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Price setting on the two sides of the Atlantic - Evidence from supermarket scanner data☆

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ABSTRACT

We compare supermarket price setting in the US and the euro area and assess its impact on food inflation. We introduce a novel scanner dataset of Germany, the Netherlands, France, and Italy (EA4) and contrast it with an equivalent dataset from the US. We find that both higher frequency and stronger state dependence of price changes contribute to higher flexibility of supermarket inflation in the US relative to the euro area. We argue that the driving force behind both factors is higher cross-sectional volatility in the US. Larger product-level fluctuations both force retailers to adjust prices more frequently and increase price misalignments, which increase the selection of large price changes. Both facts are well represented by a mildly state-dependent price-setting model, and they jointly explain over a third of the difference in food-inflation volatility between the US and the euro area as well as around a third of the difference between the inflation responses to the COVID-19 shock in Germany and Italy.

1. Introduction

Food inflation is more volatile in the US than in the euro area and responded more forcefully in the US to the COVID-19 pandemic (see Fig. 1). Price setting in the food-retail sector has macroeconomic significance because food consumption accounts for around one-fifth of total consumption in both regions and because the salience of grocery prices makes them influence households' aggregate inflation expectations (D'Acunto et al., 2021). Previous research has established that price flexibility depends both on the frequency of repricing (*how many* prices change) and the extent of state dependence in price

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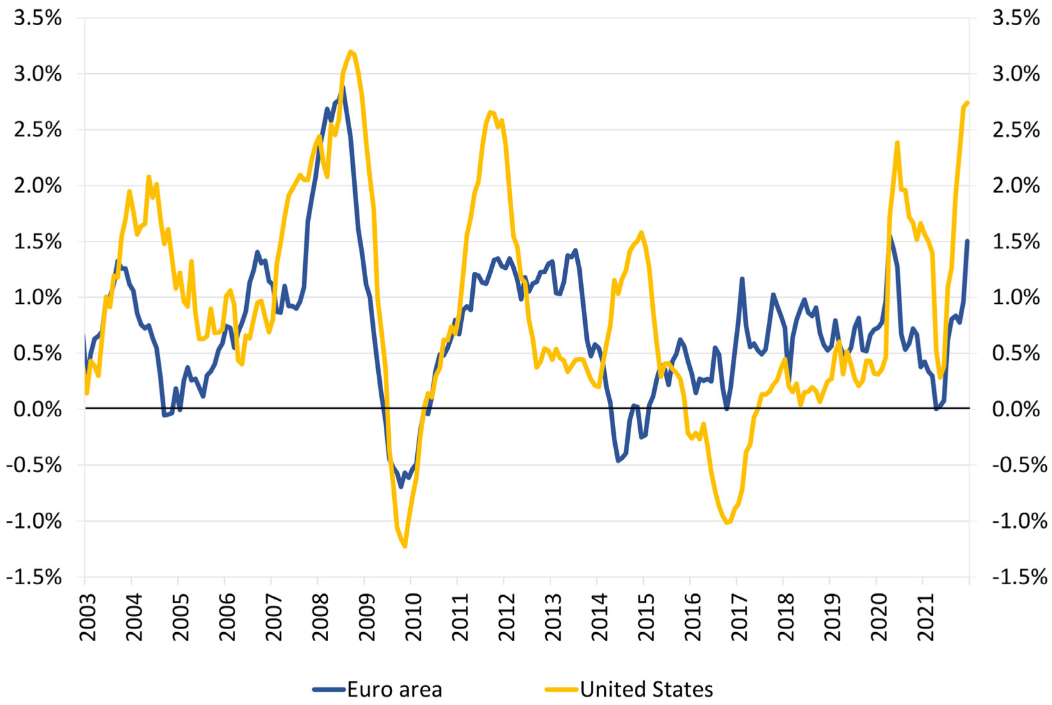

Fig. 1. Food and non-alcoholic-beverage inflation in the US and the euro area, COICOP 01, harmonized prices, year on year *Source:* OECD *Note:* The figure shows the evolution of year-on-year food and non-alcoholic-beverage inflation in the US and the euro area between 2003 and 2021. The series show clear comovement over most of the period (correlation: 59%), and US inflation shows higher volatility than euro-area inflation (standard deviations: US: 0.95%, euro area: 0.64%).

setting (*which* prices change) (Alvarez et al., 2022; Caballero and Engel, 2007; Golosov and Lucas, 2007). We use new store-level scanner data from the euro area and a corresponding dataset from the US to carefully measure these two features of supermarket price setting, and we assess their impact on the difference in food-inflation volatility.

We find that both higher frequency and stronger state dependence of price changes contribute to higher flexibility of supermarket inflation in the US relative to the euro area. We argue that the driving force behind both factors is higher cross-sectional volatility in the US. Larger product-level fluctuations both force retailers to adjust prices more frequently and raise price misalignments, which increase the selection of large price changes. Our conclusions have implications for both model selection and policy.

The paper introduces a novel store-level scanner dataset acquired from the marketing company IRi by the European Central Bank in the context of the Price-setting Microdata Analysis Network (PRISMA). The dataset covers Germany, the Netherlands, France, and Italy (EA4) between 2013 and 2017.[1] It records weekly prices of over 1.8 million products in over 37,000 stores in a spatially representative sample. We contrast it to evidence obtained from the US IRi Academic Dataset, an analogous weekly panel over the period 2001–12 of over 200,000 products in over 3000 stores covering the 50 most important US markets.

We use the datasets to characterize key features of price setting in the US and the euro area. First, we contrast the regions' standard moments about the repricing frequency and size distribution of price changes. We filter out temporary sales (Eichenbaum et al., 2014; Kehoe and Midrigan, 2015), which account for the majority of price changes but contribute only marginally to fluctuations in inflation at regular business cycle frequencies. In line with previous evidence, we find that sales-filtered reference prices change infrequently and the average absolute size of price changes is large in both regions (Klenow and Kryvtsov, 2008; Nakamura and Steinsson, 2008; Gautier et al., forthcoming). This evidence is consistent with volatile product-level shocks and price-adjustment frictions (Golosov and Lucas, 2007). We show that both the frequency and the size of price changes are substantially higher in the US. This indicates that product-level volatility is larger in the US relative to the euro area.

Second, we measure the extent of state dependence in price setting in the two regions. State dependence determines the endogenous selection of large price changes and can raise the volatility of inflation. We use the unparalleled cross-sectional granularity of the data to generate data moments that are directly informative about state dependence. In particular, we create a proxy for price misalignments as the distance of a (log) price of a product from the average price of the same

[1] For the analysis of the COVID-19 shock, we use an auxiliary dataset, which covers the period between mid-February to mid-May in 2019 and 2020 in Germany and Italy for a subset of the stores. For details, see Section 6.

product in competitors' stores that changed their prices in the same month. The price-adjusting stores' average price reveals the optimal reset price in a wide class of models (Calvo, 1983; Dotsey et al., 1999; Golosov and Lucas, 2007; Woodford, 2009). To assess the extent of state dependence, we measure both the probability of price adjustment as a function of the misalignment (adjustment hazard) and the density of misalignments, and follow the framework of Caballero and Engel (2007). We find that state dependence is higher in the US than in the euro area. It raises aggregate price flexibility by around 25% in both regions, leading to a larger absolute impact in the US, where price flexibility due to frequency is already higher. This implies that popular price-setting models that ignore state dependence (Calvo, 1983) underestimate price flexibility by roughly a third. Notably, the key difference in the extent of state dependence is driven by the more dispersed density of price misalignments, which is strongly influenced by the already established higher volatility of product-level shocks. Our conclusions about the state dependence of price changes are supported by additional data moments. Specifically, the kurtosis of standardized price changes, which decreases with higher state dependence in a wide class of models (Alvarez et al., 2022), is moderate in both regions and lower in the US than in the euro area. Furthermore, the duration hazard of reference-price changes is increasing in both regions in line with state dependence in price setting, after we control for unobserved heterogeneity.

Next, we conduct a structural analysis of the price-setting moments. The analysis confirms that higher product-level volatility is one of the key underlying causes of differences in price setting and food-inflation volatility across the two regions. We use the state-of-the-art state-dependent price-setting model of Woodford (2009) to estimate three underlying structural parameters affecting price setting: (i) the magnitude of price-adjustment (menu) costs, (ii) the standard deviation of idiosyncratic shocks, and (iii) the magnitude of information-acquisition costs, which determines the level of state dependence in the model between the time-dependent (Calvo, 1983) and fixed-menu-cost (Golosov and Lucas, 2007) extremes. The most notable difference between the US and the euro area is the higher volatility of idiosyncratic shocks in the US; both the price-adjustment and information-acquisition costs are quite similar in the two regions. The model can account for over a third of the observed difference in food-inflation volatility between the US and the euro area.

Finally, we provide evidence on responses to aggregate shocks by assessing supermarket prices in Germany and Italy during the first wave of the COVID-19 pandemic. The shock raised supermarket demand (by restricting access to food away from home) but had a limited impact on costs (because supermarkets were an essential sector and thus sheltered from lockdowns) similarly in the two countries. The comparison is interesting because the frequency of price changes is substantially lower in Germany than in Italy. The difference is mainly driven by lower idiosyncratic volatility in Germany. We document that the inflation response and the speed of pass-through are lower in Germany, and the model calibrated to the price-setting moments of the two countries can explain around a third of the difference.

Related literature: The paper is related to different strands of the literature. We contribute to the strand that compares price setting in the euro area and the US by introducing a new supermarket-scanner dataset and contrasting key price-setting moments, such as the frequency and size of price changes. Gautier et al. (forthcoming) compare price setting in the two regions using microdata underlying the Consumer Price Index. They confirm that the frequency and size of (sales-filtered) price changes are larger in the US not only in the processed-food sector, as in our sample, but also in the whole economy, albeit to a somewhat-smaller degree.

We also contribute to the literature estimating the extent of state dependence in price setting. We calculate moments that are directly informative about state dependence, such as the generalized and duration hazard functions, using the high granularity of the scanner data. We find that the generalized hazard function, which expresses the probability of price changes as a function of price misalignment, is upward sloping both in the US and in the euro area in line with state dependence in price setting. To proxy for price misalignments, we use distance from competitors' reset prices (Karadi et al., 2020), which is a valid proxy in a wide range of price-setting models. Our results confirm previous results, which use distance from competitors' prices on more restrictive samples (Campbell and Eden, 2014; Gagnon et al., 2012), and are consistent with complementary estimates using distance from an estimated cost measure (Eichenbaum et al., 2011; Gautier et al., 2022). We show, furthermore, that the duration hazard, which measures the probability of a price change as a function of the age of the price, is upward sloping in both regions when we use sales-filtered reference prices and control for unobserved heterogeneity. Upward-sloping duration hazard is in line with state-dependent pricing models (see, for example, Dotsey et al., 1999; Nakamura and Steinsson, 2008). Our evidence is different from that of Nakamura and Steinsson (2008), Klenow and Malin (2010), Campbell and Eden (2014), and Alvarez et al. (2021), who find the hazard decreasing, but in line with Fougère et al. (2007), who find it nondecreasing for most disaggregated product groups.

We assess the implications of our evidence by estimating key structural parameters of a state-of-the-art price-setting model (Woodford, 2009) in both regions. The model features fixed (menu) costs of price adjustment (Mankiw, 1985), product-level technology shocks (Golosov and Lucas, 2007), and information frictions, which allow it to capture the infrequent and large price adjustments and state dependence that we found earlier. Like Woodford (2009), Costain and Nakov (2011), and Alvarez et al. (2022), we find that state dependence raises the flexibility of the price level in both regions. We argue that higher volatility of product-level shocks in the US is the key reason behind cross-country differences in price setting and food-inflation volatility. This result is related to Vavra (2014), who, in a related framework, argues that variation of idiosyncratic volatility over time (as opposed to across countries, which this paper emphasizes) implies time-varying price flexibility over the business cycle. Higher cross-sectional volatility in the US versus the euro area has also been documented using various alternative measures. Using stock returns, Guo and Savickas (2008) and Ang et al. (2009) document higher idiosyncratic volatility in the US than in major euro-area countries (see also Bekaert et al., 2012). Relatedly,

Table 1
Data coverage.

	US	DE	FR	IT	NL
Time series	2001–12		2013–17		
# products (td)	205	370	423	698	392
# stores (td)	3.3	10.3	5.9	14.3	6.6
# observations (bn)	2.7	13.8	10.0	11.0	7.7
# 2-digit ZIPs	51	97	93	93	94
# chains	147	17	43	435	29
% in HICP/CPI	19.6	18.5	23.3	23.4	20.7
annual exp. (bn € /$)	6.2	32.8	56.2	42.2	30.0

Note: DE: Germany; FR: France; IT: Italy; NL: the Netherlands; HICP: Harmonized Index of Consumer Prices (EA4); CPI: Consumer Price Index (US)

Comin and Philippon (2005) find higher firm-level employment-growth volatility in the US than in selected euro-area countries (see also Thesmar and Thoenig, 2011).

The paper is structured as follows. Section 2 describes the data. Section 3 describes conventional moments of price changes in the two regions, including frequency, size, and higher-order dispersion measures. Section 4 presents more complex moments, including the generalized (price gap) and duration (price age) hazard functions, and it quantifies the level of state dependence in the two regions. Section 5 conducts a structural analysis, and Section 6 contrasts the price-setting responses to the COVID shock in Germany and Italy. Section 7 concludes.

2. Data

This section introduces the novel euro-area dataset and shows its key features together with its US counterpart. We also present the data-cleaning steps we take to improve the informativeness of the data for our analysis of price setting.

2.1. Data coverage

The dataset covers four euro-area countries—Germany, the Netherlands, France, and Italy (between 2013 and 2017)—and the US (between 2001 and 2012).[2] The datasets are weekly panels of total revenues (TR_{psw}) and units sold (Q_{psw}) for each product p in store s in week w. We refer to a product in a store as an item. Unit-value prices of each item are calculated as revenues over units sold ($P^{uv}_{psw} = TR_{psw}/Q_{psw}$).

2.1.1. Product coverage

The granularity of the datasets is unsurpassable: they include all products sold in each store in the sample.[3] The products are identified with their unique barcodes (EANs in the euro area and UPCs in the US).[4] The number of unique products ranges from around 370,000 to 700,000 in the euro area and is over 200,000 in the US (see Table 1).

Products sold in supermarkets include food, alcoholic and non-alcoholic beverages, personal-care products, and goods for household maintenance. They cover around 20% of the consumer basket. The expenditure distribution in the IRi samples closely approximates the true consumption pattern of households across major product categories (see Appendix A).

We conduct the analysis below using a subsample for each country to ease the computational burden. Specifically, we select a 5% random sample of EANs in each EA4 country and a 25% random sample of UPCs from the US.[5] The random choice of products ensures that the sample is representative. We include all the stores and time periods in the subsample wherever the selected products were sold in positive quantities.

2.1.2. Store coverage

The datasets are representative of the brick-and-mortar-store sales of participating supermarket chains. The participating chains include regular and discounter supermarkets as well as drug stores.[6] The store IDs are masked to protect the identity

[2] Even though the US and EA4 datasets do not overlap, this does not hinder our comparison of the key moments in our analysis, as they are fairly stable over our sample period (see, for example, Figure E.12 in the appendix on the frequency of reference-price changes).

[3] The US sample only includes products within 30 selected broad product categories: beer, blades, carbonated beverages, cigarettes, coffee, cereal, deodorant, diapers, facial tissue, frankfurters, frozen dinner, frozen pizza, household cleaner, laundry detergent, butter, mayonnaise, milk, mustard and ketchup, peanut butter, paper towels, photography supplies, razors, salty snacks, shampoo, spaghetti sauce, sugar substitutes, toilet tissue, toothbrush, toothpaste, yogurt.

[4] The EANs of *private-label* products are masked to protect the identity of the supermarket chain. We exclude private-label products from the analysis in France, where the revenues and quantities sold of all private-label EANs are aggregated by store, confounding the evolution of item-level prices.

[5] The US sample includes fewer products and stores. Choosing a relatively larger subsample makes the number of items in the US sample the same order of magnitude as in the euro-area countries.

[6] The datasets exclude hard discounters such as Lidl, Aldi, and Walmart.

of the supermarkets, but they are unique over time, which allows us to track the prices of items over time.[7] In the euro-area countries, our dataset includes 75% of the IRi stores. In two countries (Germany and Italy), some supermarket chains only share a representative sample of their stores with IRi. We upweight sample stores using projection weights created using information about the population of stores by geographic unit and store type, which is also part of the dataset (see Appendix B for details).

The euro-area datasets are spatially representative in each country. They include the location of the stores up to the first two digits of their ZIP code. The two-digit ZIP areas partition the countries into around 100 regions. The US dataset covers 50 urban markets. These markets approximately correspond to 50 metropolitan statistical areas (MSAs) out of the 384 MSAs in the mainland US in 2010 and cover 73% of the US population.[8]

2.2. Data cleaning

The focus of our analysis is reference prices (Eichenbaum et al., 2011; Kehoe and Midrigan, 2015), and we conduct a series of filtering steps to obtain them.

First, we estimate posted prices from weekly unit-value prices. We conduct two filtering steps. First, we filter out same-direction consecutive changes. We do this to minimize the impact of midweek price changes. Intuitively, a midweek price increase raises the average price only partially in the initial week and passes through fully only during the second week. Second, we round prices upward to the nearest cent to mitigate the impact of buyer-specific discounts (see Appendix C for details).

Next, we construct weekly reference prices (P^f_{psw}) as 13-week running modal prices (Kehoe and Midrigan, 2015). Reference prices capture persistent changes in prices and disregard changes that are completely reversed within weeks (temporary sales). By focusing on reference prices, we capture an overwhelming share of fluctuations in supermarket inflation at business cycle frequencies, and we filter out a large share of high-frequency variation caused by temporary sales (see Appendix D.1 for details). Temporary sales also account for a sizable fraction of the frequency of posted-price changes—almost two-thirds in most countries. Despite an ongoing debate about whether sales are an active margin for retailers to adjust to aggregate fluctuations (Anderson et al., 2017; Kehoe and Midrigan, 2015; Kryvtsov and Vincent, 2021), there is a wide consensus that most adjustment at business cycle frequencies is achieved through reference prices. Previous research has also documented that sales inflation does not respond significantly or responds only marginally to aggregate shocks (Anderson et al., 2017; Karadi et al., 2020; Gautier et al., forthcoming). This justifies our focus on the behavior of reference prices in the rest of the paper.

Last, we transform weekly data to the monthly frequency. This facilitates comparison with monthly microlevel price data underlying the official price indices, helps us concentrate on more persistent price adjustments that are more relevant at business cycle frequencies, and overcomes some of the weaknesses of the data, including the sizable share of weekly data missing because of zero sales. We define the monthly item price as the (highest) mode of the item price over the month.[9]

3. Key moments of price changes

In this section, we characterize key features of reference-price changes in supermarkets across the four euro-area countries and the US. We focus on conventional moments, including frequency, size, and kurtosis of price changes, that influence the flexibility of the aggregate price level according to the theoretical literature.

3.1. Frequency

The frequency of reference-price changes is a key indicator of price flexibility. As the first row of Table 2 shows, the average frequency[10] in EA4 supermarket prices is fairly low—only 9.5% monthly. This suggests that reference prices change infrequently, only once every 10.5 months, on average. The low frequency indicates that supermarkets face price-adjustment

[7] To guard the identity of the stores, store information is only included in our sample if there are enough stores (for example, at least three in France) by geographical area and store type. In most cases (in France and the US, for example), store information is withdrawn from the sample in these cases. In other cases (in Italy, for example), the geographical granularity becomes coarser (one-digit as opposed to two-digit ZIP areas).

[8] Therefore, even though the US sample is not spatially representative, it covers the most populous areas, providing a relevant sample of supermarkets across urban areas.

[9] Using the mode guarantees choosing one of the weekly reference prices, so the time aggregation does not introduce artificial prices. This would happen if one instead used the mean or calculated monthly unit prices. Picking the *highest* mode in case of multimodality tilts the monthly prices toward the (more persistent) reference prices, which tend to be above the sales prices.

[10] All moments are weighted by annual expenditure. Formally, monthly frequency is calculated as $\xi_t = \frac{\sum_i \omega_{it} I_{it}}{\sum_i \omega_{it}}$, where I_{it} is an indicator that takes the value 1 if the reference price of item i (a product in a particular store) changed from month $t-1$ to month t and 0 otherwise. The weights ω_{it} are annual expenditure weights. Table 2 reports average monthly moments over the sample. Average absolute size and percentiles are calculated analogously. Kurtosis is calculated using the subsample of items with at least five reference-price changes, standardized by the mean and standard deviation at the item level and weighted by expenditure.

Table 2
Key moments of reference-price changes, weighted by expenditure.

Moments	US	EA4	DE	FR	IT	NL
Frequency (%)	13.8	9.5	5.3	15.6	9.6	10.3
Size (%)	15.2	9.3	10.5	4.5	11.4	9.2
Kurtosis	2.7	3.2	2.9	3.8	3.3	2.7

Note: The table presents the frequency and average absolute size of reference-price changes as well as the kurtosis of the standardized reference-price changes, all weighted by expenditure. EA4: average of the 4 euro area countries; DE: Germany; FR: France; IT: Italy; NL: the Netherlands.

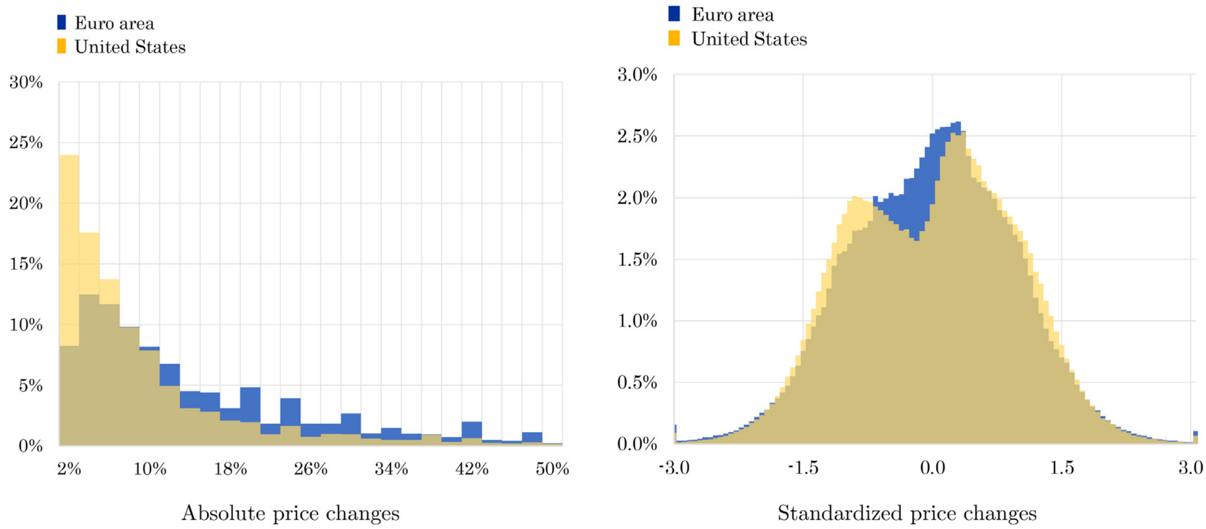

Fig. 2. Absolute and standardized reference-price-change distributions *Note:* The figure shows the absolute (left panel) and standardized (right panel) reference-price-change distributions in both regions. The size is large and dispersed in both regions, and it is larger and more dispersed in the US than in the euro area. The shape of the standardized price-change distribution is bimodal in the US, while it is unimodal in the euro area; kurtosis is lower in the US.

frictions that hinder them from adjusting prices flexibly in response to changes in costs. The price flexibility is higher in the US, where the frequency of reference-price changes is 13.8%, implying an average duration of 7 months.[11]

There is notable heterogeneity in frequency across euro-area countries. In Italy and the Netherlands, the frequency is close to the EA4 average, but it is particularly low in Germany at 5.3% (19-month average duration) and particularly high in France at 15.6% (6.5-month duration)—even higher than in the US.

3.2. Size

The average absolute size of reference-price changes is large: 9.3% in the EA4 countries, on average. Its magnitude far exceeds what could be explained by trend inflation or aggregate fluctuations, which are both small during our sample period. Instead, they indicate an important role for idiosyncratic, product-level shocks. The size of price changes is higher in the US, where it reaches 15.2%. The higher size accompanied by a higher frequency indicates a more volatile product-level environment in the US, a factor that we analyze further in a structural framework in Section 5. The size of price changes also varies across euro-area countries. The average size is particularly low in France, which, together with the high frequency, indicates lower-than-average price-setting frictions there.

The first panel of Fig. 2 shows the histograms of the absolute-price-change distributions in both areas. The size of price changes in both regions is dispersed, with many small and large price changes. Smaller price changes are more frequent, and larger price changes are less frequent in EA4 relative to the US. The dispersion of the price changes is smaller in EA4 with an interquartile range of 9%, while it is 16% in the US.

[11] The frequency is stable over time, so the issue of non-overlapping US-EA4 samples should not hinder the international comparison (see Figure E.12 in the appendix).

3.3. Higher-order moments

The shape of the price-change distribution can inform us about the extent of state dependence in price setting in a wide class of models (Alvarez et al., 2016). The second panel in Fig. 2 shows the shape of the reference-price-change distribution in both regions. The reference-price changes are standardized at the product-store level to minimize the potential bias caused by cross-product heterogeneity in the mean or standard deviation of price changes. The figures indicate a kurtosis of 2.7 in the US and 3.2 in the euro area, around a kurtosis of 3 of the Gaussian distribution.

The distribution shows some pronounced bimodality in the US with some missing mass close to zero, which is in line with the presence of fixed costs of price adjustment. At the same time, the share of small reference-price changes stays high in the US, much higher than models with strong state dependence would predict (Golosov and Lucas, 2007).

4. Evidence on state dependence: Generalized and duration hazards

The conventional moments described in the previous section provide only indirect information about an important feature of price setting: the extent of its state dependence. Previous research has established that state dependence, which influences *which* prices adjust, can have as large an impact on aggregate price flexibility as frequency, which determines *how many* prices adjust. For example, in realistic models of price setting with strong state dependence (for example, Golosov and Lucas, 2007), the price level can respond almost completely flexibly to monetary policy shocks even though only a few prices adjust. The reason is that in these models, firms face a small fixed menu cost when changing prices, so they find it optimal to adjust the highly misaligned prices. When these prices change, they change by a lot, which can offset the impact of price rigidity and make the price level flexible. In this section, we present two sets of moments that are more directly informative about the extent of state dependence than conventional moments are.

4.1. Generalized hazard

The first moment is the generalized hazard function, which expresses the probability of price adjustment as a function of price misalignments, or price gaps. The price gap is the distance between the posted price and the optimal reset price the store would set if all price-adjustment frictions were temporarily absent. The gap influences the strength of the product-level price-adjustment force: a larger price gap means that the price is further from its optimal level, and the foregone profit is larger.

A key empirical challenge is that the optimal reset price is unobservable. As a proxy, we calculate competitors' reset price (Karadi et al., 2020). This is the average reference price[12] of a product in competing stores that also changed the price of the same product in the same month.[13] The measure also controls for the permanent store- and category-level price differences caused by heterogeneity in amenities, geography, or market power. The proxy relies on three assumptions: (i) the price of the same good among price-changing competitors tracks the evolution of aggregate demand conditions and the product's wholesale price, which are the primary drivers of the optimal reset price; (ii) differences in amenities and market power between stores cause permanent store- and category-level differences between prices; and (iii) chains follow national price-setting strategies (DellaVigna and Gentzkow, 2019), so local demand conditions have an insignificant impact on the optimal reset prices. We validate our proxy by showing that the size of the price change has a very tight, almost exactly one-to-one, negative relationship with the price gap.

Formally, we formulate the competitor-reset-price gap x_{pst} for product p in store s in month t in three steps. First, we take the (logarithm of) the sales-filtered reference prices p^f_{pst}. Second, we calculate an unadjusted gap as $\tilde{x}_{pst} = p^f_{pst} - \bar{p}^f_{p(-s)t}$, where $\bar{p}^f_{p(-s)t}$ is the average reference reset price of the same product across alternative stores that changed the price of the same product in month t. Third, we deal with the persistent heterogeneity across stores (that is, chains, locations) by subtracting the average store- and category-level gap α_{cs}, and we reformulate the price gap as $x_{pst} = \tilde{x}_{pst} - \alpha_{cs}$, where product p belongs to category c.

Panel (a) in Fig. 3 shows the density of the price-gap distributions in the four euro-area countries and the US.[14] To arrive at the densities, we control for unobserved heterogeneity across items and the common impact of aggregate fluctuations by estimating item and time fixed effects[15] in a panel regression of the form

$$x_{pst} = \alpha_{ps} + \alpha_t + \varepsilon_{pst}. \quad (1)$$

[12] By concentrating on reference prices, the measure controls for the impact of temporary sales.

[13] In our baseline measure, we include *all* stores in the country that sell the product in a given week in the set of competing stores. The results are robust to using a more conservative measure, which only includes local stores (same two-digit ZIP region in the euro area and same market in the US). In particular, the average slope of the hazard and the shape of the density function stay broadly unchanged (not shown).

[14] See Appendix F for evidence on heterogeneity across euro-area countries.

[15] An alternative specification includes item and time-store fixed effects. The time-store fixed effects control for store-wide synchronization of price changes (see, for example, Bonomo et al., 2023). The specification leads to virtually identical US hazard-function estimates (not shown), suggesting that synchronization is present but plays a quantitatively insignificant role.

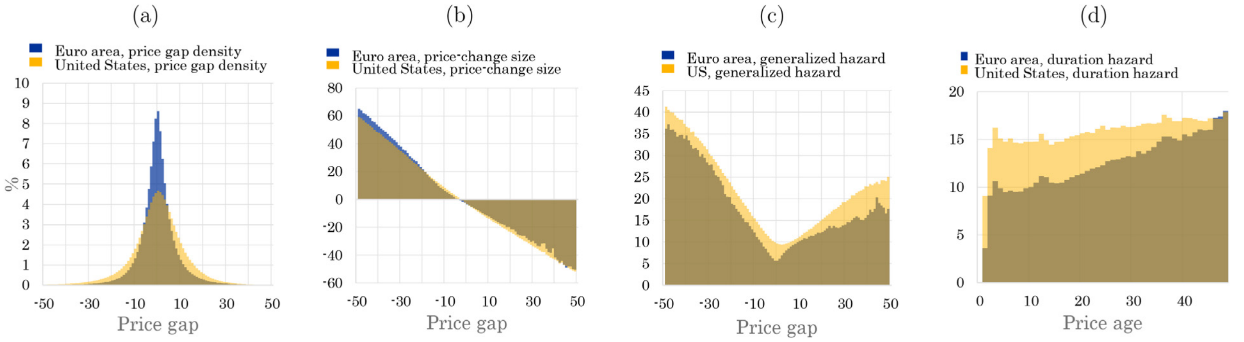

Fig. 3. Price-gap density and the size of nonzero price changes as a function of the price gap, and the generalized and duration hazards *Note:* The figures show (a) the density of the price gap, (b) the average size of nonzero reference-price changes, (c) the frequency of reference-price changes (generalized hazard) as a function of the price gap, and (d) the frequency of reference-price changes as a function of the age of the price (duration hazard) in EA4 and the US. The V-shaped generalized hazard and the increasing duration hazard indicate the presence of state dependence in price setting, albeit at a moderate level in both regions. The density indicates wide dispersion of price gaps, higher on average in the US. The size figure validates the price-gap measures by showing a tight relationship between the gap and the eventual price-change size.

We calculate the share of normalized gaps ($x_{pst} - \hat{\alpha}_{ps} - \hat{\alpha}_t$) in the 101 unit-percentage-point ranges between -50.5% and 50.5%. We censor the normalized gaps at -50.5% and 50.5%.

The figure shows that the gaps are high, on average, and higher in the US (14%) than in EA4 (10%). At the same time, the distribution is dispersed in both regions with a high mass of small gaps and a fat tail of large gaps. This is true even though we control for sales-related price changes as well as permanent differences between the store-specific prices.

We now assess the relationships between the price gap in period $t-1$ and the probability and average size of price adjustment in the following month t. We aim to estimate these relationships nonparametrically with a minimal set of structural assumptions. First, we allocate price gaps into 101 bins, each covering a unit-percentage-point range between -50.5% and 50.5%. The indicator function $I_{pst-1}^{[x_{j-1},x_j)}$ for bin j takes the value 1 when the gap $x_{pst} \in [x_{j-1}, x_j)$, and 0 otherwise. Second, we estimate a relationship coefficient (β_y^j) between the gap x and a variable of interest $y_{pst,t+1}$ (frequency or size) for each bin j using the following panel specification:

$$y_{pst,t+1} = \sum_{j=1}^{J} \beta_y^j I_{pst-1}^{[x_{j-1},x_j)} + \alpha_{ps} + \alpha_t + \varepsilon_{pst} \tag{2}$$

Here, α_{ps} are product-store fixed effects and α_t are time fixed effects. The fixed effects help us to control for unobserved heterogeneity across items and common comovement caused by aggregate fluctuations. Third, we obtain the estimated relationship as a sum of two components. The first component is the β_y^j coefficients for $j = [1, 101]$. The second component is the average of the estimated fixed effects $\text{mean}_{ps}\hat{\alpha}_{ps} + \text{mean}_t\hat{\alpha}_t$ added to each bin j. Adding the second component makes sure that the weighted average across bins approximates the sample average of the variable of interest y.

Panel (b) in Fig. 3 shows the average size of nonzero price changes as a function of the price gap in EA4 and the US. It is estimated following the above-described steps when the dependent variable is the nonzero reference-price changes $y_{pst,t+1} = \Delta p_{pst+1}^f|_{\Delta p^f \neq 0}$. The figure shows a tight, almost exactly one-to-one, negative relationship between the gap and the average nonzero price changes in the subsequent month.[16] This validates our price-gap measure by showing that stores choose to close the gap, on average, when adjusting the price.

We are now ready to turn to one of the key empirical moments we are interested in: the generalized hazard functions, shown in Panel (c) of Fig. 3. They are estimated for each region following the steps outlined above when the dependent variable is an indicator function that takes the value 1 when the reference price of product p in store s changed in period t+1, and 0 otherwise $y_{pst,t+1} = I_{pst+1}^f$. The figure shows clear evidence for state dependence in price setting in both regions: the probability of price adjustment clearly increases with the price gap as illustrated by the V shape of the hazard functions.[17] The slopes of the hazard functions, however, are moderate in both regions: the estimated probability of adjustment stays below 40% even for price gaps of 50%. The (density-weighted) average slope is 0.51 in EA4 and 0.38 in the US; the difference between the regions is caused by the larger slope at lower gaps in EA4, where the largest mass of price gaps is concentrated. Additionally, the probability of a price change is strictly positive even at zero gaps, and the hazard functions are asymmetric:

[16] The slope of the relationship is actually somewhat above one. This is consistent with the presence of concurrent item-level shocks, which hit after the gap was measured (remember that the gap is lagged by a month). If items with higher unobserved shocks are changed with a higher probability, which is in line with state dependence, the selection effect increases the average absolute size of price changes at each gap size. That the relationship is only marginally steeper than one suggests that the measured gap plays a quantitatively much more important role than the unobserved concurrent shocks.

[17] See Appendix F for evidence on heterogeneity across euro-area countries.

the probability of adjustment is higher when the item is below the competitors' reset price than when it is above. The height of the hazard function is larger in the US, in line with the higher frequency of price changes there, as documented above.

4.2. Duration hazard

An alternative way of looking at state dependence is duration hazard, which expresses the probability of price adjustment as a function of the months elapsed since the last price adjustment. In the presence of state dependence, the duration hazard is upward sloping because the probability of a price change rises as the optimal price drifts further and further from the posted price. The advantage of using granular scanner data to estimate the hazard function is that we can control for cross-item heterogeneity, which can bias the slope estimate downward.

We estimate the following panel regression:

$$I_{pst,t+1} = \sum_{j=1}^{48} \beta^j I^j_{pst-1} + \alpha_{ps} + \alpha_t + \varepsilon_{pst} \tag{3}$$

The indicator function I^j_{pst-1} takes value 1 if the reference price of product p in store s in month $t-1$ is j months old, and 0 otherwise. As with the generalized hazard, we add the average of the estimated item fixed effects and time fixed effects to the β^j coefficients in order to make the weighted average of the coefficients approximate the frequency of reference-price changes.

Panel (d) of Fig. 3 shows the results for EA4 and the US.[18] It shows that the duration hazard is upward sloping in both regions: the probability of adjustment increases with the age of the product. The slope of the adjustment hazard is higher in EA4 than in the US. In Appendix G, we show that controlling for both cross-item heterogeneity and sales-related price changes is essential to obtain upward-sloping hazards.

4.3. State dependence and price-level flexibility

In the previous section, we argued that the V-shaped generalized hazard function and the upward-sloping duration hazard function are in line with state dependence in price setting. In this section, we quantify the extent of this state dependence. A natural measure of state dependence is how much it contributes to price flexibility, specifically to the price-level impact of a permanent money shock. To measure this, we follow the framework of Caballero and Engel (2007), who showed that under mild conditions, the generalized hazard function and the density provide sufficient information to quantify the contributions of the intensive and extensive margins of adjustment. We first describe the framework and explain how the relevant objects in the model relate to our empirical moments before turning to use it to decompose an aggregate money shock to adjustment margins.

In the price-setting framework of Caballero and Engel (2007), there is a continuum of firms, each producing a single product i. Firms set the (log nominal) prices of their product (p_{it}) subject to price-adjustment frictions. If these frictions were temporarily absent, the optimal price in period t would be p^*_{it}. The optimal price is driven by both aggregate and idiosyncratic factors $p^*_{it} = m_t + \nu_{it}$. For simplicity, we assume that shocks to both m_t and ν_{it} are permanent. The aggregate shock m_t shifts the optimal nominal price of all firms, whereas the idiosyncratic shock ν_{it} affects only firm i. The gap between the price and its optimal value $x_{it} = p_{it} - p^*_{it}$ is the relevant state variable and is sufficient to characterize each firm's price-setting choice. Assuming that the product i is sold in a continuum of stores, the average price set by price-changing stores reveals the optimal price p^*_{it}, in line with our empirical application.

The firms' price-adjustment decision can be described by a generalized hazard function $\Lambda(x)$. The function takes values between 0 and 1, and its value expresses the probability of price adjustment for a firm with a price gap x. The hazard function is constant in the time-dependent Calvo (1983) model, in which the probability of adjustment is independent of the price gap. At the other extreme, in the fixed-menu-cost model (Caplin and Spulber, 1987; Golosov and Lucas, 2007), the hazard function is a step function, which takes the value 0 when the gap is within the inaction band, and 1 otherwise. Caballero and Engel (2007) show that a continuum of intermediate hazard functions can arise when the menu cost is an i.i.d. random variable as in Dotsey et al. (1999) and when the firm is subject to a rational-inattention friction as in Woodford (2009) (see also Alvarez et al., 2022).

In this economy, inflation can be expressed as

$$\pi = \int -x\Lambda(x) f(x) dx, \tag{4}$$

where $f(x)$ is the density of price gaps across firms and we suppress subscripts for notational convenience. The expression is intuitive: the inverse price gap ($-x$) is the size of the price adjustment when it takes place, and the hazard is the probability of a price adjustment taking place. Their product summed across the gap distribution and weighted by the density of the gap is, therefore, equal to the inflation rate.

[18] See Appendix F for evidence on heterogeneity across euro-area countries.

Table 3
Overall impact effect and absolute and relative contributions of adjustment margins.

Margins	US	EA4	DE	FR	IT	NL
Overall impact effect	18.4%	11.6%	8.6%	15.3%	12.3%	14.0%
Intensive (absolute)	13.9%	8.8%	5.3%	13.1%	9.0%	10.7%
Extensive (absolute)	4.5%	2.7%	3.3%	2.2%	3.3%	3.3%
Intensive (relative)	75.4%	76.4%	61.8%	85.4%	73.1%	76.3%
Extensive (relative)	24.5%	23.6%	38.2%	14.6%	26.9%	23.7%

Note: The table presents the overall impact effect of a marginal money shock and the absolute and relative contributions of the intensive- and extensive-margin effects (Caballero and Engel, 2007). It shows that stronger state dependence (extensive-margin effect) amplifies price flexibility in the US relative to EA4. EA4: average of the 4 euro area countries; DE: Germany; FR: France; IT: Italy; NL: the Netherlands.

How flexibly does the inflation rate react to a small aggregate money increase m? Caballero and Engel (2007) point out that the aggregate shock increases the optimal price of all firms, so it reduces the price gaps of each firm uniformly. The response to the aggregate shock can therefore be expressed as a derivative of the expression on the right-hand side of Equation (4) with respect to x, which implies

$$\frac{\partial \pi}{\partial m} = \underbrace{\int \Lambda(x) f(x) dx}_{\text{intensive}} + \underbrace{\int x \Lambda'(x) f(x) dx}_{\text{extensive}}, \tag{5}$$

where $\Lambda'(x)$ is the slope of the hazard function. The expression has two terms. The first term, which Caballero and Engel (2007) call the intensive margin, results in each adjusting firm changing its price by marginally more to incorporate the impact of the aggregate shock. Notably, it is exactly equal to the frequency of price adjustment, and this is the only margin that is active in the time-dependent Calvo (1983) model, which has a constant hazard. The second term is the extensive-margin effect, which takes into account any shifts in the identity of price-adjusting firms. The slope of the hazard function appears in this expression because it measures the mass of new price adjusters as the aggregate shock shifts the price-gap density. The extensive margin is powerful if the new adjusters are primarily those with large price gaps. This tends to be the case with strongly state-dependent (S,s)-type menu-cost models (Golosov and Lucas, 2007).

Our empirical estimates of the hazard function and the density of the price gap shown in Fig. 3 allow us to conduct the Caballero and Engel (2007) decomposition described by Equation (5). The intensive-margin effect is the average frequency, approximated here with the average of the hazard function weighted by the density at each bin. To obtain the extensive-margin effect, we first calculate the slope of the hazard function at each bin as the centered finite difference between subsequent bins. Second, we multiply the slope with the size of the misalignment. Third, we calculate a weighted average using the density weight of each bin.

The first row of Table 3 shows the overall impact effect of a permanent money shock in the euro area, in the US, and in each of the four euro-area countries. The second and third rows decompose these into intensive-margin and extensive-margin effects (or state dependence). The fourth and fifth rows show the relative contributions of the two channels.

The table shows that the effect is larger in the US relative to EA4 because of both stronger intensive- and extensive-margin effects. The stronger intensive-margin effect is the consequence of a higher frequency of price changes. The stronger extensive-margin effect is the consequence of stronger state dependence, which is driven by two main factors: the slope of the hazard function and the average absolute size of gaps.[19] In the simple and realistic case of a symmetric and (piecewise-) linear hazard function, the slope of the hazard is constant $|\Lambda'(x)| = \Lambda'$, where $\Lambda' > 0$ is a parameter. It is straightforward to see that in this case, the extensive-margin effect in Equation (5) is simply $\int x\Lambda'(x) f(x)dx = \Lambda' \int |x| f(x)dx$, which is the product of the slope of the hazard and the average absolute size of price gaps. The expression shows that the extensive-margin effect does not depend only on the slope of the hazard function but also the dispersion of the price gaps. Indeed, the extensive-margin effect is larger in the US even though the slope of the hazard function is somewhat higher in EA4. The reason is that the higher dispersion of the price gaps more than compensates for the lower slope. Through increasing price-gap dispersion, therefore, higher product-level volatility raises the state dependence of price setting. The relative contribution of the extensive-margin effect is around 25% in both the euro area and the US. This means that accounting for state dependence raises the price-level flexibility by around $33\% = 25\%/(1 - 25\%)$ relative to a time-dependent benchmark (Calvo, 1983).

As Table 3 also shows, there is sizable heterogeneity among euro-area countries in the size of the overall impact effect. The heterogeneity is mainly driven by differences in the intensive-margin effect, determined by the frequency of price changes. The extent of state dependence among euro-area countries is similar, with the notable exception of France, where it is substantially below average.

[19] There is a potential third factor—the covariance of the slope and the gap—but it plays a marginal role in the realistic case of an approximately linear hazard function (see Karadi et al., 2020).

5. Structural analysis

In this section, we interpret the evidence through the lens of a price-setting model (Woodford, 2009). We ask which structural features drive the differences in price setting in the food-retail sector between the US and the euro area and across euro-area countries.

5.1. Structural model

We use a quantitative price-setting model with price-adjustment costs and information frictions. It provides a microfoundation for the popular random-menu-cost models (Alvarez et al., 2022; Dotsey et al., 1999) and includes the time-dependent Calvo (1983) model and the fixed-menu-cost model of Golosov and Lucas (2007) as special cases.

We sketch the key features of the model here and direct the interested reader to the original paper for details and derivations. The paper generalizes the fixed-menu-cost model of Golosov and Lucas (2007). There is a continuum of differentiated goods (i), which are sold in a market with monopolistic competition. This market structure gives the producer of each good market power to set prices at a markup above marginal cost. The market power is determined by the elasticity of demand, which, in turn, is governed by the (constant) elasticity of the substitution parameter ε.

The production requires labor, and the product-specific productivity is subject to idiosyncratic shocks. As argued by Golosov and Lucas (2007), these shocks are necessary to explain the large absolute size of price changes. Specifically, productivity follows a random walk, with an idiosyncratic shock $z_t(i)$ with standard deviation σ_z ($A_t(i) = A_{t-1}(i) + z_t(i), z_t(i) \sim N(0, \sigma_z^2)$). All the relevant firm-level information is incorporated into the price gap, defined as the distance of its (log) price from its (log) optimal price $x_t(i) = p_t(i) - p_t^*(i)$.[20] In particular, the discounted present value of its profit is a function of the price gap, and it is maximized when the price gap is zero. The price gap fluctuates as idiosyncratic shocks hit the optimal price, and the firm does not necessarily reset it to zero because adjusting the product price ($p_t(i)$) is costly.

The firm faces two types of adjustment costs. First, as in Golosov and Lucas (2007), the firm needs to pay a fixed (menu) cost κ when it conducts a price review. After paying the cost, the firm obtains full information; it thereby learns its price gap and optimally closes it. Second, the firm needs to decide about the timing of its price review under imperfect information about the state of the economy and therefore about its price gap. The imperfect information is modeled as rational inattention, whereby the firm can obtain a costly signal $f(x)$ about the price gap, and the cost increases linearly with the informativeness (I) of the signal with a coefficient θ ($\theta I = -\theta E[\log f(x)]$)). Woodford (2009) establishes two useful results. First, the optimal policy is described by a hazard function $\Lambda_t(x_t)$: a firm chooses to obtain a signal with probability $\Lambda_t(x_t)$ as a function of its price gap x_t and conducts a price review if it receives a signal. Second, the functional form of the hazard function is well defined, it is (weakly) increasing with the (absolute value of the) price gap, and its slope depends on the information-cost parameter θ. As the cost parameter θ increases without limit, the hazard function approaches a constant, which is the time-dependent Calvo (1983) case; and as the cost parameter approaches zero, the hazard function approaches a step function as in the fixed-menu-cost case of Golosov and Lucas (2007). In between these two extremes, the theoretical hazard function shares some key features of the empirical hazard functions shown in Section 4. In particular, it is increasing with higher absolute gaps, implies a positive hazard at a zero gap, and is asymmetric with a higher probability of adjustment when prices are below the reset price.

We assess the dynamic impact of aggregate fluctuations in the model by approximating the aggregate equilibrium conditions up to a first order around the nonlinear stationary equilibrium using the method proposed by Reiter (2009).[21] As in Midrigan (2011), we assume that aggregate nominal expenditure equals the money supply $P_tY_t = M_t$. Money growth follows an exogenous autoregressive process $g_{Mt} = \rho_M g_{Mt-1} + \varepsilon_{Mt}$, with $\varepsilon_{mt} \sim N(0, \sigma_m^2)$. Money shocks can alternatively be interpreted as nominal expenditure shocks. We assume, furthermore, that the production of each product i is affected by an aggregate productivity factor A_t.[22] Aggregate productivity follows a first-order autoregressive process $A_t = \rho_A A_{t-1} + \varepsilon_{At}$, with $\varepsilon_{At} \sim N(0, \sigma_A^2)$.

5.2. Estimation

Our goal in this section is to identify the most relevant structural features that account for the differences between price setting in the US and EA4 and across euro-area countries. We do this by matching the empirical moments obtained in previous sections to estimate key structural parameters in the model.

We calibrate some parameters to levels used in the literature following Woodford (2009), with one difference. We set the elasticity of the substitution parameter (ε) to 3. This is the parameter used by Midrigan (2011), and it implies markup levels relevant for supermarkets.[23] Furthermore, we calibrate the autoregressive coefficient of the money-growth process (ρ_m) to

[20] The price gap can be equivalently expressed as the difference between the normalized price ($q_t(i)$) as defined in Woodford (2009) and its optimum ($x_t(i) = p_t(i) - p_t^*(i) = q_t(i) - q_t^*$).

[21] We extend the code used in Costain and Nakov (2011). We thank Anton Nakov for posting his code.

[22] Formally, $y_t(i) = A_t A_t(i) h_t(i)^{1/\phi}$, where $y_t(i)$ is the (log) output of firm i, A_t is an aggregate, $A_t(i)$ is firm-specific productivity, $h_t(i)$ is firm-level labor, and ϕ is a parameter governing the extent of decreasing returns to scale of labor.

[23] The parameter is below that used by Woodford (2009)—namely, 6. The lower parameter implies weaker competition and a flatter profit function, which helps us to match the consistently low slope of the empirical hazard function.

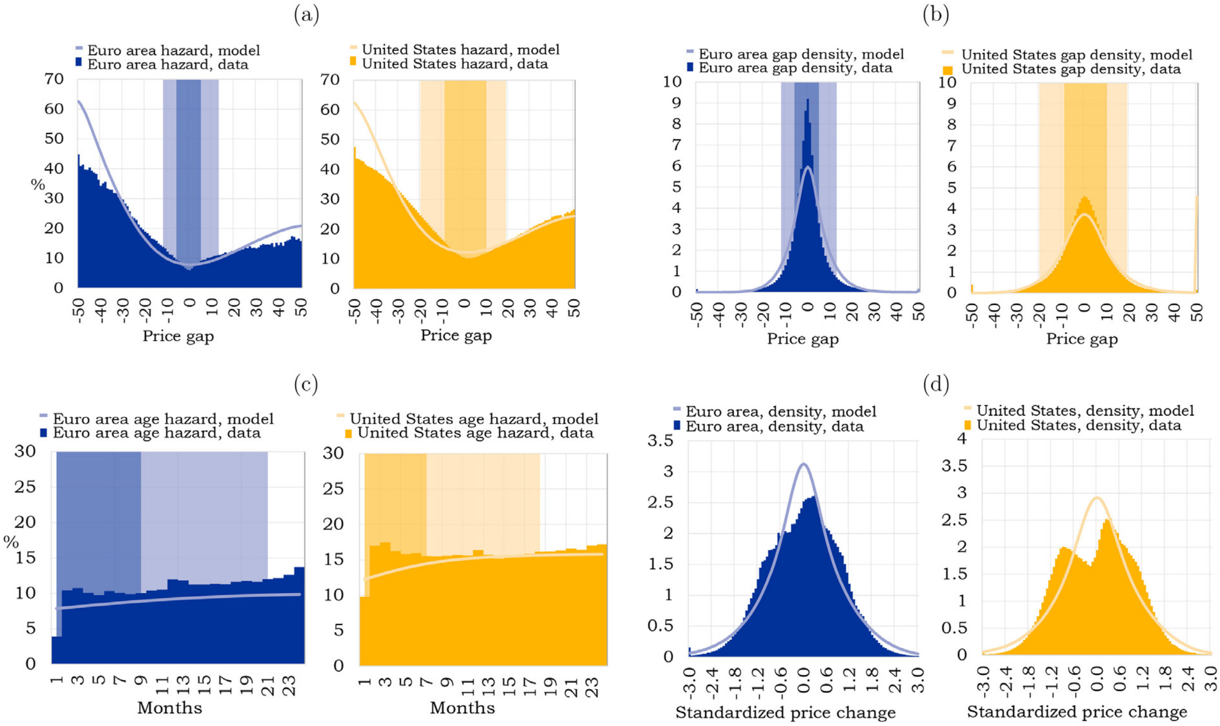

Fig. 4. Estimation, targeted and nontargeted moments *Note:* The figures show the matches of the simulated and empirical generalized hazards and price-gap densities (matched moments, Panels a and b) and the duration hazards and price-change densities (unmatched moments, Panels c and d) in the euro area (EA4) and the US. Shaded areas cover the 67% (darker) and 90% (lighter) masses of the corresponding densities.

0.61 as in Midrigan (2011), and the autoregressive coefficient of aggregate productivity (ρ_A) to 0.95, which is a standard value in the literature.

The three parameters we estimate are (i) the standard deviation of the idiosyncratic shocks (σ_z), which affects the volatility of the product-level environment, and the two parameters governing the price-adjustment costs: (ii) the review (menu) cost (κ) and (iii) the information cost (θ). We estimate these parameters by targeting three empirical moments with their simulated counterparts in the stationary equilibrium: the shape of the generalized hazard,[24] and the frequency and size of the price changes.[25] We also check how the model matches some untargeted moments, such as the duration hazard and the standardized price-change distribution.

5.3. Results

Fig. 4 shows the fit of the theoretical and empirical generalized hazards (Panel a) and densities (Panel d) for EA4 and the US. The fit is good for both the hazards and the densities, especially over the range in which most of the mass concentrates, as indicated by the shaded areas. The distribution of the gaps in the euro area is more concentrated than in the US, and the theoretical distribution partially captures this. The model is also reasonably good at matching the duration hazard (Panel c) and the standardized price-change distribution (Panel d), even though these moments were not directly targeted. In Appendix H, we show that a more realistic model, which assumes an asymmetric linear hazard function and leptokurtic idiosyncratic shock distribution (Laplace) in the euro area can match the hazard function, the shape of the gap distribution and the price-change distribution (including its unimodality in the euro area and bimodality in the US) better. However, it has essentially the same response to an aggregate money-growth shock as the baseline model, suggesting that the fit of the baseline model is sufficiently good.

Table 4 shows the estimated structural parameters for the euro area, the US, and the specific euro-area countries. Several results are worth pointing out. First, the information-cost parameters are finite, indicating the presence of state dependence

[24] The estimation algorithm minimizes the squared difference between the empirical and theoretical hazard functions, weighted by the price-gap density. The empirical hazard, calculated as the probability of price change *next month* as a function of the current price gap, is matched with a simulated hazard, which similarly expresses the probability of price change in the next month as a function of the current gap.

[25] For internal consistency of our quantitative exercise, the frequency and size measures we match here are derived from (unweighted, truncated at $+-50\%$) generalized hazard and density estimates. In particular, frequency is measured as $\sum_j \Lambda_j f_j$, and size as $\sum_j |x_j| \Lambda_j f_j / \sum_j \Lambda_j f_j$, where Λ_j is the height of the generalized hazard, f_j is the relative share of products in the price-gap bin j, and x_j is its midpoint. These measures are not equal to the

Table 4
Estimated parameters.

Parameters	US	EA4	DE	FR	IT	NL
Review cost (κ, %)	21.6	15.9	22.0	5.4	20.1	21.2
Std. dev. of idiosyncratic shocks (σ_z, %)	5.5	3.0	2.7	2.1	3.6	3.9
Information cost (θ)	0.65	0.65	0.40	0.54	0.58	1.07

Note: The table shows that state dependence is present but mild in both regions (because information frictions are high). Higher idiosyncratic-shock variation in the US plays a prominent role in explaining higher frequency and size of price changes. EA4: average of the 4 euro area countries; DE: Germany; FR: France; IT: Italy; NL: the Netherlands.

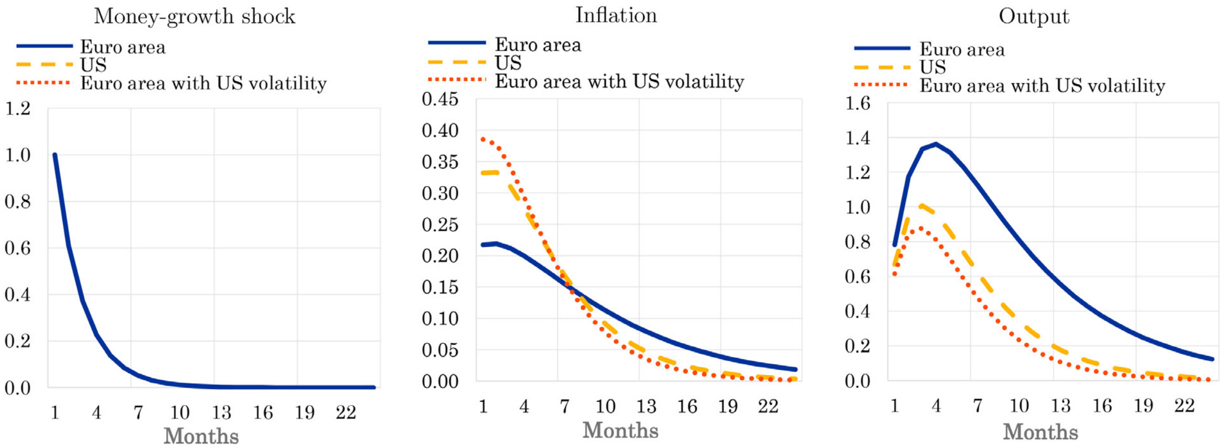

Fig. 5. Simulated response to a money-growth shock *Note:* The figures show the impulse response to a unit money-growth shock in the model calibrated to the euro area, the US, and the euro area with US idiosyncratic volatility. They show that the inflation response is weaker in the euro area, and the output response is correspondingly larger and more persistent. The difference is primarily driven by higher idiosyncratic volatility in the US.

in line with an increasing hazard function. Second, the information costs are sizable, indicating mild state dependence, which is quantitatively closer to the time-dependent Calvo (1983) model than the strongly state-dependent fixed-menu-cost model of Golosov and Lucas (2007). This is in line with flat hazard functions. Third, the information-cost parameters are actually the same across the regions, indicating a similar shape of the generalized hazard functions. Fourth, the estimated review-cost (menu cost) parameters are somewhat higher in the US. Finally, the quantitatively most relevant structural reason for the differences across the regions is the distinct standard deviation of the idiosyncratic shocks.

Fig. 5 shows impulse responses to a money-growth shock in models calibrated in the euro area and in the US and in a simulation of the euro area with US counterfactual idiosyncratic volatility. The figure shows that the inflation response is more flexible, and the output response is correspondingly smaller and less persistent in the US, and the difference in idiosyncratic volatility is responsible for most of the difference. Therefore, the volatility of the product-level environment is higher in the US, which leads to (i) higher-frequency price changes, (ii) larger price changes, and (iii) a more dispersed price-gap distribution, contributing to stronger aggregate responses both at the intensive- and extensive-adjustment margins.

Among the euro-area countries, the heterogeneity in the standard deviation of idiosyncratic shocks is also sizable and plays a key role in explaining the overall heterogeneity in price flexibility. The extent of price-adjustment frictions (κ) is similar across countries and comparable to the US, with the notable exception of France, where prices are estimated to be much more flexible. The information-cost parameter varies somewhat, but within a limited range, implying mild state dependence in all euro-area countries.

What share of the difference in the volatility in food inflation between the US and EA4 is explained by the model? The question is important because even if the model can successfully capture differences in key features of price setting, different volatilities across countries may be the consequence of numerous unmodeled factors, such as heterogeneity in the nature and magnitude of aggregate or sectoral shocks. We assess the importance of differences in price setting through a simple exercise. First, we estimate the standard deviation of aggregate money shocks σ_m to match the standard deviation of year-on-year inflation in the US in the model and the data. Then we measure the predicted inflation volatility in the model if we feed the same money shocks to the model calibrated to the euro area. We repeat the same exercise with aggregate productivity shocks (σ_A). The first three columns of Table 5 show the results. As the second row shows, assuming money

(weighted, untruncated) frequency (EA4: 9.5% versus 8.9%, US: 13.8% versus 14.1%) and size (EA4: 9.3% versus 8.0%, US: 15.2% versus 11.8%) measures reported in Sections 3.1 and 3.2, but they are close and have comparable relative magnitudes.

Table 5
Simulated inflation response.

	Inflation volatility			COVID-19 shock		
	US	EA4	Difference	DE	IT	Difference
Data	0.95%	0.64%	0.31%	0.54%	1.65%	1.11%
Model (σ_m)	0.95%	0.83%	0.12%	0.92%	1.31%	0.39%
Model (σ_A)	0.95%	0.66%	0.29%			

Note: The table shows the inflation volatility in the US and EA4 (columns 1–3) and the inflation response to the COVID shock in Germany and Italy (columns 4–6) in the data (row 1) and in the model. The second row assumes aggregate money shocks (σ_m). The third row assumes aggregate productivity shocks (σ_A). Around one-third of the observed difference is accounted for by the model. EA4: average of the 4 euro area countries; DE: Germany; IT: Italy.

(or nominal expenditure) shocks, the model correctly predicts lower inflation volatility in the euro area, but it only explains somewhat over a third of the difference observed in the data. As the third row shows, assuming productivity shocks, the model explains most of the difference in inflation volatility. It is outside the scope of the paper to assess the importance of the two shocks in driving food inflation, but arguably both types of shocks are active. We conclude that differences in price-setting frictions, though not the only factor at play, can account for a relevant share of the observed difference in inflation volatility.

6. Price setting during the COVID-19 pandemic in Germany and Italy

In this section, we analyze the price-setting response of German and Italian supermarkets to the first wave of COVID-19 lockdowns. The shock had a large, persistent, and broadly similar effect on supermarket demand in both countries. Contrasting the response in the two countries is relevant because price setting is heterogeneous across the countries: the frequency of price changes is higher in Italy than in Germany (see Table 2), and the extent of state dependence is similar between the countries (see Table 3). Price-setting models, therefore, predict higher flexibility of Italian supermarket inflation and faster pass-through of the COVID-19 shock, which we can test in the data.

6.1. Data

The analysis in this section uses an auxiliary dataset covering large German and Italian supermarkets over the three months encompassing the first wave of the COVID-19 pandemic: from mid-February till mid-May 2020. The dataset also covers the analogous period in 2019, which we use as the base period in our index calculations. The dataset covers 20 two-digit ZIP areas.[26]

Our analysis uses the 2013–17 German and Italian pre-COVID-19 sample as a benchmark to assess the significance of changes observed over the 2019–20 period. To minimize the impact of compositional shifts over time, we restrict our baseline sample to stores and products with positive sales in both the first quarter of 2013 and the sample quarter in 2020. The majority of stores are such *established* stores.[27] A sizable fraction of the products is such *established* products.[28]

6.2. Supermarkets and the first wave of the pandemic

The pandemic and the accompanying lockdown measures had a large and persistent impact on supermarket demand. During the lockdowns, access to food away from home was severely restricted, while supermarkets were deemed essential and sheltered from the lockdowns. The Italian government imposed a national lockdown on March 9, 2020, and gradually eased it only after mid-May. In Germany, a federal lockdown was introduced on March 22, and was gradually eased in early May. In both countries, supermarkets stayed open during the lockdowns, while alternative forms of access to food and beverages were restricted: restaurants, canteens, and bars were deemed unessential and closed.

Our data allow us to quantify the magnitude of the demand change because the scanner data records weekly expenditures at the store-product level. We restrict attention to established products in established stores, which are the focus of our analysis. We measure year-on-year nominal expenditure growth as the 52-week change in overall expenditure on items sold in positive quantities both in the current and base weeks.

Panels a and b of Fig. 6 show the evolution of nominal expenditure growth between mid-February to mid-May in German and Italian supermarkets. The figure shows that the expenditure growth significantly exceeded its long-term average. The in-

[26] The ZIP areas in the sample cover 16% and 40% of the population and shares of supermarket expenditures of 22% and 46% throughout 2013–17 in Germany and Italy, respectively.

[27] Established stores are 668 out of 815 total stores in Germany and 1486 out of 2387 in Italy.

[28] Established products are 57,000 out of 266,000 total products in Germany and 83,800 out of 535,500 in Italy with an expenditure share in Germany of 43.43% and in Italy of 42.43%.

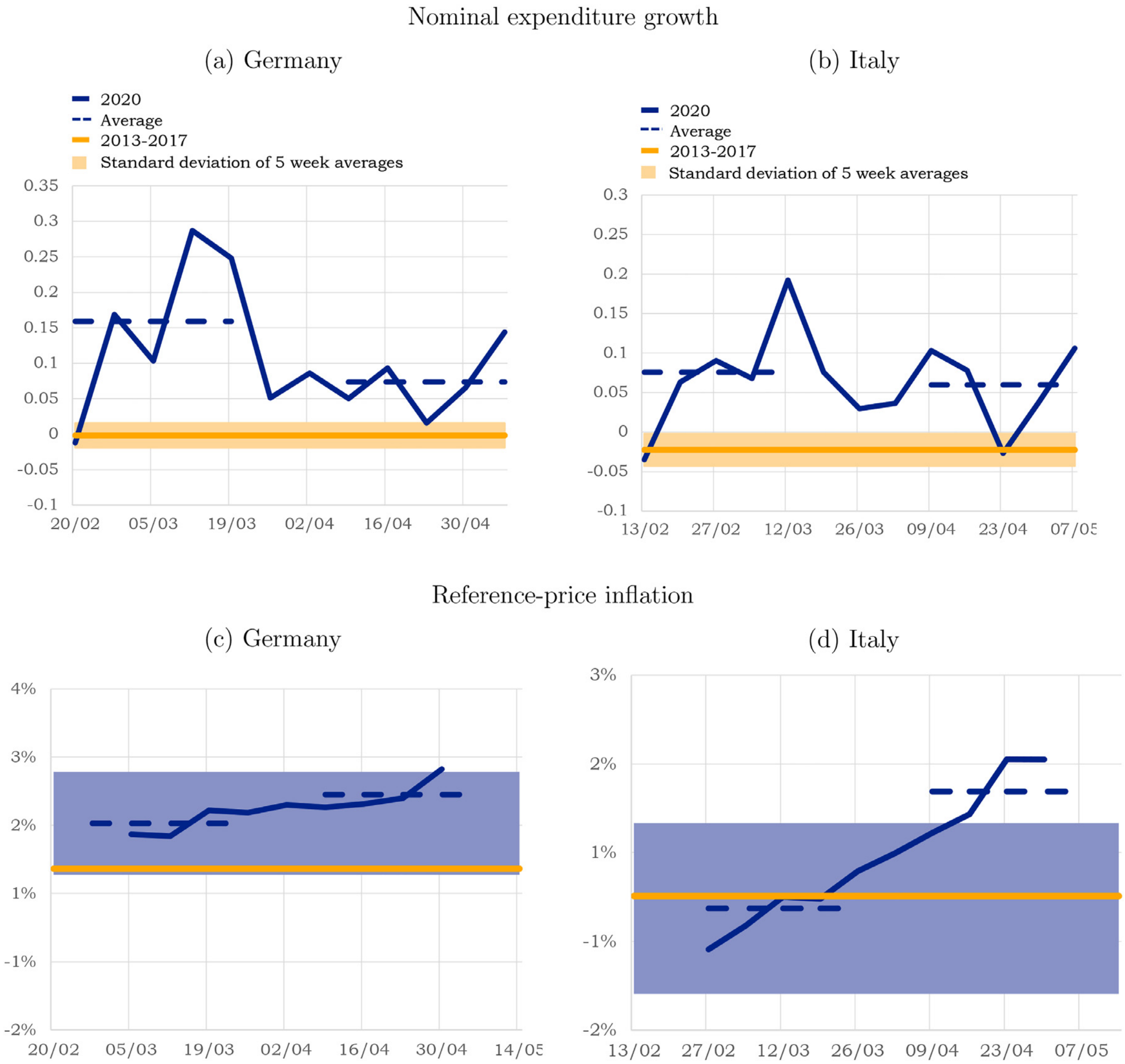

Fig. 6. Nominal expenditure growth and reference-price inflation in supermarkets during the COVID-19 pandemic, year on year *Note:* The figure shows weekly, year-on-year nominal expenditure growth (blue solid line) between mid-February and mid-May in 2020 in Germany and Italy (Panels a and b) and weekly reference-price inflation in the same period and countries (Panels c and d). Panels a and b show that the five-week-average expenditure growth (blue dashed line) exceeds the average long-term expenditure growth (yellow dashed line) by more than one standard deviation in both Germany and Italy. Panels c and d show that the increase in average five-week-average inflation over the quarter is smaller (0.54%) and within a confidence band of two standard deviations in Germany, while it is three times as large in Italy (1.65%) and clearly exceeds the band.

crease was particularly pronounced during the weeks preceding the introduction of the lockdowns. The growth rate reached as high as 19%–29% during this "stock-up shock," as households increased their home stock of nonperishable groceries for precautionary reasons. The expenditure growth during the lockdowns stayed persistently well above average. It stabilized by the end of our sample at around 7.4% in Germany and at 6% in Italy, which significantly exceeded the long-term nominal expenditure growth experienced over the 2013–17 period.

6.3. Inflation response

How did prices respond to the persistent increase in demand? Panels c and d of Fig. 6 show the evolution of reference prices in Germany and Italy (see Appendix I for the evolution of posted-price inflation). It shows that the increase between the first and third months was substantially lower in Germany (0.54%) than in Italy (1.65%), albeit from a higher initial level. The increase in Germany stayed within a confidence band of two standard deviations, while it clearly exceeded the band in Italy. This happened despite the similarity of the shock, the type of retailers, and the basket of products.

Can differences in price setting account for the differences in the inflation response? Previously we showed that prices change less frequently in Germany (see Table 2), while the extent of state dependence is similar across the two countries (Table 3). The structural model calibrated to the two countries explained this outcome with comparable price-setting frictions but substantially smaller product-level volatility and somewhat-smaller information frictions in Germany (Table 4). Table 5 shows the simulated impact of a permanent 6% nominal expenditure shock on two-month cumulative inflation (equivalent to a change in the year-on-year inflation between the third and first months in the data) in the two models calibrated to Germany and Italy. The model reproduces the more sluggish inflation response in Germany and accounts for around one-third of the difference between the countries.

7. Conclusion

This paper contrasted price setting in the euro area and the US using a novel supermarket-scanner dataset in four euro-area countries and the US. It found that the higher flexibility of food inflation in the US is driven both by the higher frequency of repricing and the stronger state dependence of price changes. It argues that the driving force behind both factors is a more volatile product-level environment in the US. The models were able to explain over a third of the differences in inflation volatility across the regions.

Our conclusions have implications for both model selection and policy. First, the evidence is in line with models with sizable nominal rigidities in both regions, which amplify the impact of monetary and fiscal policy on the real economy. The greater nominal rigidities in the euro area imply that, at least in the food sector, changes in nominal expenditure growth have a smaller impact on prices and a larger impact on quantities than in the US. Second, the evidence presented in the paper supports state dependence in price setting. Even though we find that the estimated magnitude of state dependence has a mild impact on price flexibility in response to small aggregate shocks, state dependence necessarily implies that prices endogenously become more flexible after large aggregate shocks and higher trend inflation (Alvarez et al., 2019; Costain et al., 2022; Karadi and Reiff, 2019). Third, the sizable differences in the implied product-level volatility between the US and the euro area raise important questions for future research. Although in the simplest class of price-setting models, product-level volatility matters only insofar as it influences frequency and state dependence (Alvarez et al., 2022), in more complicated models, it can have an independent impact on price flexibility, as high product-level volatility can make retailers limit their attention to aggregate fluctuations (Mackowiak and Wiederholt, 2009), which could mitigate their responsiveness to aggregate shocks. Its key role in driving differences across regions also highlights the importance of further research to understand better the underlying sources of the product-level volatility, including whether they are the consequence of larger shocks or greater responsiveness to these shocks (Berger and Vavra, 2019).

Transparency declaration

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Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jmoneco.2023.05.009

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