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# State-dependent or time-dependent pricing? New evidence from a monthly firm-level survey: 1980–2017[☆]

Huw D. Dixon[a,*], Christian Grimme[b]

[a] Cardiff Business School and CESifo, United Kingdom
[b] Ifo Institute, Munich, Germany

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ABSTRACT

We examine the relative importance of time and state dependence in the price-setting decisions of firms using a monthly panel of German firms over the period 1980–2017. We propose a refined version of time dependence by introducing different hazard functions for price increases and decreases. We find three sets of results. First, time dependence is much more important for price setting than what the previous literature has found. Second, 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. Third, time dependence for price increases and decreases look completely different from each other. Our empirical results support the notion that theoretical models should integrate both time and state dependence.

## 1. Introduction

Theoretical models of price adjustment divide into two broad classes: time-dependent and state-dependent models. In time-dependent models, the probability of price change depends on the time elapsed since the previous change.[1] 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.[2] 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 affecting individual firms such as its orders, business situation and expectations.[3] 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.

Our contribution is threefold. First, we propose a refined version of time dependence by introducing hazard dummies which allow the probability of price increases (decreases) to vary with the duration since the previous price increase (decrease). Second, using this refined version, time dependence is much more important for price setting than what the previous literature has found. Price increases are best predicted by the interaction of firm-specific state and time-dependent factors, whilst each of the two factors alone can only explain a small fraction of price increases. For price cuts, time dependence is much more important than state

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* Corresponding author.
*E-mail address:* dixonh@cardiff.ac.uk (H.D. Dixon).

1 See, e.g., Taylor (1980), Calvo (1983) and their generalizations Sheedy (2010), Dixon and Le Bihan (2012), and Taylor (2016).

2 See, e.g., Sheshinski and Weiss (1977), Alvarez and Lippi (2014), and Alvarez et al. (2016b).

3 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.

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dependence. Additionally, we find that macroeconomic variables are much less important than firm-specific and time-dependent effects. Third, time dependence for price increases and decreases look significantly different from each other. The former has the familiar 12-month spikes, whereas the latter falls away monotonically, but is persistently positive for the first 12 months.

We use the micro data of the monthly Ifo Business Cycle Survey which covers on average 3500 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. This is a huge advantage to the more commonly used CPI data sets, which do not provide information on the individual price-setter's characteristics. An additional advantage of our data set is that it includes firm-level expectations, which are absent from data based on financial statements. 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.

We obtain our benchmark results using a multinomial logit model which integrates price increases and decreases (which are mutually exclusive events) into a single estimation model. The model combines macroeconomic variables with firm-specific variables and our refined version of time dependence. This model can explain 46% of all price decreases and 38% of all increases. In comparison, if we just use the hazard dummies we can only predict 45% of price cuts and 25% of increases; if we just use firm-specific effects, we can predict only 31% of decreases and 17% of increases. This suggests that theoretical models should allow for the interactions between state and time dependence and hence supports efforts in this direction by Alvarez et al. (2016a) and Nakamura and Steinsson (2010).

Modelling time dependence, the conventional approach bundles price increases and decreases together into "price changes". Using only a single set of hazards, time dependence alone explains only a very small fraction of price increases and decreases, 0.5% and 0.6%, respectively. Even when combined with firm-specific effects, the conventional approach to hazards can predict only 37% of price decreases and increases, respectively. Therefore, modelling hazards the conventional way reduces the importance of time dependence for price setting. This result challenges the conventional approach of bundling price increases and decreases together.

Our finding that price increases are more likely at certain intervals is perfectly consistent with the notion that firms regularly review prices. However, we also find that the hazard rate for price reductions does not follow this pattern since the hazard is elevated throughout the first 12 months. This behaviour may be explained by asymmetric price adjustment in response to competitors' prices. Given variable demand elasticity, it is possible that an individual firm is more likely to follow a competitors' price cut than a price rise. This follows because (unlike models with constant elasticities) profit functions are asymmetric in a firm's relative price, which means that a too high relative price above one decreases profits by less than a too low relative price, even if they are equally large in absolute terms. A negative price shock will then directly cause a subset of firms to reduce their prices, which will then induce further rounds of price reductions as other firms respond. Therefore, our empirical findings suggest that a theoretical model of price adjustment should also consider asymmetries, perhaps by using a combination of periodic price review plans and a quasi-kinked demand curve (Kimball, 1995; Beck and Lein, 2019). The periodic review element could extend the Nakamura and Steinsson (2010) Calvo plus model, but with "low menu costs" arriving at regular intervals rather than randomly (more of a "Taylor plus" approach).

The remainder of this paper is structured as follows. The next section gives an overview of the literature and how we contribute to it. In Section 3 we describe the data and the construction of the hazard dummies. Section 4 presents the empirical results and discusses the implications of our findings for theory. Robustness checks are provided in Section 5. The last section concludes.

## 2. Review of the empirical literature

Overall, empirical studies that look at the importance of both state- and time-dependent factors for firm-level price setting are scarce, because they require firm-specific data. The only empirical paper that we know of that looks at both these factors and analyses their relative importance is Lein. She estimates price-setting models based on 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. Our data set is monthly, covers a longer time period and refers to a much larger economy than Lein. Furthermore, we find that refining the method to capture time dependence shows that the interaction of time and state dependence explains a much larger fraction of price increases than the sum of each of the two factors alone. Explaining price increases, we find that state and time dependence reinforce each other. In addition, price cuts are mostly explained by time-dependent factors instead of a mixture of state and time dependence as Lein observes.

Besides, we contribute to two strands of the literature on price-setting behaviour that are closely linked: (i) studies of firms using survey data and (ii) studies using CPI micro price-quote data.[4] Aside from Lein, the closest paper to ours is Carlsson and Skans (2012), who 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 analysing the frequency of price adjustments as we do.

[4] One of the topics that our qualitative data cannot address is that of selection as in Carvalho and Kryvtsov (2021) and Karadi et al. (2021), which requires data on the prices set which is absent in our data.

Bachmann et al. (2019) examine the effect of firm-level volatility on price setting using the same German data set 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).[5]

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 argues that when annual inflation is below 10% to 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 firm-specific information provided by the kind of survey we are using.

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 the hazard rate for all price changes, but leave out all state-dependent effects and follow a purely descriptive approach.[6]

Two further studies use CPI data to look at hazard rates in greater detail. Fougère et al. (2007) consider the role of time and state dependence using French CPI price-quote data from 1994–2003. They look at a highly disaggregated level at the hazard function. They find that time dependence is important in about 65% of the products (where products are aggregated using CPI weights). They also use macroeconomic variables such as inflation to explore state dependence, which they also find important. However, they lack the firm-specific data in our approach. Their results are however perfectly consistent with ours.

Dias et al. (2007) adopt a similar approach using the Portuguese CPI price-quote data from 1992–2001. Using a parametric quarterly model, they allow for both time dependence and covariates of sectoral inflation and output growth to capture state dependence. Again, the authors find that both state and time dependence are present in the behaviour of Portuguese firms in this data set, albeit without the availability of time-varying firm-specific factors.

## 3. 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.

### 3.1. Description of the data

The Ifo Business Cycle 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 (IBS-IND, 2017). Before 1991 the data only contains West-German firms. At the beginning of our sample, the average number of participants is approximately 5400; at the end the number declines to 2100.[7] Participation in the survey is voluntary; 12% of all firms are one-time respondents. Attrition is low with firms participating for 7.4 years on average. Exiting firms are replaced by suitable new firms to maintain a sample that is representative of the German manufacturing sector: The survey covers all relevant sectors of German manufacturing as well as all firm sizes.

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 become unfavourable, *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.

[5] 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.

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

[7] Technically, 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, 2020), so that the results are not affected if these observations are dropped. Therefore, we use the terms "firm" and "product" interchangeably. Further details are in Online Appendix A.

**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 Cycle 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.

**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.

### *3.2. 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). 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) and Bachmann et al. (2019). 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).

We include several sets of dummies in addition to the hazard dummies, which are described in Section 3.3. 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 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 aggregate information about the macroeconomic environment. Specifically, we consider aggregate inflation and aggregate output growth. An increase in overall inflation should lead to a decline in the firm's relative price which should raise the probability of repricing. Higher aggregate output growth should raise the capacity utilization raising the incentive for price increases. 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.[8] 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.[9] Furthermore, as argued in Dixon et al. (2020), the use of both the month-on-month and annual changes can be seen as reflecting the behavioural dimension of the aspect of information processing. This is the way that the data on prices and production are published and how the managers making the decisions think about the data.[10]

Finally, the four aggregate variables are lagged to take into account that firms observe aggregate information only with some lag. Considering these publication lags, inflation is lagged for two months and output for three months. Lagging these variables also avoids potential endogeneity issues.

### 3.3. 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).[11] This corresponds to the standard approach to estimating the survival function.[12] 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 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.

With our estimation method there is a baseline hazard. If the hazard dummies are all zero ($Hi(t) = 0$ for $i \in [1, 2, 3, 4]$), then we see Calvo-like behaviour: the probability of a price change is unaffected by the duration whether for price increases or decreases. However, whilst the behaviour is Calvo-like in that it does not depend on the duration when the dummy is zero, it is very un-Calvo-like in that the hazard will still vary with firm-specific and other explanatory variables. A non-zero hazard dummy indicates that the hazard is different for that particular duration.

We find that the two hazards $H1(t)$ and $H3(t)$ are significantly non-zero for some durations, whilst the two cross-hazards $H2(t)$ and $H4(t)$ are close to zero even if statistically significant. Hence in our benchmark model we just use and report hazards $H1(t)$ and $H3(t)$.[13] These two hazards capture more than 88% of all the changes: in our data, 49.8% of all changes are increases following a previous increase, 38.6% are decreases following a previous decrease, and only 6.0% are a decrease following an increase and 5.6% are an increase following a decrease.

[8] As a robustness check, we consider an output gap measure instead of growth in Section 5. We find that this does not make any substantive difference.

[9] In Online Appendix B we replace the four aggregate variables and include, instead, 12 lags of the month-over-month growth rates of inflation and industrial production, respectively. This is to analyse the effects of the whole lag structure of the aggregate variables on the price decision. We find that as long as the firm-specific state variables are left out, several of the first lags of the aggregate variables are significant. When we include firm-specific state variables and time dependence only the contemporaneous inflation rate remains strongly significant.

[10] The press releases by the German Statistical Office feature both the month-on-month and annual changes of prices and production, respectively.

[11] The only other paper to jointly estimate the hazards for price increases and decreases to our knowledge is Stahl (2005), which was not published except as a working paper.

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

[13] The estimates for the full four hazard model are found in Appendix B and in Online Appendix C.

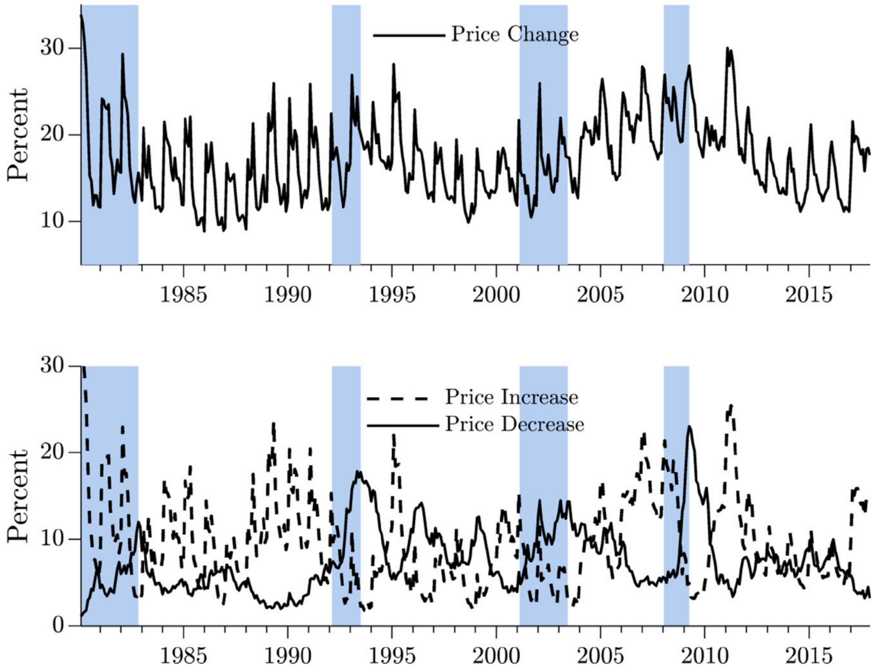


**Fig. 1.** Frequency of price changes.
*Notes*: Upper panel: Frequency of price changes; lower panel: frequency of price increase and price decreases. All data is monthly. Shaded regions show recessions as dated by the German Council of Economic Experts: 1980m1–1982:m11, 1992:m2–1993:m7, 2001:m2–2003:m6, and 2008:m1–2009m4.

Hazard dummies can allow for very general patterns of time dependence.[14] Lein 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.

### 3.4. Discussion of the data

We now look at some of the key data. Fig. 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, Fig. 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.

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., 2020). The variables are monthly and annual inflation, monthly and annual output growth along with various dummies controlling for seasonal effects, German reunification and the introduction of the Euro. Theory would suggest that aggregate 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).[15]

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 cancelling out when we look at all price changes. The signs of coefficients are all as expected and similar

[14] 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.

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

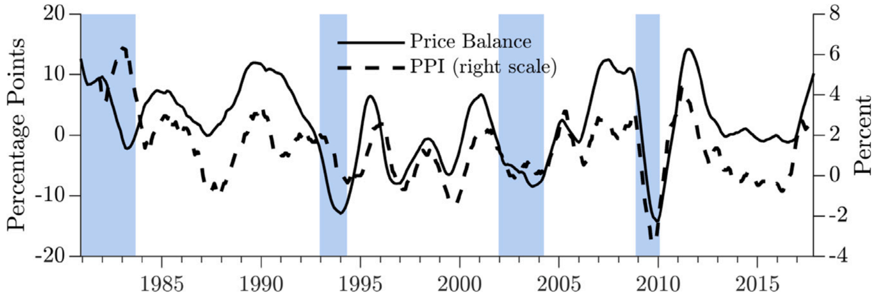


**Fig. 2.** Comparison ifo-data with official data.
*Notes*: Price Balance: Balance statistics of price statements of Ifo-sample of manufacturing firms; fraction of price increases minus fraction of price decreases. PPI: producer price inflation as published by the German Statistical Office, month-over-month 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.

**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 | 0.045 | 0.186 | NA | 0.177 | 0.020 | 0.149 | 0.048 | 0.150 | 0.026 |
| Frequ Up | 0.096 | 0.054 | 0.109 | NA | 0.106 | 0.021 | 0.097 | 0.037 | 0.085 | 0.027 |
| Frequ Down | 0.075 | 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 2017. 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. (2020) 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 | 0.214** | 0.560*** | −0.346*** |
| | (0.069) | (0.077) | (0.068) |
| Infly | 0.769*** | 1.267*** | −0.497*** |
| | (0.161) | (0.207) | (0.122) |
| Mpm | 0.003 | 0.008 | −0.005 |
| | (0.004) | (0.006) | (0.005) |
| Mpy | −0.069 | 0.116** | −0.185*** |
| | (0.054) | (0.041) | (0.030) |
| No. of obs. | 452 | 452 | 452 |
| R-squared | 0.65 | 0.68 | 0.68 |

*** 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.

to Gagnon (2009), Vavra (2014) and Dixon et al. (2020). Note how our results echo Gagnon (2009): there are clear and significant effects of inflation and output on both price increases and decreases, but when we look at all price changes together the effects partly cancel out and lead to a weaker or insignificant effect. Whilst these simple aggregate regression results are interesting, we will need to explore how they look when we add the micro data.

Fig. 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%). 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%)

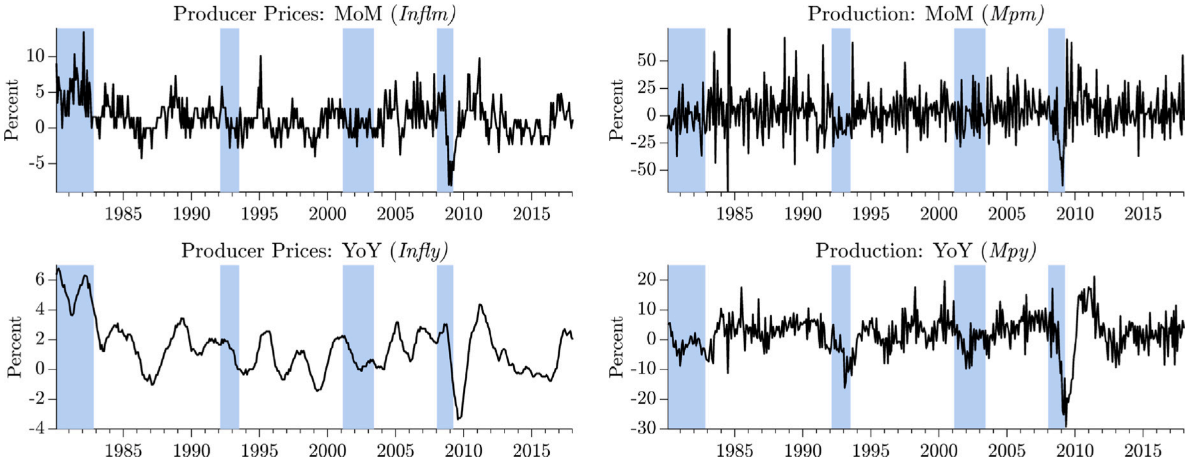


**Fig. 3.** Producer prices and manufacturing production.
*Notes*: PPI: producer price inflation as published by the German Statistical Office. Production: manufacturing production as published by the German Statistical Office. All data is monthly. The upper panels depict month-over-month (MoM) rates (annualized), the lower panels year-over-year (YoY) 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.

We conclude this section with some brief remarks about the attributes of the price-spells. For the main results, we are restricted to the use of uncensored spells, since we need to know how the spell began and ended in terms of the direction of price change.[16] There are 2,32,657 uncensored spells, with a mean duration of 4.7 months, the range being 1 to 269 months. Whilst the most common price spell lasts one month, 2.8% last for at least 24 months and 1.3% for at least 36 months. The uncensored spells represent 75% of all price spells (with 6.5% left-truncated spells, 7.3% right-truncated spells, and 6.8% truncated at both ends). In Appendix A we show the Hazard functions and distributions for both censored and uncensored spells.

## 4. Estimating the determinants of price decisions

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. As benchmark we use the multinomial logit (MLogit) model, which provides a direct estimate of the probabilities and allows for the determinants of price increases and decreases to differ. In addition, a great advantage of the MLogit estimation method is that it is able to estimate all four hazards together.

The MLogit is in effect a method of classification, which seeks to classify particular combinations of independent variables as giving rise to a particular choice. In the robustness section we alternatively estimate an ordered probit model, which 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 MLogit model which allows for a more general possibility. In the robustness section and in Online Appendix E, we will also examine other alternatives used in the literature, including separate probit and linear panel fixed effects models for price increases and decreases.

We estimate four specifications for our MLogit model. All specifications include sectoral dummies, seasonal dummies, and dummies for reunification, for the introduction of the Euro, and for crises (the financial crisis and other recessions). Table 5 reports marginal effects of the MLogit model. The first model, shown in column (1), focuses on the macroeconomic variables alone. Column (2) contains, in addition, the hazard dummies $H1(t)$ and $H3(t)$. The model in column (3) includes the firm-specific variables in addition to the macroeconomic variables, but without hazard dummies, while column (4) also includes hazard dummies.

Note that the number of observations in columns (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 1.1 million to 840,000. 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.[17]

[16] 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.

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

**Table 5**
Benchmark results with multinomial logit model.

| Depend. Var.: | (1) | | (2) | | (3) | | (4) | |
|---|---|---|---|---|---|---|---|---|
| | Price ↓ | Price ↑ | Price ↓ | Price ↑ | Price ↓ | Price ↑ | Price ↓ | Price ↑ |
| Inflm | −0.305*** | 0.716*** | −0.188*** | 0.610*** | −0.012 | 0.075*** | −0.011*** | 0.036*** |
| | (0.033) | (0.039) | (0.015) | (0.031) | (0.008) | (0.010) | (0.003) | (0.005) |
| Infly | −0.223*** | 2.019*** | 0.129*** | 1.191*** | −0.070*** | 0.209*** | 0.014** | 0.023* |
| | (0.041) | (0.108) | (0.019) | (0.065) | (0.019) | (0.026) | (0.005) | (0.009) |
| Mpm | −0.005*** | 0.008*** | −0.004*** | 0.006*** | 0.000 | 0.001 | −0.000 | 0.000 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.000) | (0.001) | (0.000) | (0.000) |
| Mpy | −0.193*** | 0.217*** | −0.086*** | 0.133*** | −0.005 | 0.002 | 0.003** | −0.000 |
| | (0.020) | (0.015) | (0.007) | (0.011) | (0.003) | (0.004) | (0.001) | (0.002) |
| Unific | 0.046*** | −0.003 | 0.015*** | −0.000 | 0.008*** | 0.008*** | 0.001*** | 0.002*** |
| | (0.005) | (0.002) | (0.001) | (0.002) | (0.001) | (0.001) | (0.000) | (0.000) |
| Euro | 0.005* | 0.053*** | −0.000 | 0.044*** | 0.005*** | 0.014*** | 0.001*** | 0.006*** |
| | (0.002) | (0.004) | (0.001) | (0.003) | (0.001) | (0.002) | (0.000) | (0.001) |
| Fin Crisis | 0.010*** | 0.001 | 0.019*** | −0.009*** | −0.005*** | 0.002 | 0.001* | 0.000 |
| | (0.003) | (0.004) | (0.002) | (0.003) | (0.001) | (0.002) | (0.000) | (0.001) |
| Other Crises | 0.023*** | −0.045*** | 0.014*** | −0.035*** | −0.001 | −0.004*** | 0.000 | −0.001** |
| | (0.003) | (0.003) | (0.001) | (0.002) | (0.001) | (0.001) | (0.000) | (0.000) |
| Expprice Up | | | | | −0.019*** | 0.298*** | −0.005*** | 0.135*** |
| | | | | | (0.002) | (0.014) | (0.000) | (0.007) |
| Expprice Down | | | | | 0.263*** | −0.025*** | 0.022*** | −0.006*** |
| | | | | | (0.021) | (0.002) | (0.002) | (0.001) |
| Order Up | | | | | 0.000 | 0.018*** | −0.001*** | 0.009*** |
| | | | | | (0.001) | (0.001) | (0.000) | (0.001) |
| Order Down | | | | | 0.018*** | −0.006*** | 0.008*** | −0.003*** |
| | | | | | (0.002) | (0.001) | (0.001) | (0.000) |
| Statebus Up | | | | | −0.012*** | 0.015*** | −0.003*** | 0.005*** |
| | | | | | (0.001) | (0.001) | (0.000) | (0.000) |
| Statebus Down | | | | | 0.031*** | −0.007*** | 0.006*** | −0.002*** |
| | | | | | (0.003) | (0.001) | (0.001) | (0.000) |
| Expbus Up | | | | | −0.001 | 0.005*** | −0.000* | 0.002*** |
| | | | | | (0.001) | (0.001) | (0.000) | (0.000) |
| Expbus Down | | | | | 0.016*** | −0.001 | 0.005*** | −0.001** |
| | | | | | (0.002) | (0.001) | (0.000) | (0.000) |
| Input Costs | | | | | −0.053*** | 0.089*** | −0.014*** | 0.037*** |
| | | | | | (0.007) | (0.007) | (0.001) | (0.002) |
| Uncertainty | | | | | 0.004*** | 0.002** | 0.001*** | 0.000* |
| | | | | | (0.001) | (0.001) | (0.000) | (0.000) |
| Hazard Dummies | no | no | yes | yes | no | no | yes | yes |
| No. of obs. | 1,097,139 | | 1,097,139 | | 837,469 | | 837,469 | |
| Pseudo $R^2$ | 0.05 | | 0.26 | | 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, two sets of hazard dummies, $H1(t)$ and $H3(t)$, and seasonal dummies. Aggregate inflation is lagged by two months, aggregate production by three months, and price expectations by one month.

*Overall performance of the model.* 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. 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. The pseudo $R^2$ does not change compared to model (2). The firm-level state variables seem to be informative for firms' price-setting. However, aggregate output growth now becomes insignificant and much smaller, whilst the coefficients for aggregate inflation 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).

In sum, the model's overall performance is about the same in a model with only firm-specific variables, model (3), or with only time dependence, model (2). However, model (4) gives the best results, when *both* time and state dependence are used.

*Impact of macroeconomic variables.* 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 0.036 pp; if *infly* increases by 1 pp, then the same probability increases by 0.023 pp. Hence, the coefficient on (annualized) *inflm* is of the same order as annual inflation, *infly*. 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.

*Impact of firm-specific state variables.* The firm-specific state variables in models (3) and (4) have the expected signs. Including hazard dummies, model (4), the firm-specific effects all remain significant but are smaller in size compared to model (3). 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.

*Impact of hazard dummies.* The hazard dummies show the marginal effect (above or below the baseline probability) in terms of time since the last price increase or decrease. The hazard function in Fig. 4 is simply one method of representing the distribution of durations, which we see in alternative form in Fig. A.1 in Appendix A.[18] 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). A hazard equal to zero means that the probability equals the baseline probability.[19]

We have two sets of hazard dummies: $H1(t)$ for price increases (following a previous increase) and $H3(t)$ for price cuts (following a previous cut). In Fig. 4a and 4b we depict the implied hazard probabilities, derived by combining the hazard dummies with the baseline probabilities (footnote  as is). We depict the hazards for the full-model regression (4) with state variables. Lastly, in Fig. 4c we depict the hazard ratio, the ratio of the probability of a price cut divided by the probability of a price increase for the full model with firm-specific variables.[20]

In the first period both $H1(t)$ and $H3(t)$ show a high value, which reflects that there are many one period price-spells. Afterwards, the two hazard dummies, however, exhibit very different patterns. For the hazard $H1(t)$ depicted in Fig. 4b, the implied probability of a price rise following a price rise falls off relatively fast, reaching the baseline at 7 months. However, there are Taylor-like spikes around 12 months, 24 months and 36 months; there also is a smaller spike around 6 months.[21] In between these periods, the probability of a price increase is largely independent of its duration and just depends on the baseline probability and any other explanatory variables such as macro or firm-specific factors. For the model with firm-specific state variables, the probability of a price increase one month after a previous increase is 23 pp higher relative to the baseline probability, after 12 months the probability is 11 pp higher, and after 24 months it is 5 pp higher.[22] The pattern of hazards with periodic spikes is a very common feature of micro-price CPI and PPI data, although standard approaches combine price increases and decreases.

For the hazard $H3(t)$ depicted in Fig. 4a, the implied probability of a price cut starts high and declines over the first year until it is close to its baseline. This contrasts to the hazard $H1(t)$, where the hazard is closer to baseline. If we look at the hazard ratio in Fig. 4c, we can see that in the first eleven months the ratio is well above 1 reaching a peak of 2 at month 3 and is always above 1.2. The probability of a price-cut is far more likely than a price increase until month 12, when it drops and thereafter remains below or close to 1. A firm that lowers its price is, thus, relatively likely to reduce its price again within a year. For the model with firm-specific state variables, the probability of a price decrease one month after a previous decrease is 31 pp higher relative to the baseline probability of 1.1%, after 6 months the probability is 6 pp higher, and after 12 months it is 4 pp higher.

One may argue that the initial fall in the hazards reflects heterogeneity across firms since some firms' prices could be highly flexible. To tackle this issue we follow two strategies. First, to show that unobserved heterogeneity does not affect the shape of the hazards, we additionally estimate both a linear fixed effects model and a fixed effects logit model. The results can be found in

[18] See Online Appendix F for a table of the hazard dummy estimates $H1(t)$ and $H3(t)$.

[19] The baseline probability is computed when all dummy variables are zero and the aggregate variables, equal their respective sample mean. The baseline probability for a price decrease is 1.1%, for a price increase it is 2.3%.

[20] In Online Appendix C we show the estimates for the two cross-hazards $H2(t)$ and $H4(t)$: when firm-specific variables are present they are close to zero (often slightly negative for price increases), although still significant given the large sample. All four sets of hazards are depicted in Fig. B.1 in Appendix B.

[21] One possibility that the spikes are only present for price increases could be that (annual) inflation was positive throughout this period. In a prolonged period of negative inflation, periodic review might give rise to spikes in price decreases. We would like to thank a referee for pointing this out.

[22] The exclusion of firm-specific state variables increases the size of these spikes. This may be partly due to the firm-specific state variables picking up also sector-specific characteristics. To analyse whether there is sector-specific seasonality, we also interacted the monthly dummies with sector dummies. Overall, the hazards do not change much. Results are available upon request.

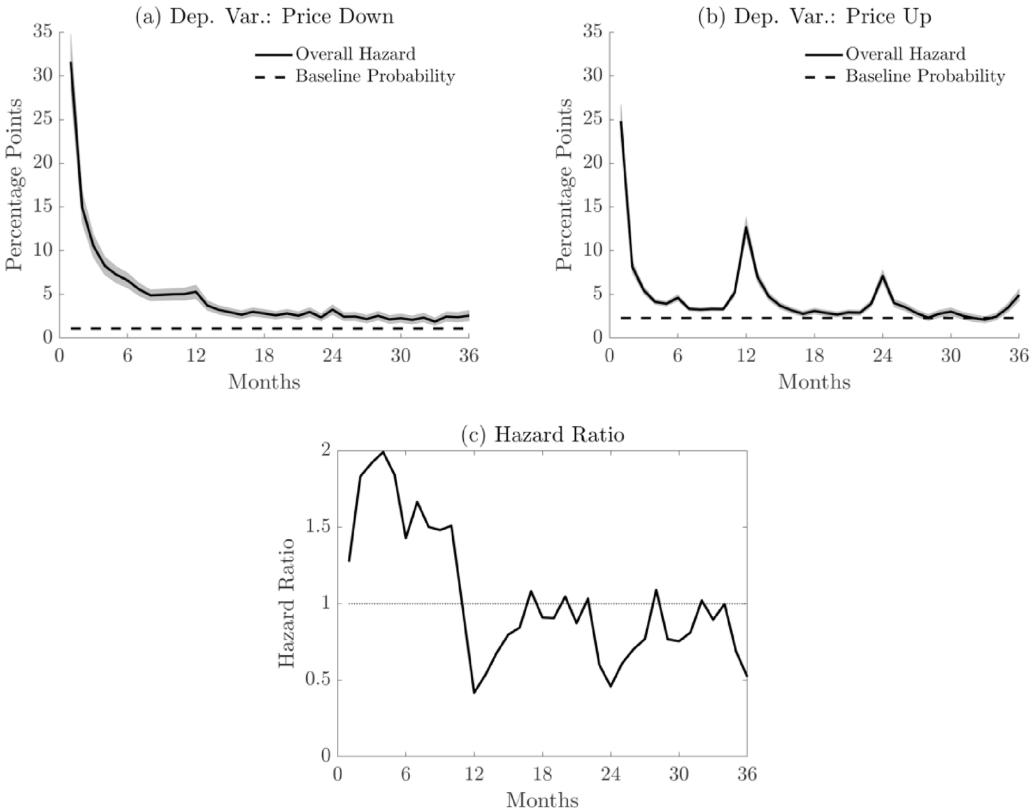


**Fig. 4.** Hazards.
*Notes*: The figure is derived from the estimation of the multinomial logit model including macroeconomic and firm-specific state variables and hazard dummies as explanatory variables (model (4) in Table 5). Panel (a) plots the marginal probability of a price cut H3(t) plus the baseline probability with the dotted line being the baseline component. Panel (b) plots the corresponding marginal probability of a price increase and the corresponding baseline probability. In both cases the effect of the hazard dummy is simply the difference between the baseline and the overall hazard. The shaded area represents the 95% confidence interval. Panel (c) depicts the hazard ratio, the ratio of the probability of a price cut divided by the probability of a price increase; the dotted line represents a hazard ratio of one.

Online Appendix G.1. The shape of the hazards remains very similar. We see the familiar spikes every 12 months for $H1(t)$. Also, we find that $H3(t)$ is downward sloping, but remains positive for the first 12 month in contrast to $H1(t)$.

The second strategy revolves around the idea that some observed characteristics which are heterogeneous across firms may drive the results. Specifically, we look at (i) firms of different size, (ii) firms that have, overall, more or less rigid prices, and (iii) sectoral affiliation. Online Appendix G.2 provides the results. Overall, the shape of the hazards remains very similar within each of the three specifications.

*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 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:

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

**Table 6**
Relative importance of the sets of variables in the benchmark model.

| Sets of variables | Share correctly predicted | | |
|---|---|---|---|
| | $\hat{p}_c^-/p^-$ | $\hat{p}_c^+/p^+$ | CC $R^2$ |
| Agg | 0.0 | 0.3 | 0.2 |
| Agg + Haz | 44.6 | 25.5 | 33.9 |
| Agg + Haz + Micro | 45.6 | 37.8 | 41.2 |
| Agg + Micro | 30.9 | 17.5 | 23.3 |
| Haz + Micro | 45.6 | 37.8 | 41.2 |
| Micro | 30.9 | 17.3 | 23.2 |
| Haz | 44.9 | 25.0 | 33.6 |

*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. All models include sectoral and seasonal dummies, dummies for reunification, for the introduction of the Euro, and for crises. Agg: includes the aggregate variables inflation and production. Haz: includes two sets of hazard dummies. Micro: includes the firm-specific variables concerning expected prices, business situation and expectation, orders, uncertainty, and input cost.

where $N$ is the total number of observations and $N_c$ is the number of price realizations correctly predicted by our model. Eq. (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 $p^j$ denotes the number of actual price increases ($j = +$), decreases ($j = -$), and no price changes ($j =$ no), $\hat{p}_c^j$ describes the number of correctly predicted price increases ($j = +$), decreases ($j = -$), and no price changes ($j =$ no), and $N_c$ equals $\hat{p}_c^+ + \hat{p}_c^- + \hat{p}_c^{no}$. In each of the three products summed in Eq. (2), the first fraction describes the share of correctly predicted observations $j$ with respect to the number of realizations $j$, and 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 9.6% of observations (price increases) and 7.3% (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 $R^2$).[23] 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 46% of decreases and 38% of increases. On their own, hazard dummies explain 45% of cuts and 25% of increases; firm-specific effects correctly predict 31% of decreases and 17% of increases. Time dependence, as captured by the hazard dummies, is more important than firm-specific effects for predicting price decreases. 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.

From this analysis we derive two important insights. First, time dependence on its own is very important for price decreases. 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 one is 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 Fig. 4, the time-dependent hazard is almost zero (from the baseline probability) at 7 months following a price increase. That means that a powerful state-dependent effect is required to elicit a price increase. On the other hand, in the first six months following a price cut, the time-dependent probability remains high (see the left panel of Fig. 4), indicating that moderate firm-specific state effects might be enough to elicit a price decrease. For both price increases and decreases, the hazard increases 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.

[23] Online Appendix D provides the results based on the Count $R^2$ and Adjusted Count $R^2$.

**Table 7**
Relative importance of the sets of variables: 1 vs. 2 vs. 4 sets of hazards.

| 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 $R^2$ |
| | Benchmark (2 Hazard sets) | | | 1 Hazard set | | | 4 Hazard sets | | |
| Agg + Haz | 44.6 | 25.5 | 33.9 | 6.4 | 3.8 | 5.0 | 44.8 | 26.2 | 34.4 |
| Agg + Haz + Micro | 45.6 | 37.8 | 41.2 | 37.1 | 36.8 | 36.9 | 45.8 | 37.9 | 41.3 |
| Haz + Micro | 45.6 | 37.8 | 41.2 | 37.0 | 36.8 | 36.9 | 45.8 | 37.9 | 41.3 |
| Haz | 44.9 | 25.0 | 33.6 | 0.5 | 0.6 | 0.6 | 45.2 | 25.9 | 34.2 |

*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. All models include sectoral and seasonal dummies, dummies for reunification, for the introduction of the Euro, and for crises. Agg: includes the aggregate variables inflation and production. Haz: includes either two sets of hazard dummies, one set, or four sets. Micro: includes the firm-specific variables concerning expected prices, business situation and expectation, orders, uncertainty, and input cost.

*How many hazards?* We adopt two sets of hazards in our benchmark 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 benchmark 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 0.1 and 0.6 pp. Turning to the one-hazard model, this model does much worse without the micro and aggregate variables than the two-hazard model we have adopted in the paper; the deterioration in the CC $R^2$ is between 4 and 33 pp.[24] This suggests that the standard approach in the existing literature is far from the best.

*Implications of our findings for theory.* What are the implications of our findings for the theory of price setting? Firstly, there is a baseline price reset probability which is Calvo like. With the MLogit model, we can see that there is a significant role for state-dependent factors influencing the baseline: macroeconomic, firm- and industry-specific factors make a price increase (decrease) more or less likely relative to the baseline. The signs of the effects are largely in line with what we would expect in theory. We can think of this as being a "Calvo plus" story along the lines of Nakamura and Steinsson (2010) or Alvarez et al. (2016a).

What about the time dependency captured by the estimated hazards? First, the fact that price changes are more likely at certain intervals (6 months, 12 months) is perfectly consistent with the finding that firms regularly review prices.[25] If firms have a regular schedule for reviewing prices, then prices are more likely to change when the prices are under review. The findings for the hazard rate for price increases is thus not surprising. What is new is that the hazard rate for price reductions is different and does not follow the same pattern. The price-reduction hazard is elevated for the first 12 months and is thereafter close to the baseline probability.

One possibility lies in asymmetric price adjustment in response to competitors prices. It has long been argued that an individual firm is more likely to follow a competitor's price cut than a price rise.[26] A negative price shock will then directly cause a subset of firms to reduce their prices, which will then induce further rounds of price reductions as other firms respond. This cascade effect would increase the probability of a price cut for some time. Seaton and Waterson (2013) found some evidence of this kind of "Edgeworth cycle" occurring between large British grocery retailers. Our data set only represents a subset of German firms and we do not have the price data, so we cannot explore this issue directly, but believe it is an interesting issue to be addressed when the data includes price data and covers most firms.

## 5. Robustness and alternatives

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

Why use a MLogit 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

[24] See Fig. B.2 in Appendix B for a figure of the estimates.

[25] See, for instance, the classic studies in the United States by Blinder (1991, 1994), Blinder et al. (1998), the Bank of England Study published as Hall et al. (2000), and the various studies in the Euro zone under the inflation persistence network, including Dhyne et al. (2006) and the references therein.

[26] Recent papers with this property include Beck and Lein (2019) and Koga et al. (2019).

**Table 8**
Ordered probit model.

| Depend. Var.: | (1) | | (2) | | (3) | | (4) | |
|---|---|---|---|---|---|---|---|---|
| | Price ↓ | Price ↑ | Price ↓ | Price ↑ | Price ↓ | Price ↑ | Price ↓ | Price ↑ |
| Inflm | −0.409*** | 0.782*** | −0.227*** | 0.462*** | −0.088*** | 0.120*** | −0.066*** | 0.086*** |
| | (0.024) | (0.032) | (0.010) | (0.016) | (0.010) | (0.013) | (0.007) | (0.009) |
| Infly | −0.722*** | 1.381*** | −0.205*** | 0.416*** | −0.189*** | 0.257*** | 0.012 | −0.016 |
| | (0.044) | (0.063) | (0.013) | (0.026) | (0.021) | (0.028) | (0.011) | (0.014) |
| Mpm | −0.004*** | 0.008*** | −0.003*** | 0.006*** | −0.001 | 0.001 | −0.001* | 0.001* |
| | (0.001) | (0.001) | (0.000) | (0.001) | (0.000) | (0.001) | (0.000) | (0.001) |
| Mpy | −0.172*** | 0.330*** | −0.066*** | 0.134*** | −0.010** | 0.014** | 0.005* | −0.006* |
| | (0.010) | (0.014) | (0.003) | (0.006) | (0.004) | (0.005) | (0.002) | (0.003) |
| Unific | 0.017*** | −0.028*** | 0.004*** | −0.007*** | −0.001* | 0.002* | −0.002*** | 0.002*** |
| | (0.001) | (0.002) | (0.000) | (0.001) | (0.001) | (0.001) | (0.000) | (0.000) |
| Euro | −0.009*** | 0.020*** | −0.007*** | 0.016*** | −0.004*** | 0.006*** | −0.003*** | 0.005*** |
| | (0.001) | (0.003) | (0.001) | (0.001) | (0.001) | (0.001) | (0.000) | (0.001) |
| Fin Crisis | 0.009*** | −0.016*** | 0.011*** | −0.019*** | −0.005** | 0.007** | 0.002 | −0.002 |
| | (0.002) | (0.004) | (0.001) | (0.002) | (0.001) | (0.002) | (0.001) | (0.001) |
| Other Crises | 0.030*** | −0.045*** | 0.015*** | −0.025*** | 0.001* | −0.002* | 0.001** | −0.002** |
| | (0.002) | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) | (0.000) | (0.000) |
| Expprice Up | | | | | −0.040*** | 0.311*** | −0.028*** | 0.203*** |
| | | | | | (0.003) | (0.008) | (0.001) | (0.005) |
| Expprice Down | | | | | 0.346*** | −0.061*** | 0.094*** | −0.034*** |
| | | | | | (0.010) | (0.003) | (0.004) | (0.001) |
| Order Up | | | | | −0.010*** | 0.017*** | −0.009*** | 0.015*** |
| | | | | | (0.001) | (0.001) | (0.001) | (0.001) |
| Order Down | | | | | 0.018*** | −0.018*** | 0.016*** | −0.015*** |
| | | | | | (0.001) | (0.001) | (0.001) | (0.001) |
| Statebus Up | | | | | −0.013*** | 0.023*** | −0.005*** | 0.008*** |
| | | | | | (0.001) | (0.001) | (0.000) | (0.001) |
| Statebus Down | | | | | 0.030*** | −0.027*** | 0.013*** | −0.013*** |
| | | | | | (0.002) | (0.001) | (0.001) | (0.001) |
| Expbus Up | | | | | −0.004*** | 0.007*** | −0.003*** | 0.005*** |
| | | | | | (0.001) | (0.001) | (0.000) | (0.001) |
| Expbus Down | | | | | 0.014*** | −0.015*** | 0.010*** | −0.010*** |
| | | | | | (0.001) | (0.001) | (0.001) | (0.001) |
| Input Costs | | | | | −0.092*** | 0.125*** | −0.051*** | 0.067*** |
| | | | | | (0.006) | (0.007) | (0.003) | (0.004) |
| Uncertainty | | | | | 0.002*** | −0.003*** | 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. | 1,097,139 | | 1,097,139 | | 837,741 | | 837,741 | |
| Pseudo $R^2$ | 0.03 | | 0.22 | | 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, two sets of hazard dummies, $H1(t)$ and $H3(t)$, and seasonal dummies. Aggregate inflation is lagged by two months, aggregate production by three months, and price expectations by one month.

decreases might be because of random sales promotions or a decrease of a competitor's price; 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 described by the interaction of time dependence and firm-specific state variables. Aggregate variables do not help much at all in correctly predicting price changes.

**Table 9**
Relative importance of the sets of variables.

| 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 $R^2$ |
| | (a) Ordered probit | | | (b) Output gap | | | (c) Time-fixed effects | | |
| Agg | 0.0 | 0.0 | 0.0 | 0.2 | 0.3 | 0.2 | 0.0 | 3.0 | 1.7 |
| Agg + Haz | 45.5 | 21.5 | 32.0 | 44.5 | 25.5 | 33.8 | 44.5 | 27.5 | 34.9 |
| Agg + Haz + Micro | 40.9 | 32.5 | 36.1 | 45.6 | 37.8 | 41.2 | 45.8 | 37.9 | 41.3 |
| Agg + Micro | 30.4 | 8.4 | 17.9 | 30.9 | 17.5 | 23.3 | 31.0 | 18.7 | 24.1 |
| Haz + Micro | 40.9 | 32.5 | 36.1 | 45.6 | 37.8 | 41.2 | 45.6 | 37.8 | 41.2 |
| Micro | 30.2 | 8.3 | 17.8 | 30.9 | 17.3 | 23.2 | 30.9 | 17.3 | 23.2 |
| Haz | 47.8 | 20.3 | 32.2 | 44.9 | 25.0 | 33.6 | 44.9 | 25.0 | 33.6 |

*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. All models include sectoral and seasonal dummies, dummies for reunification, for the introduction of the Euro, and for crises. Agg: includes the aggregate variables inflation and production (Panels (a) and (b)), Panel (c) includes time-fixed effects instead. Haz: includes two sets of hazard dummies. Micro: includes the firm-specific variables concerning expected prices, business situation and expectation, orders, uncertainty, and input cost.

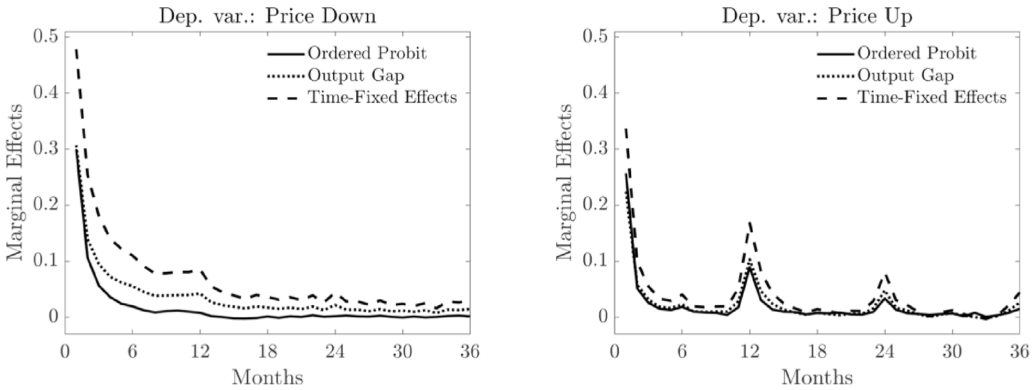


**Fig. 5.** Hazards of robustness-models.
*Notes*: The figure reports marginal effects, that is, the variation from the baseline hazard. The lines for *Ordered Probit* and *Output Gap* are derived from models that include macroeconomic and firm-specific state variables and hazard dummies as explanatory variables; for *Time-Fixed Effects*, the macroeconomic variables are replaced by time-fixed effects.

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 benchmark 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 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 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 4, 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 from 0.2 to 1.7 pp. But, the overall story remains the same.

In Fig. 5 we show the marginal hazards $H3(t)$ and $H1(t)$ for our three alrternative specifications. Whilst they do differ in terms of the level, the pattern of the hazards is similar across the alternatives.

So, we can see that the conclusions of our study are robust to a range of alternatives. In Online Appendix E, we consider three more alternatives: First, we replace the two aggregate inflation variables by the cumulative inflation rate (see,e.g., Berardi et al., 2015; Loupias and Sevestre, 2013; Fougère et al., 2007). Second, we use simple probit models for all price changes to see whether

**Table 10**
Multinomial logit model with output gap.

| Depend. Var.: | (1) | | (2) | | (3) | | (4) | |
|---|---|---|---|---|---|---|---|---|
| | Price ↓ | Price ↑ | Price ↓ | Price ↑ | Price ↓ | Price ↑ | Price ↓ | Price ↑ |
| Inflm | −0.318*** | 0.818*** | −0.202*** | 0.674*** | −0.013 | 0.074*** | −0.010*** | 0.035*** |
| | (0.034) | (0.043) | (0.015) | (0.033) | (0.008) | (0.010) | (0.003) | (0.005) |
| Infly | −0.102** | 1.926*** | 0.137*** | 1.172*** | −0.069*** | 0.217*** | 0.009 | 0.029** |
| | (0.034) | (0.102) | (0.019) | (0.063) | (0.020) | (0.026) | (0.005) | (0.009) |
| Output Gap | −0.451*** | 0.672*** | −0.165*** | 0.373*** | −0.010 | −0.014 | 0.013*** | −0.012** |
| | (0.047) | (0.045) | (0.013) | (0.029) | (0.008) | (0.010) | (0.003) | (0.005) |
| Unific | 0.051*** | −0.011*** | 0.017*** | −0.005** | 0.008*** | 0.008*** | 0.001*** | 0.003*** |
| | (0.005) | (0.002) | (0.001) | (0.002) | (0.001) | (0.001) | (0.000) | (0.000) |
| Euro | −0.000 | 0.064*** | −0.002** | 0.051*** | 0.005*** | 0.013*** | 0.001*** | 0.006*** |
| | (0.002) | (0.005) | (0.001) | (0.003) | (0.001) | (0.002) | (0.000) | (0.001) |
| Fin Crisis | 0.044*** | −0.038*** | 0.035*** | −0.031*** | −0.005*** | 0.002 | 0.000 | 0.001 |
| | (0.005) | (0.004) | (0.003) | (0.003) | (0.001) | (0.002) | (0.000) | (0.001) |
| Other Crises | 0.033*** | −0.053*** | 0.020*** | −0.042*** | −0.001 | −0.004*** | 0.000 | −0.001*** |
| | (0.004) | (0.003) | (0.001) | (0.002) | (0.001) | (0.001) | (0.000) | (0.000) |
| Expprice Up | | | | | −0.019*** | 0.298*** | −0.005*** | 0.135*** |
| | | | | | (0.002) | (0.014) | (0.000) | (0.007) |
| Expprice Down | | | | | 0.263*** | −0.025*** | 0.023*** | −0.006*** |
| | | | | | (0.021) | (0.002) | (0.002) | (0.001) |
| Order Up | | | | | 0.000 | 0.018*** | −0.001*** | 0.009*** |
| | | | | | (0.001) | (0.001) | (0.000) | (0.001) |
| Order Down | | | | | 0.018*** | −0.005*** | 0.008*** | −0.003*** |
| | | | | | (0.002) | (0.001) | (0.001) | (0.000) |
| Statebus Up | | | | | −0.012*** | 0.015*** | −0.003*** | 0.005*** |
| | | | | | (0.001) | (0.001) | (0.000) | (0.000) |
| Statebus Down | | | | | 0.030*** | −0.007*** | 0.006*** | −0.003*** |
| | | | | | (0.003) | (0.001) | (0.001) | (0.000) |
| Expbus Up | | | | | −0.001 | 0.005*** | −0.000* | 0.002*** |
| | | | | | (0.001) | (0.001) | (0.000) | (0.000) |
| Expbus Down | | | | | 0.016*** | −0.001 | 0.005*** | −0.001** |
| | | | | | (0.002) | (0.001) | (0.000) | (0.000) |
| Input Costs | | | | | −0.053*** | 0.090*** | −0.014*** | 0.038*** |
| | | | | | (0.007) | (0.007) | (0.001) | (0.002) |
| Uncertainty | | | | | 0.004*** | 0.002** | 0.001*** | 0.000* |
| | | | | | (0.001) | (0.001) | (0.000) | (0.000) |
| Hazard Dummies | no | no | yes | yes | no | no | yes | yes |
| No. of obs. | 1,099,757 | | 1,099,757 | | 837,741 | | 837,741 | |
| Pseudo $R^2$ | 0.05 | | 0.26 | | 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, two sets of hazard dummies, $H1(t)$ and $H3(t)$, 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.

the positive effects of a variable on price increase is offset by a negative effects of this variable on price decreases as in Gagnon (2009). Third, we look at the results from probit models for price increases and decreases separately.

## 6. 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, one needs both hazard dummies and firm-specific effects to get the best results. These findings 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

**Table 11**
Multinomial logit model with time-fixed effects.

| Depend. Var.: | (1) | | (2) | | (3) | | (4) | |
|---|---|---|---|---|---|---|---|---|
| | Price ↓ | Price ↑ | Price ↓ | Price ↑ | Price ↓ | Price ↑ | Price ↓ | Price ↑ |
| Unific | 0.101*** | −0.452*** | 0.064*** | −0.465*** | 0.001 | 0.082* | −0.005 | 0.055* |
| | (0.019) | (0.022) | (0.018) | (0.023) | (0.015) | (0.039) | (0.007) | (0.026) |
| Euro | −0.013*** | 0.192*** | −0.021*** | 0.207*** | 0.011 | −0.036** | 0.001 | −0.018* |
| | (0.003) | (0.021) | (0.004) | (0.022) | (0.014) | (0.014) | (0.006) | (0.007) |
| Fin Crisis | 0.154*** | −0.542*** | 0.108*** | −0.469*** | −0.025** | −0.059*** | −0.011** | −0.026*** |
| | (0.027) | (0.020) | (0.025) | (0.025) | (0.009) | (0.013) | (0.004) | (0.007) |
| Other Crises | 0.008* | 0.094*** | −0.004 | 0.139*** | 0.001 | −0.034** | 0.001 | −0.017** |
| | (0.003) | (0.018) | (0.003) | (0.019) | (0.008) | (0.012) | (0.004) | (0.006) |
| Expprice Up | | | | | −0.035*** | 0.438*** | −0.011*** | 0.212*** |
| | | | | | (0.009) | (0.036) | (0.003) | (0.036) |
| Expprice Down | | | | | 0.360*** | −0.055*** | 0.046*** | −0.011*** |
| | | | | | (0.056) | (0.011) | (0.013) | (0.003) |
| Order Up | | | | | −0.000 | 0.033*** | −0.003** | 0.016*** |
| | | | | | (0.001) | (0.006) | (0.001) | (0.003) |
| Order Down | | | | | 0.029*** | −0.012*** | 0.017*** | −0.006*** |
| | | | | | (0.007) | (0.002) | (0.005) | (0.001) |
| Statebus Up | | | | | −0.020*** | 0.030*** | −0.006*** | 0.009*** |
| | | | | | (0.005) | (0.005) | (0.002) | (0.002) |
| Statebus Down | | | | | 0.047*** | −0.015*** | 0.013*** | −0.005*** |
| | | | | | (0.012) | (0.003) | (0.004) | (0.001) |
| Expbus Up | | | | | −0.001 | 0.010*** | −0.001 | 0.004*** |
| | | | | | (0.001) | (0.002) | (0.001) | (0.001) |
| Expbus Down | | | | | 0.025*** | −0.003 | 0.011*** | −0.002* |
| | | | | | (0.006) | (0.002) | (0.003) | (0.001) |
| Input Costs | | | | | −0.066*** | 0.110*** | −0.022** | 0.037*** |
| | | | | | (0.020) | (0.021) | (0.007) | (0.009) |
| Uncertainty | | | | | 0.007*** | 0.003** | 0.001** | 0.001* |
| | | | | | (0.002) | (0.001) | (0.000) | (0.000) |
| Hazard Dummies | no | no | yes | yes | no | no | yes | yes |
| No. of obs. | 1,103,466 | | 1,103,466 | | 837,741 | | 837,741 | |
| Pseudo $R^2$ | 0.07 | | 0.27 | | 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, two sets of hazard dummies, $H1(t)$ and $H3(t)$, and seasonal dummies. Price expectations are lagged by one month.

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 behaviour. Existing models that combine state dependence with time dependence include Alvarez et al. (2016a) and Nakamura and Steinsson's 2010 "Calvo plus" 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. The difference between the hazard functions for increases and decreases might in part be due to the interaction of firms collectively reacting to negative shocks in a staggered manner. Further research might explore theoretical models that include a quasi-kinked demand curve à la Kimball (1995) and Beck and Lein (2019). However, testing such models would require a more comprehensive data set than we use in this paper.

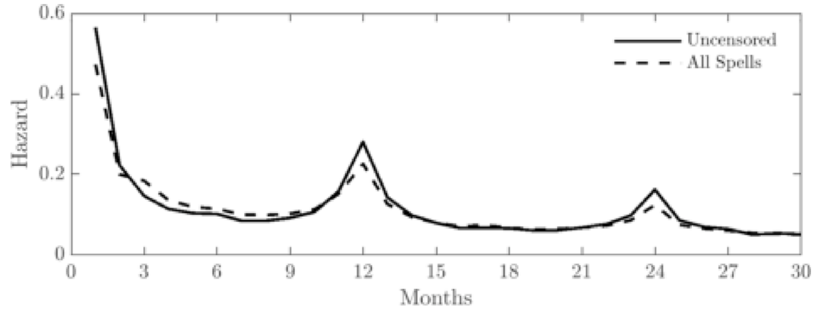


**Fig. A.1.** Hazard function for uncensored spells and all spells.
*Notes*: The hazards are computed using the Kaplan–Meier non-parametric estimator. The solid line is derived from the raw, uncensored data. The dashed line is derived under the assumption that the observed portion ends with a change and begins after a change.

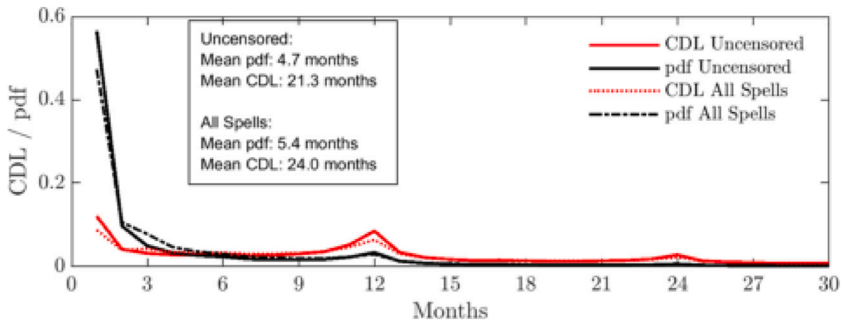


**Fig. A.2.** PDF durations and CDL.
*Notes*: The lines are derived from the survivor estimates. The CDL-estimates weight spells by length. Given the Kaplan–Meier estimates of the survival function, $S(i)$ (the proportion of price-spells that last more than i periods) for $i = 0, 1, \dots, F$ with $S(0) = 1$ and $S(F) = 0$ and $1 \geq S(i) > 0$ for $i = 1, \dots, F-1$. The hazard function is then: $h(i) = (S(i-1) - S(i))/S(i-1)$ for $i = 1, \dots, F-1$ with $h(F) = 1$. The pdf of price-spell durations is then $d(i) = S(i-1)h(i)$ for $i = 1, \dots, F$. The CDL is $\alpha(i) = i.d(i)/\sum_{j=0}^{F} S(j)$.

## Appendix 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–Meier 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 Fig. A.1 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 and 24 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 57% of uncensored spells and 47% of all spells change after one month (i.e. there are a lot of one-month spells).

The pdf of price-spell durations shows that the mean spell is 4.7 months for the uncensored sample, but 5.4 for all spells (see Fig. A.2). For the cross sectional distribution (CDL), which weights spells by length, the means are 21.3 and 24.0 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.

## Appendix B. Different sets of hazards

See Figs. B.1 and B.2

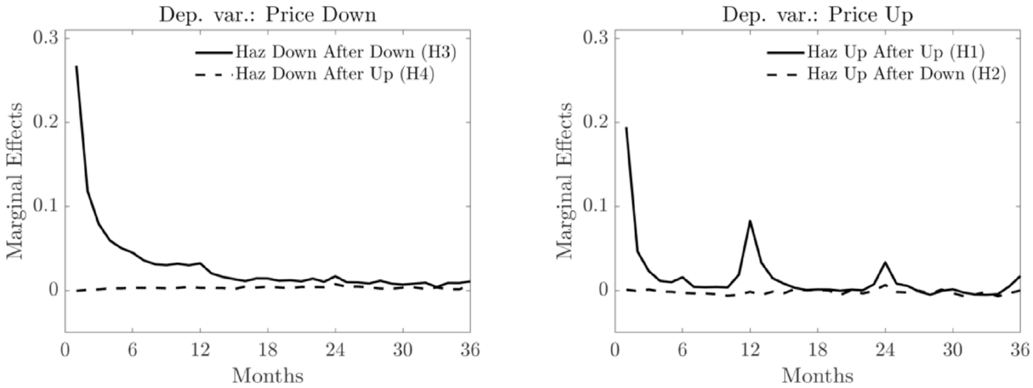


**Fig. B.1.** Four sets of hazards.
*Notes*: The figure reports marginal effects, that is, the variation from the baseline hazard. All lines are derived from the multinomial logit model including macroeconomic and firm-specific state variables and four sets of hazard dummies as explanatory variables.

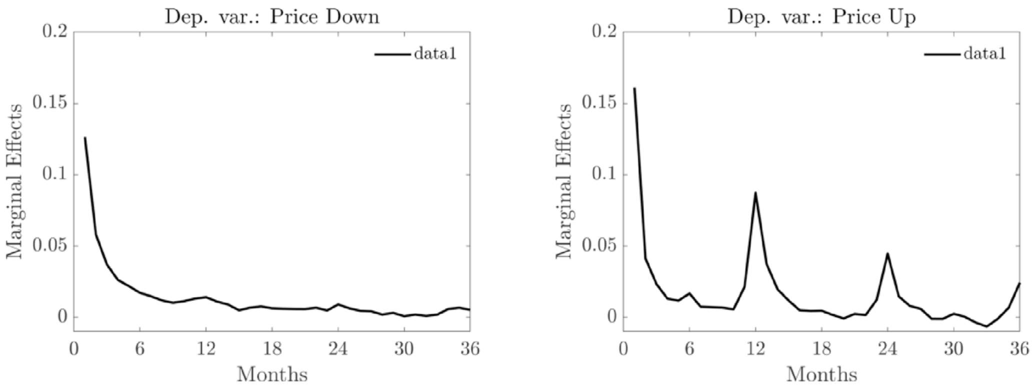


**Fig. B.2.** One set of hazards.
*Notes*: The figure reports marginal effects, that is, the variation from the baseline hazard. All lines are derived from the multinomial logit model including macroeconomic and firm-specific state variables and one set of hazard dummies as explanatory variables. Here, hazards give the probability of a price change (either up or down) *t* periods after the previous price change (up or down).

## Appendix C. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.euroecorev.2022.104319.

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