 months 24 pp higher; after 24 months 8 pp higher. For a price cut one month after a previous cut, it is 49 pp higher, after six months 6 pp higher, after 12 months 3.9 pp.

The Relative Importance of Time and State Dependence Since the estimates show that the factors underlying price increases and decreases are different, we now consider the relative importance of the three sets of variables (hazard dummies, macro variables, firm-specific variables) for explaining price increases and decreases, respectively. While the improvement in the model's total performance is captured by the pseudo R^2, we are particularly interested in the importance of the three types of variable sets in explaining price increases and price decreases separately. To do so, we need to look at the ability of each set to predict whether the price goes up or down for each firm at each point in time.

We do this by relying on a different goodness-of-fit measure: the Count R^2. The Count R^2 measures the proportion of correctly predicted price changes (see, e.g., Long and Freese, 2006, Greene and Hensher, 2010). For each firm and time period, we compute the probability of a price increase, a price decrease, and a no price change; each of the three values lies between 0 and 1, and they sum up to 1. For each firm-date combination we use as the model's prediction, the outcome which has a probability that exceeds 0.5. The predicted price change is correct if the actual price change realization (increase, decrease, or no change) is the same as the predicted price change (increase, decrease, or no change).

The simplest version of Count R^2 is:

$$\text{Count } R^2 = \frac{N_c}{N} \ , \tag{1}$$

where N is the total number of observations and N_c is the number of price realizations correctly predicted by our model. Equation (1) can be decomposed into the proportions of price increases, decreases and no change that were correctly predicted:

$$\text{Count } R^2 = \frac{\hat{p}_c^+}{p^+}\frac{p^+}{N} + \frac{\hat{p}_c^-}{p^-}\frac{p^-}{N} + \frac{\hat{p}_c^{no}}{p^{no}}\frac{p^{no}}{N} \ , \tag{2}$$

where $\hat{p}^j$ denotes the number of actual price increases ($j = +$), decreases ($j = -$), and no price changes ($j = \text{no}$), $\hat{p}_c^j$ describes the number of correctly predicted price increases ($j = +$), decreases ($j = -$), and no price changes ($j = \text{no}$), and N_c equals $\hat{p}_c^+ + \hat{p}_c^- + \hat{p}_c^{no}$. Within each sum, the first fraction describes the share of correctly predicted observations j with respect to the number of realizations j, the second fraction shows the share of realizations j with respect to the total number of all realizations.

Note that in 83% of observations there is no price change and this is the most likely outcome most of the time, so a correct prediction of no change does not tell us much about how good a model is. We therefore focus on the first two terms of the decomposition: price changes, which comprise respectively 9.3% of observations (price increases) and 7.4% (decreases). So, we propose to use the Change Count R^2: the proportion of price changes correctly predicted, subdivided into proportion of correctly predicted increases and decreases, each weighted by their relative share of all price changes:

$$\text{Change Count } R^2 = \frac{\hat{p}_c^+}{p^+}\,\frac{p^+}{p^+ + p^-} + \frac{\hat{p}_c^-}{p^-}\,\frac{p^-}{p^+ + p^-} \,. \tag{3}$$

Table 6 presents the share of correct predictions for price increases and decreases and their weighted average, the Change Count R^2 (CC R^2). Turning to the shares of correct predictions, the macroeconomic variables on their own do not carry enough information to explain price changes. If we combine them with the hazard dummies and firm-specific factors we can explain 43% of decreases and 36% of increases. On their own, hazard dummies explain 40% of cuts and 13% of increases; firm-specific effects correctly predict 29% of decreases and 14% of increases. Time-dependence, as captured by the hazard dummies, is more important than firm-specific effects for predicting price-decreases; and only a bit less important for price increases. However, the combination of both hazards and firm-specific effects is needed to explain price increases, as neither is much good on its own. If we add macroeconomic variables to the other two the effect is negligible.

Table 6: Relative Importance of the Sets of Variables in the Baseline Model

	Share Correctly Predicted		
Sets of Variables	$\hat{p}_c^-/p^-$	$\hat{p}_c^+/p^+$	CC R^2
Agg	0.0	0.0	0.0
Agg + Haz	39.2	15.1	25.8
Agg + Haz + Micro	43.3	35.7	39.0
Agg + Micro	28.9	13.7	20.2
Haz + Micro	43.3	35.7	39.0
Micro	28.9	13.5	20.1
Haz	40.0	12.8	24.6

Notes: Share Correctly Predicted: share of correctly predicted observations for price increases and decreases with respect to the number of realizations for price increases and decreases. All numbers are in percent. The measures are estimated from the multinomial logit models in Table 5. Agg: the model includes the aggregate variables inflation and production. Haz: the model includes two sets of hazard dummies. Micro: the model includes the firm-specific variables concerning expected prices, business situation and expectation, orders, uncertainty, and input cost.

From this analysis we derive two important insights. First, time dependence on its own is very important for price decreases, which might be explained by product life-cycle effects. Note that the hazard dummies are different from the monthly dummies which capture seasonality and are present in all the estimates. Second, for price increases, we need the interaction between hazard dummies and firm-specific state variables to get a reasonable proportion of correct predictions. The interaction of time- and state-dependent variables means that you are far more likely to get a price increase when there is a combination of state- and time-dependent effects at the same time. For example, looking at the right panel of Figure 4, the time-dependent hazard is almost zero (from benchmark) at 7 months following a price increase. That means that a powerful state-dependent effect is required to elicit a price change. On the other hand, in the first six months following a price cut the time-dependent probability remains high, indicating that moderate firm-specific state effects might be enough to elicit a change. For both increases and decreases, there is an increase in the hazard at twelve months, indicating that a more moderate state dependence might lead to a change. The bigger the time-dependent hazard, the smaller the state-dependent effect required to trigger a change.

How Many Hazards? We adopt two sets of hazards in our baseline estimation. We now show that this is superior to the standard approach with just one set of hazards that combines price increases and decreases. Also, we show that using four instead of two sets does not improve the model by much.

Table 7 compares the percentage of correctly predicted outcomes for our baseline two-hazard model with both alternatives using our Mlogit model. As we can see, the four-hazard model does have higher predictive power, but only very little. The improvement in the CC R^2 is between 0.2 and 1.3 pp. Turning to the one-hazard model, this model does much worsewithout the micro and aggregate variables than the two-hazard model we have adopted in the paper. This suggests that the standard approach in the existing literature is far from the best.

4 Robustness and Alternatives

We provide three alternative model specifications to check the robustness of our baseline findings. First, we switch to an ordered probit model. Second, we replace the aggregate production variables in the baseline model with an output gap measure. Third, we drop the aggregate variables from the baseline model and include time-fixed effects instead.

Table 7: Relative Importance of the Sets of Variables: 1 vs. 2 vs. 4 Sets of Hazards

	Share Correctly Predicted								
	$\hat{p}_c^-/p^-$	$\hat{p}_c^+/p^+$	CC R^2	$\hat{p}_c^-/p^-$	$\hat{p}_c^+/p^+$	CC R^2	$\hat{p}_c^-/p^-$	$\hat{p}_c^+/p^+$	CC R^2
Sets of Variables	Baseline (2 Hazard Sets)			1 Hazard Set			4 Hazard Sets		
Agg + Haz	39.2	15.1	25.8	3.6	1.6	2.5	38.3	17.4	26.6
Agg + Haz + Micro	43.3	35.7	39.0	35.3	34.7	35.0	43.7	35.8	39.8
Haz + Micro	43.3	35.7	39.0	35.3	34.8	35.0	43.7	35.8	39.2
Haz	40.0	12.8	24.6	0.2	0.1	0.1	38.6	16.1	25.9

Notes: Share Correctly Predicted: share of correctly predicted observations for price increases and decreases with respect to the number of realizations for price increases and decreases. All numbers are in percent. The measures are estimated from multinomial logit models. Agg: the model includes the aggregate variables inflation and production. Haz: the model includes either two sets of hazard dummies, one set, or four sets. Micro: the model includes the firm-specific variables concerning expected prices, business situation and expectation, orders, uncertainty, and input cost.

Why use a multinomial logit and not an ordered probit? The MLogit finds the best classification system for explaining price increases and decreases and does not require any particular natural ordering across the outcomes. The ordered probit approach in contrast requires a natural ordering of the dependent variable and is best interpreted as reflecting a latent variable which itself has a natural ordering and is influenced by the independent variables. If the independent variables generate a high value of the latent variable, they will generate a high value of the dependent variable. There is thus the presumption of a single process generating outcomes. It is certainly possible to interpret price changes in this way: the unobserved latent variable is the gap between the optimal flexible price and the actual price. If the gap is large and positive, then the firm is more likely to raise its price. If the gap is small in absolute value, the firms will keep its price constant. If the gap is sufficiently negative the firm will be more likely to cut price. However, the Mlogit is more general in the sense that it allows for different factors to influence price increases and decreases. For example, price decreases might be because of random sales promotions; a price increase (decrease) might be more likely after an earlier increase (decrease).

However, whilst our preferred approach is the MLogit, we find almost the same results if we estimate the ordered probit model (see Table 8). The main difference is that when we include the firm-specific variables and the hazard dummies the annual inflation ceases to be significant for both price increases and decreases. Also, in the ordered probit model annual output growth is marginally significant for both price increases and decreases, whereas in the MLogit model it is marginally significant for only decreases.

The relative importance of the variables in terms of the proportion of correct predictions is similar to the MLogit results (see Panel (a) in Table 9). Price decreases are well explained by time dependence, while price increases are best desribed by the interaction of time dependence and firm-specific state variables. Aggregate variables do not help us much at all in correctly predicting price changes.

Many researchers prefer to use the output gap instead of output growth to ensure stationarity of the industrial output series, where the "gap" is between the actual output level and some estimate of "trend" output. Our reasoning for using growth was that in the post-crisis world there is much less confidence about what is the natural rate (or NAIRU). However, Table 10 shows that using the output gap in the baseline model makes little difference to the results using output growth, although the changes in the coefficients for output reflect the difference in variables used.

When we turn to the correctly predicted price changes, the output gap formulation yields the same results (reported to one decimal lace) as we had with growth (see Panel (b) in Table 9). This is not surprising since the macro variables do not matter much when it comes to predicting individual firm decisions to change price. Changing how you measure one of the macro variables (output growth to output gap) is unlikely to change this.

Lein (2010) used time-fixed effects rather than specific macroeconomic variables and we next replicate this approach. If we just have the time dummies, the pseudo R^2 is still very low (see Table 11). This indicates that our choice of output and inflation are not misleading and are almost as good as the time dummies. Hazard dummies and firm-specific effects greatly improve the pseudo R^2 as in our preferred case.

Again, if we look at the proportions of price changes correctly predicted and compare them with the model in Section 3, the results are very similar (see Panel (c) in Table 9). The time-fixed effects dummies do a little better than our chosen macro-variables; the CC R^2 increases by 0.1 to 0.8 pp. But, the overall story remains the same.

So, we can see that the conclusions of our study are robust to a range of alternatives. In Appendix C, we consider two more alternatives: a linear panel fixed effects model and simple probit models for all price changes and price increases and decreases separately.

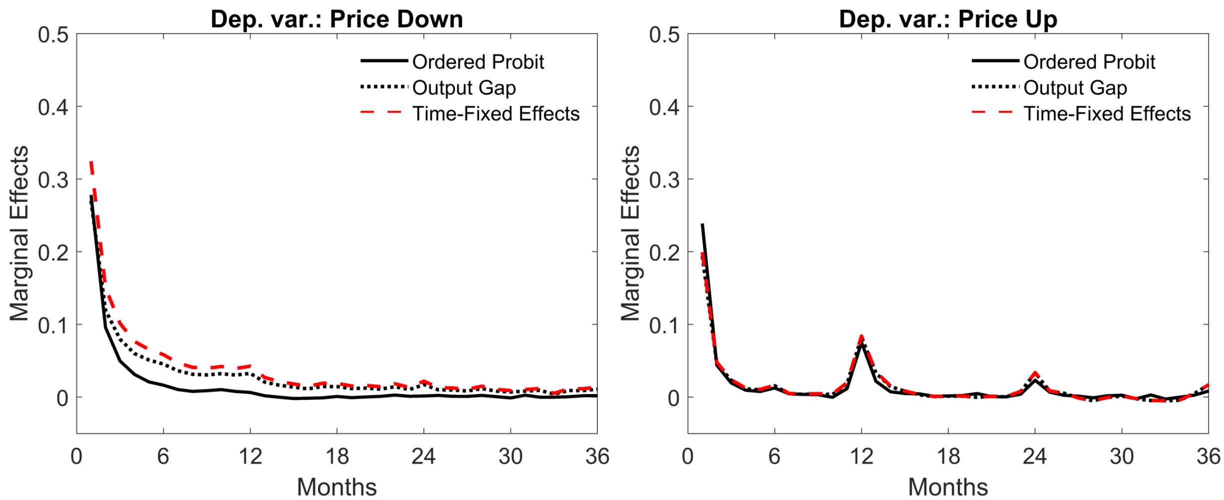
Table 8: Ordered Probit Model

	(1)		(2)		(3)		(4)	
Depend. Var.:	Price ↓	Price ↑	Price ↓	Price ↑	Price ↓	Price ↑	Price ↓	Price ↑
Inflm	-0.271***	0.559***	-0.148***	0.343***	-0.068***	0.096***	-0.048***	0.077***
	(0.015)	(0.022)	(0.006)	(0.012)	(0.008)	(0.011)	(0.005)	(0.008)
Infly	-0.459***	0.947***	-0.145***	0.336***	-0.138***	0.196***	0.002	-0.004
	(0.026)	(0.043)	(0.008)	(0.019)	(0.016)	(0.023)	(0.008)	(0.013)
Mpm	-0.003***	0.006***	-0.002***	0.005***	-0.001	0.001	-0.001*	0.001*
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
Mpy	-0.119***	0.246***	-0.045***	0.105***	-0.008**	0.011**	0.006**	-0.009**
	(0.006)	(0.010)	(0.002)	(0.004)	(0.003)	(0.004)	(0.002)	(0.003)
Unific	0.014***	-0.024***	0.005***	-0.010***	-0.000	0.000	-0.001*	0.001*
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Euro	-0.005***	0.011***	-0.004***	0.009***	-0.003***	0.004***	-0.002***	0.004***
	(0.001)	(0.002)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Fin Crisis	0.004*	-0.007**	0.005***	-0.010***	-0.004***	0.006**	0.001	-0.001
	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Other Crises	0.020***	-0.032***	0.009***	-0.017***	0.001*	-0.002*	0.001	-0.001
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Expprice Up					-0.033***	0.302***	-0.021***	0.212***
					(0.002)	(0.007)	(0.001)	(0.005)
Expprice Down					0.331***	-0.051***	0.081***	-0.032***
					(0.009)	(0.003)	(0.003)	(0.001)
Order Up					-0.008***	0.014***	-0.007***	0.014***
					(0.001)	(0.001)	(0.000)	(0.001)
Order Down					0.015***	-0.016***	0.012***	-0.014***
					(0.001)	(0.001)	(0.001)	(0.001)
Statebus Up					-0.011***	0.020***	-0.004***	0.008***
					(0.001)	(0.001)	(0.000)	(0.001)
Statebus Down					0.025***	-0.022***	0.010***	-0.012***
					(0.001)	(0.001)	(0.001)	(0.001)
Expbus Up					-0.004***	0.005***	-0.002***	0.004***
					(0.001)	(0.001)	(0.000)	(0.001)
Expbus Down					0.011***	-0.013***	0.007***	-0.009***
					(0.001)	(0.001)	(0.000)	(0.001)
Input Costs					-0.075***	0.107***	-0.039***	0.063***
					(0.005)	(0.006)	(0.002)	(0.003)
Uncertainty					0.002***	-0.002***	0.000	-0.000
					(0.000)	(0.001)	(0.000)	(0.000)
Hazard Dummies	no	no	yes	yes	no	no	yes	yes
No. of obs.	1,613,872		1,613,872		1,015,178		1,015,178	
Pseudo R^2	0.02		0.21		0.23		0.33	

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table reports marginal effects; clustered (by firm) standard errors are in parentheses. Included in the models but not shown in the table are a constant, industry-specific dummies, hazard dummies, and seasonal dummies. Aggregate inflation is lagged by two months, aggregate production by three months, and price expectations by one month.

Figure 5: Hazards of Robustness-Models



Notes: The figures report marginal effects. The lines for *Ordered Probit* and *Output Gap* are derived from models that include macroeconomic and firm-specific state variables and hazard dummies as explanatory variables; for *Time-Fixed Effects*, the macroeconomic variables are replaced by time-fixed effects.

Table 9: Relative Importance of the Sets of Variables

	Share Correctly Predicted								
	$\hat{p}_c^-/p^-$	$\hat{p}_c^+/p^+$	CC R^2	$\hat{p}_c^-/p^-$	$\hat{p}_c^+/p^+$	CC R^2	$\hat{p}_c^-/p^-$	$\hat{p}_c^+/p^+$	CC R^2
Sets of Variables	(a) Ordered Probit			(b) Output Gap			(c) Time-Fixed Effects		
Agg	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0
Agg + Haz	35.1	7.4	19.7	39.2	15.2	25.7	38.2	17.7	26.6
Agg + Haz + Micro	38.5	30.3	33.8	43.3	35.7	39.0	43.5	35.7	39.1
Agg + Micro	27.4	5.0	14.6	28.9	13.6	20.2	29.0	14.9	21.0
Haz + Micro	38.5	30.4	33.8	43.3	35.7	39.0	43.3	35.7	39.0
Micro	27.4	5.0	14.6	28.9	13.5	20.1	28.9	13.5	20.1
Haz	37.4	5.1	19.2	40.0	12.8	24.6	40.0	12.8	24.6

Notes: Share Correctly Predicted: share of correctly predicted observations for price increases and decreases with respect to the number of realizations for price increases and decreases. All numbers are in percent. Panel (a) is estimated from an ordered probit model, Panels (b) and (c) are estimated from multinomial logit models. Agg: the model includes the aggregate variables inflation and production (Panels (a) and (b)), Panel (c) includes time-fixed effects instead. Haz: the model includes two sets of hazard dummies. Micro: the model includes the firm-specific variables concerning expected prices, business situation and expectation, orders, uncertainty, and input cost.

Table 10: Multinomial Logit Model with Output Gap

	(1)		(2)		(3)		(4)	
Depend. Var.:	Price ↓	Price ↑	Price ↓	Price ↑	Price ↓	Price ↑	Price ↓	Price ↑
Inflm	-0.197***	0.595***	-0.090***	0.347***	-0.006	0.060***	-0.008**	0.035***
	(0.019)	(0.032)	(0.007)	(0.017)	(0.006)	(0.008)	(0.003)	(0.005)
Infly	-0.073**	1.289***	0.065***	0.598***	-0.049***	0.160***	0.008	0.050***
	(0.022)	(0.071)	(0.009)	(0.032)	(0.014)	(0.019)	(0.005)	(0.010)
Output Gap	-0.308***	0.492***	-0.087***	0.212***	-0.012*	-0.014	0.011***	-0.020***
	(0.029)	(0.033)	(0.006)	(0.015)	(0.006)	(0.008)	(0.002)	(0.005)
Unific	0.033***	-0.015***	0.011***	-0.006***	0.005***	0.005***	0.001***	0.002***
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Euro	-0.003*	0.030***	-0.001***	0.018***	0.001*	0.007***	0.001**	0.004***
	(0.001)	(0.003)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Fin Crisis	0.035***	-0.016***	0.018***	-0.009***	-0.002*	0.004**	0.001	0.002**
	(0.004)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Other Crises	0.021***	-0.040***	0.009***	-0.021***	-0.001	-0.003***	0.000	-0.000
	(0.002)	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
Expprice Up					-0.013***	0.276***	-0.004***	0.158***
					(0.001)	(0.013)	(0.000)	(0.007)
Expprice Down					0.235***	-0.016***	0.023***	-0.005***
					(0.019)	(0.002)	(0.002)	(0.001)
Order Up					0.001*	0.015***	-0.001***	0.010***
					(0.001)	(0.001)	(0.000)	(0.001)
Order Down					0.014***	-0.004***	0.008***	-0.003***
					(0.002)	(0.001)	(0.001)	(0.000)
Statebus Up					-0.009***	0.012***	-0.002***	0.006***
					(0.001)	(0.001)	(0.000)	(0.000)
Statebus Down					0.023***	-0.005***	0.005***	-0.003***
					(0.002)	(0.001)	(0.000)	(0.000)
Expbus Up					0.000	0.004***	-0.000	0.003***
					(0.001)	(0.001)	(0.000)	(0.000)
Expbus Down					0.012***	-0.001	0.005***	-0.001*
					(0.001)	(0.001)	(0.000)	(0.000)
Input Costs					-0.039***	0.071***	-0.013***	0.041***
					(0.005)	(0.005)	(0.001)	(0.003)
Uncertainty					0.004***	0.002***	0.001***	0.001***
					(0.001)	(0.000)	(0.000)	(0.000)
Hazard Dummies	no	no	yes	yes	no	no	yes	yes
No. of obs.	1,619,373		1,619,373		1,015,178		1,015,178	
Pseudo R^2	0.05		0.24		0.26		0.38	

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table reports marginal effects; clustered (by firm) standard errors are in parentheses. Included in the models but not shown in the table are a constant, industry-specific dummies, hazard dummies, and seasonal dummies. Aggregate inflation is lagged by two months, the output gap – constructed using aggregate production and the one-sided HP-filter – by three months, and price expectations by one month.

Table 11: Multinomial Logit Model with Time-Fixed Effects

	(1)		(2)		(3)		(4)	
Depend. Var.:	Price ↓	Price ↑	Price ↓	Price ↑	Price ↓	Price ↑	Price ↓	Price ↑
Unific	0.055***	-0.162***	0.031***	-0.140***	0.007	0.028	0.004	0.021
	(0.009)	(0.015)	(0.007)	(0.014)	(0.006)	(0.017)	(0.004)	(0.012)
Euro	-0.002	0.066*	-0.006***	0.122***	0.000	-0.019**	-0.003	-0.011**
	(0.001)	(0.026)	(0.002)	(0.027)	(0.004)	(0.006)	(0.002)	(0.004)
Fin Crisis	0.031***	-0.078***	0.024***	-0.054***	0.001	0.003	0.002	-0.001
	(0.005)	(0.019)	(0.005)	(0.015)	(0.003)	(0.009)	(0.002)	(0.005)
Other Crises	0.005***	0.027	0.000	0.096***	0.002	-0.008	0.000	-0.004
	(0.001)	(0.018)	(0.001)	(0.017)	(0.003)	(0.007)	(0.002)	(0.004)
Expprice Up					-0.014***	0.332***	-0.005***	0.161***
					(0.003)	(0.035)	(0.001)	(0.026)
Expprice Down					0.232***	-0.021***	0.029***	-0.005***
					(0.035)	(0.004)	(0.006)	(0.001)
Order Up					0.001	0.019***	-0.001***	0.010***
					(0.001)	(0.003)	(0.000)	(0.002)
Order Down					0.014***	-0.005***	0.010***	-0.003***
					(0.003)	(0.001)	(0.002)	(0.001)
Statebus Up					-0.009***	0.016***	-0.003***	0.006***
					(0.002)	(0.003)	(0.001)	(0.001)
Statebus Down					0.022***	-0.006***	0.007***	-0.003***
					(0.004)	(0.001)	(0.002)	(0.001)
Expbus Up					0.000	0.006***	-0.000	0.003***
					(0.001)	(0.001)	(0.000)	(0.001)
Expbus Down					0.012***	-0.000	0.006***	-0.001
					(0.002)	(0.001)	(0.001)	(0.000)
Input Costs					-0.028***	0.059***	-0.012***	0.022***
					(0.007)	(0.011)	(0.003)	(0.005)
Uncertainty					0.004***	0.003***	0.001***	0.001***
					(0.001)	(0.001)	(0.000)	(0.000)
Hazard Dummies	no	no	yes	yes	no	no	yes	yes
No. of obs.	1,630,376		1,630,376		1,015,178		1,015,178	
Pseudo R^2	0.06		0.25		0.26		0.38	

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table reports marginal effects; clustered (by firm) standard errors are in parentheses. Included in the models but not shown in the table are a constant, monthly time-fixed effects, industry-specific dummies, hazard dummies, and seasonal dummies. Price expectations are lagged by one month.

5 Conclusion

Our results show that both time-dependent and firm-specific effects are important in determining firms' pricing decisions. Macroeconomic variables play a role, but only a minor one. For price decreases, the hazard dummies are most important and the firm-specific effects add only a little. For price increases, you need both hazard dummies and firm-specific effects to get the best results. These results are very robust across estimation methodologies and alternative specifications.

The main innovation of the paper is the use of much more general hazard dummies than other papers. We have shown that the best way to model time-dependence is to allow for different hazards for price increases and price decreases. The hazards for these look completely different from each other, and the conventional approach of bundling them together cannot capture all the salient features of the data. Our proposed methodology can be applied to existing CPI and PPI data so long as we use uncensored price-spells. We will need to know whether a price spell begins with a price decrease or increase and whether it ends with an increase or decrease.

The implications of our results are that we should not treat time- and state-dependence as two mutually exclusive alternatives. They are complimentary approaches. There are clear seasonal and duration dependent elements to pricing. However, what happens to the firm also matters and may override the time dependence. This suggests that perhaps we can capture both aspects in a model where the costs of changing price have a duration dependence, and that large or sustained shocks can lead to deviations from standard behavior. Existing models that combine state dependence with time dependence include Alvarez et al. (2016b) and Nakamura and Steinsson's (2010) CalvoPlus model. However, both of these papers have a very specific approach to modelling time dependence based on the Calvo model, namely there is a constant probability of obtaining a low or zero cost of price adjustment. As we can see from the hazard dummies we have estimated, there is a need to differentiate between price increases and decreases and to allow for a general (non-constant) hazard function. This is a matter for future research.

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A Price Spells: Uncensored and Censored

We describe the aggregate picture of price-spells over the whole data set in terms of three different perspectives estimated according to the Kaplan-Meyer non-parametric method:

1. The hazard function, giving the probability of a price change conditional on the number of periods since the last price-change,

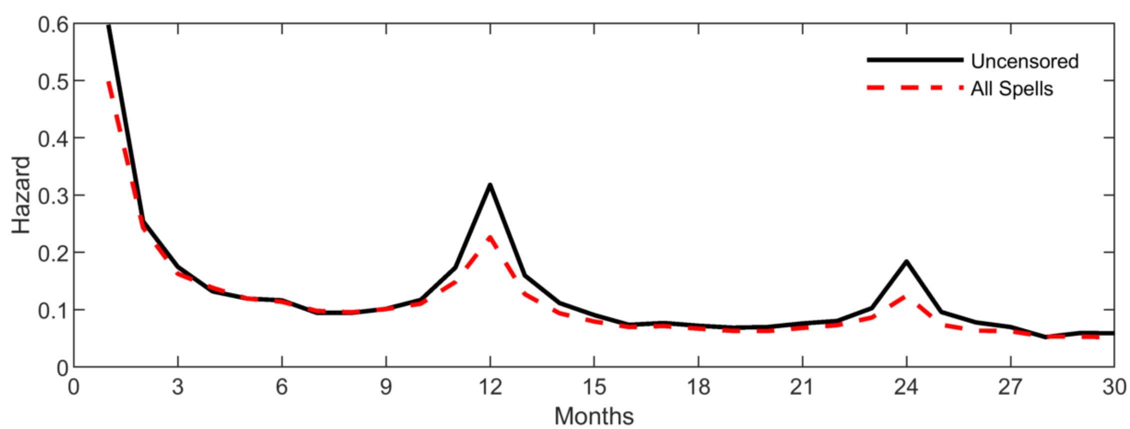
2. the pdf distribution of price spell durations,

3. the cross-sectional distribution of completed spells.

For the formal description of how 1–3 are related, see Dixon (2012) or Dixon and Tian (2017). We do this for two populations: first, all spells (both censored and uncensored), and secondly for just the uncensored spells.

The hazard function for all spells is derived under the assumption that the observed portion ends with a change and begins after a change. In Figure 6 we compare the hazard function for the uncensored data with all spells: it lies above the hazard for all spells most of the time. Both hazards exhibit big peaks at 12, 24 and 36 months and a slightly less pronounced peak at 48 months. This should alert us to the fact that time dependence is important in this data. However, the biggest peak is at 1 month, indicating that almost 60% of uncensored spells and 50% of all spells change after one month (i.e. there are a lot of one-month spells).

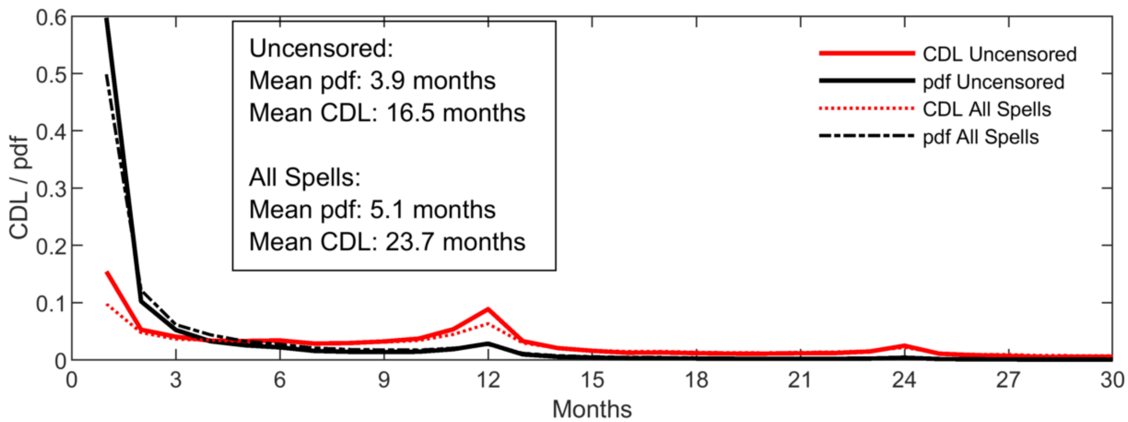
Figure 6: Hazard Function for Uncensored Spells and All Spells



Notes: The hazards are computed using the Kaplan-Meyer non-parametric estimator. The black solid line is derived from the raw, uncensored data. The red dashed line is derived under the assumption that the observed portion ends with a change and begins after a change.

The pdf of price spell durations shows that the mean spell is 3.9 months for the uncensored sample, but 5.1 for all spells (see Figure 7). For the cross sectional distribution (CDL), which weights spells by length, the means are 16.5 and 23.7 months, respectively. Hence the sample of uncensored spells we use has significantly shorter lived spells than the whole sample. However, since we are not seeking to estimate average durations but the determinants of price changes, this should not matter much.

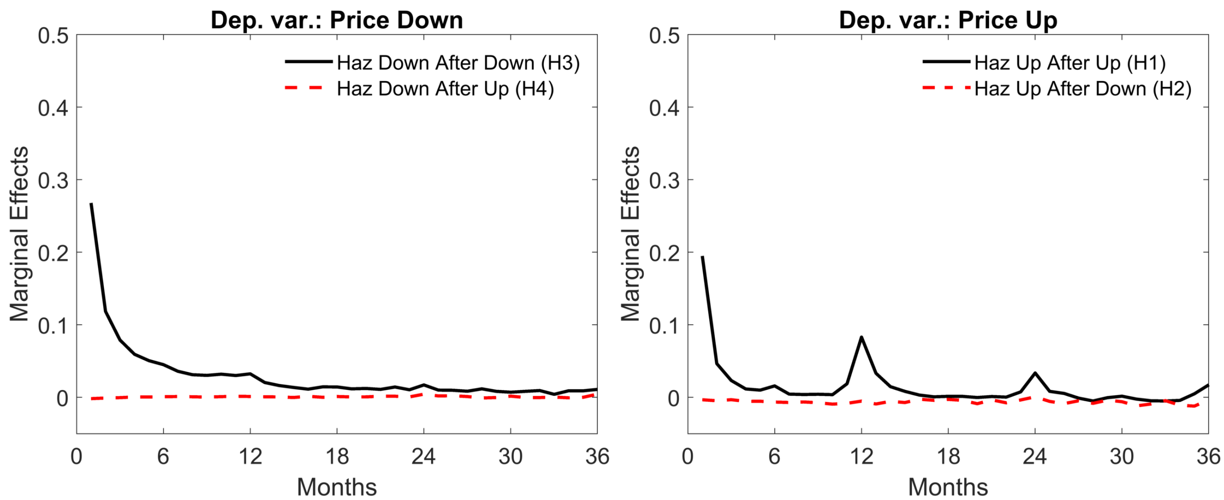
Figure 7: PDF Durations and CDL



Notes: The lines are derived from the survivor estimates. The CDL-estimates weight spells by length. Given the Kaplan-Meyer estimates of the survival function, $S(i)$ (the proportion of price spells that last more than i periods) for $i = 0, 1, \ldots, F$ with $S(0) = 1$ and $S(F) = 0$ and $1 \geq S(i) > 0$ for $i = 1, \ldots, F-1$. The hazard function is then: $h(i) = (S(i-1) - S(i))/S(i-1)$ for $i = 1, \ldots, F-1$ with $h(F) = 1$. The pdf of price-spell durations is then $d(i) = S(i-1)h(i)$ for $i = 1, \ldots, F$. The CDL is $\alpha(i) = i.d(i)/\sum_{j=0}^{F} S(j)$.

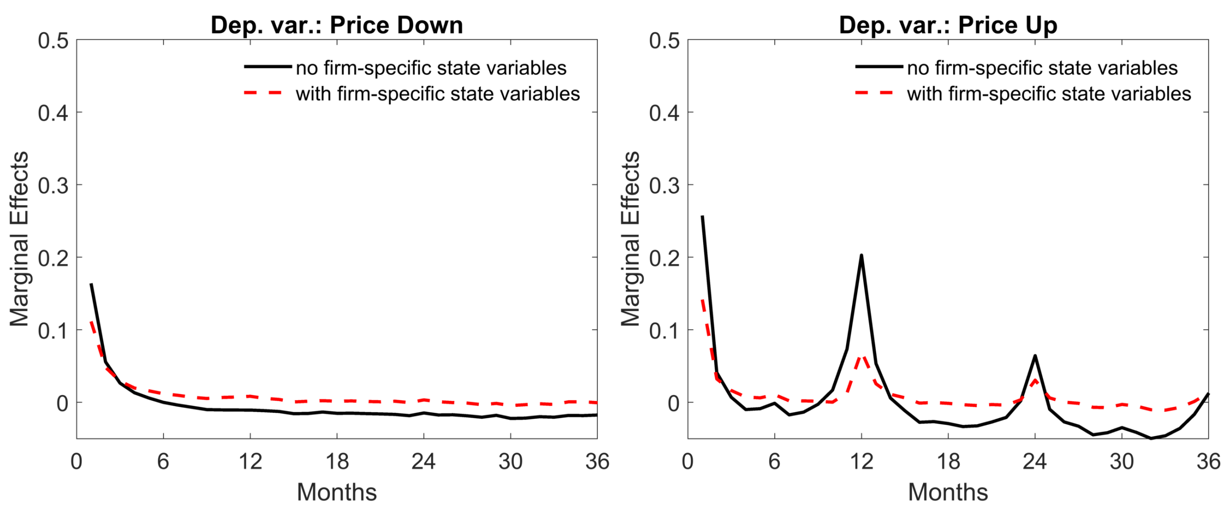
B Different Sets of Hazards

Figure 8: Four Sets of Hazards



Notes: The figures report marginal effects. All lines are derived from the multinomial logit model including macroeconomic and firm-specific state variables and hazard dummies as explanatory variables. The model includes four sets of hazard dummies instead of two sets as in the baseline model.

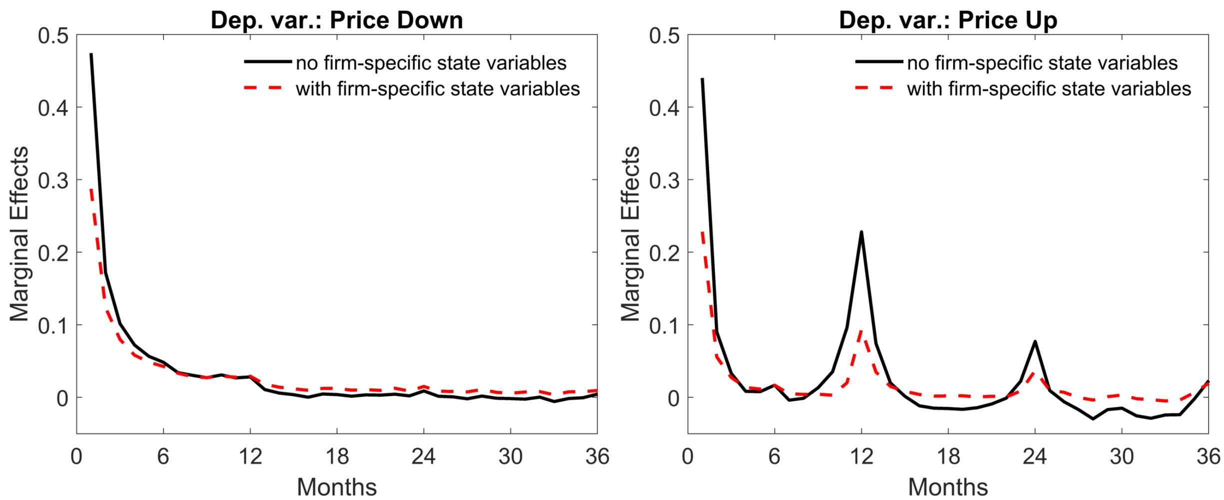
Figure 9: One Set of Hazards



Notes: The figures report marginal effects. All lines are derived from the multinomial logit model including macroeconomic and firm-specific state variables and hazard dummies as explanatory variables. The model includes one set of hazard dummies instead of two sets as in the baseline model.

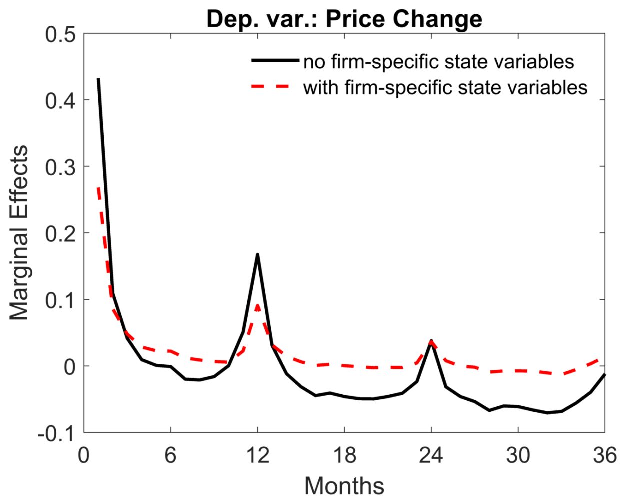
C Further Robustness Checks

Figure 10: Hazards of Probit Model with Price Decreases and Increases



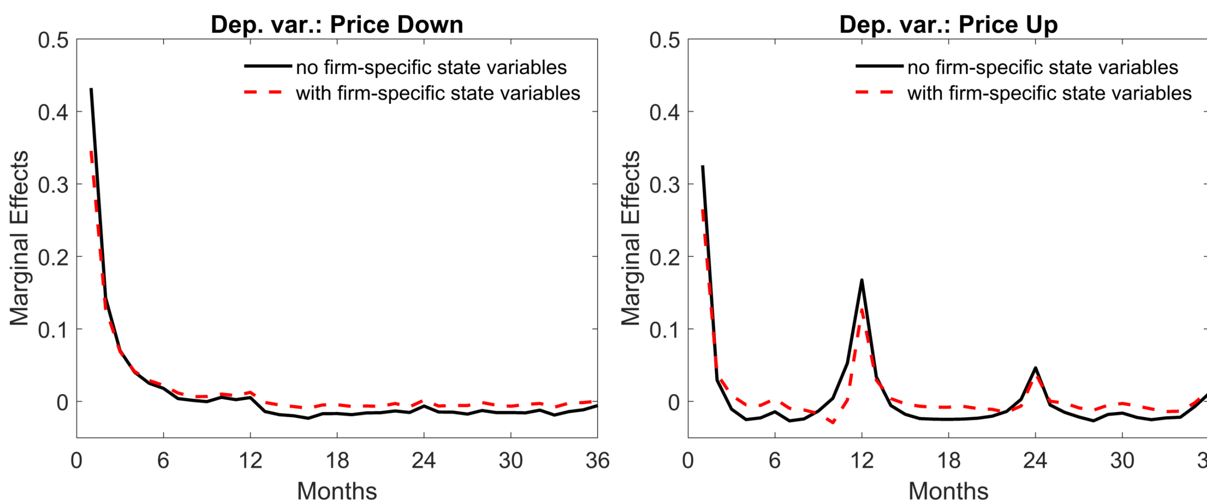
Notes: The figures report marginal effects. The black solid lines are derived from the estimation of the multinomial logit model with macroeconomic variables and hazard dummies as explanatory variables (model (2) in Table 12), the red dashed lines are derived from the model including macroeconomic and firm-specific state variables and hazard dummies as explanatory variables (model (4) in Table 12).

Figure 11: Hazards of Probit Model with Price Change



Notes: The figures report marginal effects. The black solid lines are derived from the estimation of the probit model with macroeconomic variables and hazard dummies as explanatory variables (model (2) in Table 13), the red dashed lines are derived from the model including macroeconomic and firm-specific state variables and hazard dummies as explanatory variables (model (4) in Table 13).

Figure 12: Hazards of Linear Panel Fixed Effects Model



Notes: The figures report coefficients. The black solid lines are derived from the estimation of the linear panel fixed effects model with macroeconomic variables and hazard dummies as explanatory variables (models (3) and (4) in Table 14), the red dashed lines are derived from the model including macroeconomic and firm-specific state variables and hazard dummies as explanatory variables (models (7) and (8) in Table 14).

Table 12: Probit Model with Price Decreases and Increases

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Depend. Var.:	Price ↓	Price ↑	Price ↓	Price ↑	Price ↓	Price ↑	Price ↓	Price ↑
Inflm	-0.190***	0.551***	-0.083***	0.354***	-0.009	0.074***	-0.011***	0.051***
	(0.018)	(0.025)	(0.007)	(0.016)	(0.006)	(0.010)	(0.003)	(0.006)
Infly	-0.185***	1.331***	0.032***	0.682***	-0.063***	0.182***	0.012**	0.034**
	(0.027)	(0.061)	(0.008)	(0.031)	(0.015)	(0.023)	(0.005)	(0.011)
Mpm	-0.002***	0.006***	-0.002***	0.004***	0.000	0.001	-0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
Mpy	-0.135***	0.187***	-0.045***	0.101***	-0.005*	0.004	0.003*	-0.002
	(0.012)	(0.010)	(0.003)	(0.006)	(0.003)	(0.004)	(0.001)	(0.002)
Unific	0.029***	-0.010***	0.011***	-0.005***	0.005***	0.005***	0.001***	0.002***
	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Euro	0.001	0.023***	-0.001	0.014***	0.002*	0.008***	0.000*	0.005***
	(0.001)	(0.002)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Fin Crisis	0.012***	0.013***	0.008***	0.003*	-0.003*	0.004**	0.001**	0.000
	(0.002)	(0.003)	(0.001)	(0.002)	(0.001)	(0.002)	(0.000)	(0.001)
Other Crises	0.015***	-0.033***	0.006***	-0.019***	-0.001	-0.003***	0.000**	-0.001*
	(0.002)	(0.002)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
Expprice Up					-0.013***	0.286***	-0.005***	0.184***
					(0.001)	(0.011)	(0.000)	(0.007)
Expprice Down					0.273***	-0.021***	0.037***	-0.010***
					(0.016)	(0.002)	(0.003)	(0.001)
Order Up					0.001*	0.018***	-0.001***	0.013***
					(0.001)	(0.001)	(0.000)	(0.001)
Order Down					0.015***	-0.005***	0.009***	-0.004***
					(0.002)	(0.001)	(0.001)	(0.000)
Statebus Up					-0.009***	0.015***	-0.002***	0.007***
					(0.001)	(0.001)	(0.000)	(0.001)
Statebus Down					0.025***	-0.006***	0.006***	-0.003***
					(0.002)	(0.001)	(0.001)	(0.000)
Expbus Up					0.000	0.006***	-0.000	0.003***
					(0.001)	(0.001)	(0.000)	(0.000)
Expbus Down					0.013***	-0.001	0.006***	-0.001**
					(0.001)	(0.001)	(0.001)	(0.000)
Input Costs					-0.042***	0.085***	-0.014***	0.048***
					(0.005)	(0.007)	(0.001)	(0.003)
Uncertainty					0.004***	0.003***	0.001***	0.001***
					(0.001)	(0.001)	(0.000)	(0.000)
Hazard Dummies	no	no	yes	yes	no	no	yes	yes
No. of obs.	1,613,872	1,613,872	1,613,872	1,613,872	1,015,178	1,015,178	1,015,178	1,015,178
Pseudo R^2	0.05	0.04	0.30	0.19	0.28	0.25	0.43	0.34

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table reports marginal effects; clustered (by firm) standard errors are in parentheses. Included in the models but not shown in the table are a constant, industry-specific dummies, two sets of hazard dummies (price down for models (1), (3), (5), and (7), price up for models (2), (4), (6), and (8)), and seasonal dummies. Aggregate inflation is lagged by two months, aggregate production by three months, and price expectations by one month.

Table 13: Probit Model with Price Change

	(1)	(2)	(3)	(4)
Depend. Var.: Price Change				
Inflm	0.217***	0.157***	0.039***	0.020***
	(0.016)	(0.012)	(0.009)	(0.006)
Infly	0.777***	0.415***	0.071**	-0.037***
	(0.045)	(0.026)	(0.022)	(0.010)
Mpm	0.005***	0.002*	0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.000)
Mpy	-0.090***	-0.050***	-0.013**	-0.003
	(0.008)	(0.005)	(0.004)	(0.002)
Unific	0.027***	0.016***	0.012***	0.006***
	(0.002)	(0.001)	(0.001)	(0.001)
Euro	0.022***	0.012***	0.008***	0.004***
	(0.003)	(0.002)	(0.001)	(0.001)
Fin Crisis	0.032***	0.018***	0.005**	0.001
	(0.003)	(0.002)	(0.002)	(0.001)
Other Crises	-0.007***	-0.004***	-0.003***	-0.001*
	(0.001)	(0.001)	(0.001)	(0.000)
Expprice Up			0.229***	0.143***
			(0.008)	(0.005)
Expprice Down			0.343***	0.128***
			(0.010)	(0.005)
Order Up			0.022***	0.011***
			(0.001)	(0.001)
Order Down			0.015***	0.010***
			(0.001)	(0.001)
Statebus Up			0.011***	0.004***
			(0.001)	(0.001)
Statebus Down			0.026***	0.013***
			(0.002)	(0.001)
Expbus Up			0.006***	0.003***
			(0.001)	(0.000)
Expbus Down			0.018***	0.011***
			(0.001)	(0.001)
Input Costs			0.040***	0.017***
			(0.004)	(0.002)
Uncertainty			0.007***	0.002***
			(0.001)	(0.000)
Hazard Dummies	no	yes	no	yes
No. of obs.	1,613,872	1,613,872	1,015,178	1,015,178
Pseudo R^2	0.03	0.17	0.18	0.28

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table reports marginal effects; clustered (by firm) standard errors are in parentheses. Included in the models but not shown in the table are a constant, industry-specific dummies, one set of hazard dummies for price change, and seasonal dummies. Aggregate inflation is lagged by two months, aggregate production by three months, and price expectations by one month.

Table 14: Linear Panel Fixed Effects Models with Price Decreases and Increases

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Depend. Var.:	Price ↓	Price ↑	Price ↓	Price ↑	Price ↓	Price ↑	Price ↓	Price ↑
Inflm	-0.306***	0.537***	-0.199***	0.418***	-0.073***	0.173***	-0.063***	0.140***
	(0.012)	(0.015)	(0.009)	(0.012)	(0.013)	(0.016)	(0.011)	(0.014)
Infly	-0.359***	1.085***	-0.085***	0.700***	-0.139***	0.262***	-0.012	0.058*
	(0.031)	(0.030)	(0.018)	(0.022)	(0.031)	(0.032)	(0.021)	(0.024)
Mpm	-0.002***	0.006***	-0.003***	0.004***	-0.000	0.002*	-0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Mpy	-0.219***	0.137***	-0.111***	0.097***	-0.028***	-0.002	0.008	-0.005
	(0.007)	(0.005)	(0.004)	(0.004)	(0.007)	(0.006)	(0.005)	(0.005)
Unific	0.032***	-0.010***	0.018***	-0.007***	0.009***	0.010***	0.005***	0.008***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Euro	0.003	0.008***	0.000	0.006***	0.001	0.010***	0.000	0.008***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Fin Crisis	0.022***	0.010***	0.018***	0.005**	0.000	0.011***	0.003	0.006**
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Other Crises	0.023***	-0.026***	0.013***	-0.019***	-0.001	-0.003**	-0.001	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Expprice Up					-0.033***	0.285***	-0.021***	0.245***
					(0.001)	(0.002)	(0.001)	(0.002)
Expprice Down					0.359***	-0.032***	0.205***	-0.015***
					(0.004)	(0.001)	(0.003)	(0.001)
Order Up					0.002*	0.031***	-0.003***	0.029***
					(0.001)	(0.001)	(0.001)	(0.001)
Order Down					0.031***	-0.008***	0.031***	-0.008***
					(0.001)	(0.001)	(0.001)	(0.001)
Statebus Up					-0.012***	0.030***	-0.004***	0.021***
					(0.001)	(0.001)	(0.001)	(0.001)
Statebus Down					0.054***	-0.010***	0.036***	-0.006***
					(0.002)	(0.001)	(0.001)	(0.001)
Expbus Up					-0.004***	0.012***	-0.004***	0.010***
					(0.001)	(0.001)	(0.001)	(0.001)
Expbus Down					0.032***	-0.002	0.029***	-0.002
					(0.001)	(0.001)	(0.001)	(0.001)
Input Costs					-0.080***	0.162***	-0.049***	0.116***
					(0.006)	(0.007)	(0.004)	(0.005)
Uncertainty					0.005***	0.001	0.001*	0.000
					(0.001)	(0.001)	(0.001)	(0.001)
Hazard Dummies	no	no	yes	yes	no	no	yes	yes
No. of obs.	1,613,872	1,613,872	1,613,872	1,613,872	1,015,178	1,015,178	1,015,178	1,015,178
R^2	0.01	0.02	0.18	0.13	0.17	0.17	0.26	0.24

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table reports coefficients; clustered (by firm) standard errors are in parentheses. Included in the models but not shown in the table are a constant, two sets of hazard dummies (price down for models (1), (3), (5), and (7), price up for models (2), (4), (6), and (8)), and seasonal dummies. Aggregate inflation is lagged by two months, aggregate production by three months, and price expectations by one month.

D Business Survey Data

D.1 Detailed Description

Table 15: Frequency of Observations

Group of Firms ("Sector")	Number of employees 0 –19	20 – 99	100 – 999	$\geq$ 1000	Total
Food and tobacco	18.7	39.7	34.7	6.9	6.2
Textile products	6.9	34.5	52.1	6.5	7.5
Leather	13.3	41.0	39.8	5.9	1.5
Cork and wood products	32.2	45.3	19.2	3.4	4.1
Furniture and jewelery	10.6	34.4	50.7	4.3	5.0
Paper and publishing	15.7	42.3	38.2	3.8	15.2
Elect. and opt. equipment	8.3	29.4	48.5	13.7	11.8
Chemical products	11.4	31.0	40.8	16.7	3.7
Rubber and plastic	13.7	42.1	37.1	7.1	6.8
Other non-metallic products	14.5	36.6	43.2	5.8	6.1
Metal products	10.3	37.8	44.2	7.7	13.9
Machinery and equipment	5.1	27.3	53.1	14.4	15.3
Transport equipment	3.5	15.1	42.6	38.7	2.6
Manufacturing	11.6	35.3	43.7	9.4	

Notes: In the first four columns, the table provides the shares of observations for each firm size group within each group of firms ("Sector"). The fifth columns provides the share of each group of firm ("Sector") in total manufacturing.