A Nearby Wake-Up Call for Price Reactions

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Abstract

We propose a new explanation for competitive price reactions: the nearby wake-up call. A price change of a product-item in a store is a wake-up call to competitors, prompting them to reassess the item's fundamentals. Although, nearby competitors are more attentive to new information and thus strongly update their beliefs. We structure our empirical analysis around a stylized learning model, linking competitors' attention to their geographical distance from the first-moving store. The empirical results, based on unique daily price data including stores' geolocations across France, support the nearby wake-up call explanation through various validity analyses and robustness checks.

JEL Codes: D40, E31, L11, L81, R32.

Keywords: Nearby wake-up call, competitive price reactions, geographical distance, learning attention.

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1. Introduction

Competitive price reactions are important for understanding how firms update the prices of their product-items in response to market adjustments under competition. Traditional explanations for competitive price reactions are related to price-*following* responses, where competitors tend to decrease prices after price reductions implemented by a competing firm, but they are less likely to follow price increments (which is explained by the classic kinked-demand theory).[1] Nevertheless, studies on price responses in general assume an environment without frictions in the competitors' learning process. We propose, and empirically test, a new explanation for competitive price reactions that considers learning constraints: the nearby wake-up call.

According to this explanation, the fact that the price of an item changes in a store serves as a wake-up call to competitors. This wake-up call prompts competitors to reassess this item's fundamentals by acquiring and learning new knowledge related to the item, for example, from the information revealed in the new price of the first-moving store. In particular, competitors should be more attentive to such information when the economic benefits derived from the new knowledge exceed the opportunity costs of diverting their attention from other tasks. In this sense, there are important economic benefits by competitors to be had from learning about the nearby market environment (where they directly compete with other stores), and there is evidence that geographical proximity reduces the effort required to obtain new information disclosed by other agents (see, e.g., Fik, 1988 and Malmberg and Maskell, 2002). Consequently, under the nearby wake-up call explanation, after a price change (i.e., a wake-up call), nearby competitors should be more attentive to new information and thus strongly update their beliefs.[2]

1. See, e.g., Tirole (1988), p. 243, and Maskin and Tirole (1988).
2. The nearby wake-up call explanation echoes the intuitions behind the recent literature on strategic inattention in competition models that are used to understand inflation dynamics, in which firms with fewer competitors tend to be less attentive to acquiring new information about their competitors' beliefs. Thus, this strategic inattention increases monetary non-neutrality (see Afrouzi, 2024).

As a roadmap for our empirical analysis, we adopt a stylized learning model based on information theory tools, and provide intuitions behind the mechanism and a motivating framework for this new potential explanation of competitors' price reactions. The model includes a set of competitive stores that sell a single item with a stochastic fundamental value, v_t. At the beginning of each date t, when store managers set the item's price for that date, they do not observe its fundamental value. This is because the value of v_t depends on daily unpredictable factors (such as weather conditions, traffic congestion, amongst others), which may affect both item deliveries by the producer and the willingness of consumers to acquire the item. Thus, store managers set the item's price based on their selling costs and their *expectations* about the item's fundamental value. In addition, as in actual retail markets, managers' prior beliefs about the item's fundamental value are heterogeneous (for example, due to different resources devoted to the analysis of the local market and/or because of behavioral biases such as overconfidence), which results in different prices across stores for the same exact article (i.e., price dispersion among retailers).

At the beginning of a given date, a store (store $Init$) initiates the dynamics by changing the price of the item because its manager, after analyzing the local market conditions, obtains some new information about the item's fundamental value on that date. Such price updating is a wake-up call for local competitors, inducing them to learn from the information revealed in the new price of the store that decided the initial price change (which is cheaper than to perform their own local market analysis). Without learning frictions, this learning process increases the *homogeneity* of item's prices across stores, since competitors' prices have a *common* factor that is generated by learning from the same information signal about the item's fundamental value, which is produced by (and disclosed in the new price of) the store $Init$. Nevertheless, there are learning frictions, because competitors have limited attention capacities (see, e.g., Kahneman, 1973; and Johnston and Pashler, 1998). We use the concept of entropy (from information theory) to characterize the amount of attention used to learn

the new piece of information, which decreases as a function of the geographical distance between the store making the initial price change and its competitors. Thus, the amount of attention devoted to learning by managers of competing stores should be larger for nearby competitors.

This stylized model provides a testable empirical implication about the nearby wake-up call explanation: after a price change in the store $Init$ (a wake-up call), the updated price of a nearby competitor $CompNear$, $p^{New}_{CompNear}$, is closer to the new price of the store implementing the initial price change, p^{New}_{Init}, than the updated prices of competitors that are far away, $CompFar$, $p^{New}_{CompFar}$. In other terms, after a wake-up call, $|p^{New}_{CompNear} - p^{New}_{Init}|$ is smaller than $|p^{New}_{CompFar} - p^{New}_{Init}|$. This is because, as explained above, the amount of attention used by competitors, which they assign to learn the *common* information disclosed in the new price of the store $Init$, becomes larger as the competitors' distance from the information source decreases.

Testing this empirical implication is different from the empirical analysis performed by previous literature that examines the price-*following* behavior of competitors (see, e.g., Dickson and Urbany, 1994; and Shin, 2004). Studies in this literature analyze price-*following* strategies investigating whether or not competitors decrease (increase) prices as a consequence of an initial price decrease (increase) in a given store. This means that the analysis focuses on whether the price reactions of competitors follow the *same direction* as the price of the store that moves first. Differently, as suggested by the motivating framework for the nearby wake-up call explanation, we delve into whether the updated prices of competitors are closer (in absolute value) to the new price of the store that implements the initial price change. Moreover, we extend the analysis to examine the impact of the geographical proximity of competitors on how closely their price approaches the new price of the store that moves first.

We test this empirical implication for the nearby wake-up call explanation by using unique price data on grocery sales in medium and large supermarkets across France. The data contain prices at

the store-barcode level on a daily basis. In the dataset, each single item has a barcode, which corresponds to a unique combination of product-brand-volume(weight)-packaging. For instance, there is a single barcode for the item corresponding to: the product category related to zero sugar soda, brand Coca-Cola, one liter volume, and in a bottle packaging format. The data also include the geolocation of each store (i.e., the latitude and longitude coordinates) and the retail chain to which the store belongs. Importantly, prices in this dataset reflect those paid by consumers in a physical store on a given date. This is crucial due to potential differences between online and brick-and-mortar stores' pricing (see Cavallo, 2017).

We reduce identification and endogeneity concerns in several dimensions. Firstly, information flows are not directly observable, and identifying the potential social influence of competitors is empirically challenging due to the reflection problem (Manski, 1993). To alleviate this issue, we use an instrumental variable (IV) approach, following previous literature on competitive reactions of retailers (see, e.g., Olivares and Cachon, 2009; Habte and Holm, 2022). Secondly, we mitigate endogeneity issues due to simultaneity between initial price changes and price reactions of competitors. Thus, if a store changes the price of an item on date t, price reactions of competitors can happen only between $t+1$ and $t+\Delta_{Eval}$ (where $\Delta_{Eval} \geq 1$), within a Rad km radius around the geolocation of the store that implements the initial price change. This also helps to mitigate reverse causality because, at any point in time, initial price changes are not likely to be affected (at least directly) by the future price reactions of competitors. Furthermore, this data filter helps to reduce the impact of noisy observations related to price reactions that are far in the future and/or far away from the geographical area of competition, which are not likely to be price responses of competitors induced by the initial price changes.[3]

3. We set the evaluation period to one calendar week (i.e., $\Delta_{Eval} = 7$), as this is sufficient time for other store competitors to update prices, but sufficiently short to avoid observing other initial price changes under normal conditions. We set the geographical area of evaluation to a 5 km radius around the store with the initial price change (i.e., $Rad = 5$ km), because 5 km implies a frictionless travel time of 10 minutes at 30 km/h, which is the typical speed limit in many French urban areas. However, we also use other parameter values as a robustness check.

Thirdly, we reduce endogenity concerns resulting from transitory price reductions (e.g., due to items that are close to expiry and/or because of an excess of inventory). Thus, we exclude observations where, within a window of one week, there is more than one price change in the same store for the same item inside the geographical area of competition (for both stores implementing the initial price change and competing stores that have price reactions). Fourthly, we reduce endogeneity arising from price changes imposed by brand managers of producers (e.g., items' price increases or reductions due to pricing strategies of brand managers), which may simultaneously generate initial price changes in stores from different retail chains. Indeed, we eliminate observations related to initial price changes (and the respective price reactions of competitors that are triggered by these initial price movements), where initial price changes are simultaneously observed on a given date in stores of two (or more) different retail chains within the local retail market. Fifthly, we also mitigate endogeneity issues related to simultaneous price changes in stores belonging to the same retail chain, which might also bias our results due to an over-weighting of the price dynamics of retail chains with a large number of stores, by randomly selecting only one store for each retail chain inside the geographical area of competition.

We find evidence supporting the nearby wake-up call explanation for competing price responses. After an initial price change for an item in a given store (a wake-up call), the updated prices of nearby competitors are closer to the new price of the store with the initial price change than the updated prices of competitors located further away. This is in line with the motivating framework used to provide the intuition behind the nearby wake-up call explanation. This empirical evidence is observed after including control variables related to demographic features such as income per capital at the municipality level, and accounting for differences between rural and urban local retail markets. In addition, the results are robust to controlling for potential unobserved variables that might influence the price reactions of competitors (e.g., diverse selling costs, differences in the items'

demand and/or seasonal effects), through the inclusion of time fixed effects, store-size fixed effects, fixed effects related to the retail chains to which stores belong, region fixed effects, and product category fixed effects.[4]

Interestingly, we find a stronger effect of the geographical distance on how the updated prices of competitors are adjusted to the new initial price when the first implemented price change is a decrease than when it is an increase. This asymmetric effect of distance on the updated prices of competitors is consistent with studies that examine whether store managers tend to follow competitors' price reductions more than competitors' price increases (see, e.g., Dickson and Urbany, 1994; and Shin, 2004).

While our empirical analysis is based on a stylized learning model, which provides intuitions behind the mechanisms for the nearby wake-up call explanation, an important question remains: how can we ascertain that the amount of attention devoted by competitors, to learn the information revealed in the new price of the store making the initial price change, decreases as a function of the geographical distance from the information source? We cannot definitively answer this question due to the unobservability of both competitors' learning dynamics and their information sets. Nevertheless, to indirectly address this question, we develop different hypotheses to investigate the behavior of price reactions across various scenarios, which are empirically tested. These hypotheses are based on previous studies related to attention drivers and the effect of geographical proximity on information flows. This validity analysis is crucial as it provides insights into whether the nearby wake-up call explanation aligns with actual market dynamics.

The first hypothesis is grounded on previous studies emphasizing that agents should allocate more attention to learning new information, if such new knowledge generates more benefits than costs (see, e.g., Peng and Xiong, 2006; and Mondria and Quintana-Domeque, 2013). According to this

4. We include store-size fixed effects and retail chain fixed effects for both the stores implementing the initial price changes and the stores whose prices change as a reaction.

perspective, mistakes in pricing *essential* items (e.g., due to paying little attention to learning the information revealed in competitors' prices) can result in significant economic losses, as these items constitute a substantial portion of stores' sales. Therefore, after an initial price change in an item that is *essential* for consumers, competitors should be more attentive to learning the new information revealed in the new price, *independently* of the distance from the information source. Thus, in the case of essential items, we expect a weaker effect of the geographical distance on how the updated prices of competitors converge to the new initial price. In line with this first hypothesis, after an initial price change, we find a reduced association of the geographical distance with how the updated prices of competitors are adjusted to the new price, when the analysis involves an essential item, compared to the case of other items.

Our second hypothesis is based on the learning literature, highlighting that the amount of attention used to learn new knowledge depends on the characteristics of the information source (see, e.g., Wolff, Jarodzka, and Boshuizen, 2021). For instance, price responses of competitors should vary depending on the size of the store that initiates the price change. Indeed, on the one hand, if store managers are evaluated relative to their peers, a store manager should be more attentive to the actions of managers in large stores due to reputational concerns, given that large stores are relevant players in their competitive area (see, e.g., Chevalier and Ellison, 1999). On the other hand, similarly to the arguments used for the first hypothesis, mistakes in price setting by competitors due to a failure to learn new information disclosed in the prices of large stores can result in substantial losses, since *large* stores are major competitors and can easily attract consumers away. Therefore, we expect that, following an initial price change by a *large* store, competitors should be more attentive to any information revealed in the new price, *regardless* of their distance from the large store with the new price. Thus, we anticipate that geographical distance should have a weaker influence on how competitors adjust their prices in response to an initial price change, when the change originates

from a large store, compared to other ones. Consistent with this second hypothesis, we observe an attenuated relationship between geographical distance and the adjustment of competitors' prices in response to the initial price change, when a large store is the first mover.

Our third hypothesis concerns the probability of price reactions. As geographical proximity reduces the costs of acquiring new information, and it is economically beneficial to learn and better understand the surrounding market conditions, managers of competing stores should allocate more attention to learning, the closer they are to the information source. Consequently, we expect that, after an initial price change, the probability of price reactions (the probability of competitors' wake-ups) should increase, as the average distance of competitors from the store with the initial price change decreases. In line with this third hypothesis, we show that, following an initial price change, the likelihood of price reactions rises as competitors' average distance from the store initiating the price change decreases.[5]

The fourth and final hypothesis is related to the potential influence of market concentration on our results (i.e., when a large number of stores of a single retail chain are located in a given geographical area of competition). Indeed, market concentration has been shown to affect the competitive environment (see, e.g., Asplund and Friberg, 2002; Smith, 2004; Barros, Brito, and Lucena, 2006; Allain, Chambolle, Turolla, and Villas-Boas, 2017). Thus, one might think that the geographical distance between the store implementing the initial price change and its competitors might be a proxy for market concentration.

We acknowledge this concern, but there is an important remark to be made. As explained in regards to the data filters used in our analysis to mitigate endogeneity issues, the competitive price responses used in our study *do not* include all stores of a retail chain. This is important since market

5. Additionally, we find evidence that this negative relationship, between the probability of price reactions and the average distance of competitors from the store with the initial price movement, is less intense both for essential items and when the store with the initial price change is large, which is consistent with the first and second hypotheses, respectively.

concentration is directly related to the number of stores of a given retail chain in the area of competition. Instead, we randomly select only one store per retail chain inside the geographical area of competition, which reduces the concerns about the potential association between market concentration and the geographical distance between the store with the initial price change and its competitors. Consequently, in regards to the fourth hypothesis, we expect that our empirical strategy should enable us to mitigate in our estimates the influence of market concentration. We test this fourth hypothesis by including a market concentration measure in our empirical analysis. Specifically, we use the Herfindahl–Hirschman index (HHI) based on the number of stores per retail chain in the geographical area of competition. In line with this fourth hypothesis, we find that the results remain qualitatively similar when we take into account market concentration in the empirical analysis.

The paper is organized as follows. Section 2 reviews the literature. Section 3 presents the motivating framework. Section 4 describes the empirical implementation in terms of the data and the empirical strategy used in our study. Section 5 reports the main findings and a set of validity analyses. Finally, Section 6 concludes.

2. Literature review

Our paper is related to the large literature that examines price reactions among retail competitors after a price change in a given store. In this literature, several studies examine whether there are asymmetric price reactions, in terms of store managers tending to follow competitors' price cuts but not price increases, which is theoretically formalized in the classic kinked-demand theory (see, e.g., Tirole, 1988, p. 243; Maskin and Tirole, 1988). For instance, Dickson and Urbany (1994) and Shin (2004) provide evidence supporting asymmetric price reactions in the retail grocery industry and in the retail gasoline industry, respectively. Thus, based on the evidence of asymmetric price reactions, some studies focus their analysis on understanding competitive price reactions under promotional

prices, which are necessarily price cuts (e.g., Pesendorfer, 2002; and Volpe, 2013). Differently to this literature, but complementing it, we offer an additional reason for price reactions of competitors: the nearby wake-up call explanation, which is based on learning frictions related to the limited attention capacity of competing stores.

Our paper is therefore connected to the psychological studies on attention (see, e.g., Kahneman, 1973; and Johnston and Pashler, 1998). In particular, our study is related to the economic literature suggesting that agents should increase the amount of attention devoted to acquiring new knowledge when the economic benefits gained from this information surpass the opportunity costs of redirecting their focus from other duties (see, e.g., Peng and Xiong, 2006; and Mondria and Quintana-Domeque, 2013). Within this framework, there is evidence that gaining knowledge about the nearby market environment offers important economic advantages. For instance, the geographical distance is a key element in observing the movements of consumers after price changes, as it directly affects the travel costs of consumers wanting to change stores. Thus, the intensity of competitors' price reactions should be a decreasing function of the distance between competitors (see, e.g., Fik, 1988). Moreover, geographical proximity should make the efforts to acquire information less intense (e.g., Malmberg and Maskell, 2002).[6] Consequently, geographical proximity should generate stronger information flows (e.g., Jaffe, Trajtenberg, and Henderson, 1993; Audretsch and Feldman, 1996; and Eriksson, 2011).[7]

Furthermore, our paper is related to the literature that examines the effect of competition on price pass-through, in terms of how firms modify prices after changes in their own costs, including the cost to buy the product-items from producers (which is associated to the fundamental value of the items) and other selling-related costs (see, e.g., Levy, Dutta, Bergen, and Venable, 1998; Slade,

6. This is in line with the literature that shows that fund managers have superior performance in portfolios in which the investments are geographically nearby (e.g., Coval and Moskowitz, 2001).

7. There is evidence that the positive effect of geographical proximity on information spillovers is still important despite the improvements in communication technologies in the last century (Sonn and Storper, 2008).

1998; Moorthy, 2005; and Amiti, Itskhoki, and Konings, 2019). In this sense, our paper is also associated with the studies that show that a lower level of competition increases price stickiness and monetary non-neutrality (e.g., Alvarez et al., 2006; Fabiani et al., 2006; Wang and Werning, 2022). This literature is particularly connected to the intuitions behind our study, which are reflected in the motivating framework for the nearby wake-up call explanation for price reactions of competitors (see Section 3). In this motivating framework, the price change of an item in a store is a wake-up call to competitors, prompting them to reassess this item's fundamentals. Nevertheless, nearby competitors are more attentive to new information and thus strongly update their beliefs. Consequently, different competing stores do not update prices in the same way after new fundamental information is revealed by the first-moving store. Thus, the intuitions behind the nearby wake-up call explanation are connected the recent literature on strategic inattention in competition models used to understand inflation dynamics. In this literature, firms with fewer competitors are less attentive to acquiring new information about their competitors' beliefs, which amplifies monetary non-neutrality (see, e.g., Afrouzi, 2024).

Finally, our paper is also associated with papers that investigate the effect of competition on items' price levels. For instance, there is a positive association between price levels and retailers' market concentration (see, e.g., Asplund and Friberg, 2002; Smith, 2004; Barros, Brito, and Lucena, 2006; Allain, Chambolle, Turolla, and Villas-Boas, 2017), although this positive relationship can be affected by modifications in retail regulations (see Biscourp, Boutin, and Vergé, 2013). Differently, but complementarily to this, we examine how competitors adjust their prices in relation to the new price of a store that moves first, and how such adjustment is affected by the geographical proximity between the competitors and the store implementing the initial price change.

3. Motivating framework

As a roadmap for our empirical analysis, we consider a motivating learning model. The objective of this stylized model is to provide the intuition behind the mechanisms for the nearby wake-up call explanation for competitive price reactions, in terms of the impact of the stores' geolocations on their price re-assessments after initial price changes.

Consider a retail market with I stores that sell a single item, where there are no multiple stores belonging to a single retail chain (i.e., in the retail market, stores are independent from each other). The geolocation of store $i \in \{1,2,...,I\}$ is given by the vector G_i, which includes the latitude and longitude coordinates. There are two dates, $t = 0,1$. The stores have different selling costs, $\{c_1, c_2, ..., c_I\}$, which are constant over both dates. The selling costs reflect the costs associated with electricity, marketing costs, fees of intermediaries, wages (including the managers' salaries), the cost of renting the store, amongst other costs related to the selling process. We assume that the selling costs of the stores are publicly known and are obtained from a normal distribution; thus, $c_i \sim N(\bar{c}, 1/\tau_c)$, where c_i is identically and independently distributed across stores.

The fundamental value of the item sold by stores, v_t, changes over time, following a normal distribution, denoted by $v_t \sim N(\bar{v}, 1/\tau_v)$. The fundamental value of the item is identically and independently distributed across periods. At the beginning of each date t, when managers have to set the price of the item, they do not observe the value of v_t for that date. This is due to the fact that v_t is influenced by daily unpredictable factors, such as weather conditions and traffic congestion, among other factors, which could impact both the producer's ability to deliver the item and consumers' willingness to purchase it. However, the value of v_t is observed at the end of date t, when the unpredictable factors are realized.

As in actual retail markets, the prior beliefs of the store managers about the fundamental value of the item are heterogeneous (because of, for example, different resources devoted to the analysis of the local market and/or because of behavioral biases such as overconfidence). Thus, the prior belief of the manager of store i is $v_{t,i} \sim N(\bar{v}_i, 1/\tau_v)$, where $\bar{v}_i = \bar{v} + h_i$ with $h_i \sim N(0, 1/\tau_h)$, in which h_i is also identically and independently distributed across stores. Managers 'agree to disagree' in the sense that each manager knows the other managers' prior beliefs.

Managers are risk-neutral and competitive, in the sense that they set prices to cover the selling cost and their expected fundamental value of the item. Thus, at the beginning of $t = 0$, the price set for the item by store i is:

$$p_{0,i} = c_i + E_i[v_0] = c_i + \bar{v}_i. \tag{1}$$

At the beginning of $t = 1$, store $Init$ updates the price of the item. This is because the manager of store $Init$, after analyzing the local market, has some new information about the item's fundamental at $t = 1$. Let $s_{1,Init}$ be the signal that reflects the new information the manager of store $Init$ has, which is independent and normally distributed:

$$s_{1,Init} = v_1 + \varepsilon \quad where \quad \varepsilon \sim N(0, \tau_\varepsilon) \tag{2}$$

Then, using Bayesian updating at $t = 1$ for the expected fundamental value of the item as seen by the manager of store $Init$, the price set for the item by this store is:

$$\begin{aligned} p_{1,Init} &= c_{Init} + E_{Init}[v_1] \\ &= c_{Init} + \bar{v}_{Init} + (s_{1,Init} - \bar{v}_{Init}) \frac{\tau_\varepsilon}{\tau_v + \tau_\varepsilon} \\ &= c_{Init} + \bar{v}_{Init} + Update_{Init} \quad with \quad Update_{Init} = (s_{1,Init} - \bar{v}_{Init}) \frac{\tau_\varepsilon}{\tau_v + \tau_\varepsilon}. \end{aligned} \tag{3}$$

Here, $Update_{Init}$ is the price change of store $Init$ at $t = 1$, which is observed by the managers of the other stores in the same retail market. Thus, $Update_{Init}$ is an alert, a wake-up call for competitors to learn from the new information revealed by store $Init$ in its new price, $s_{1,Init}$, regarding the unknown value of v_1 (which is cheaper than to perform their own local market analysis). However,

managers of competing stores might not be completely attentive to this new piece of information, because they must also devote time (and attention) to other tasks related to the selling process, such as marketing strategies, accounting registers, negotiating with producers, among other store administration duties.

We use the concept of entropy (from information theory, as in as in Sims, 2003) to characterize the amount of attention used by managers of competing stores in their learning process. In a nutshell, the entropy of a random variable measures its uncertainty. Thus, for example, the entropy of the fundamental value of the item at $t = 1$, $H(v_1)$, is given by:

$$H(v_1) = \frac{1}{2}\ln\left(\frac{1}{\tau_v}\right) + \ln(2\pi e) \tag{4}$$

because v_1 is normally distributed. Thus, the entropy $H(v_1)$ increases as the uncertainty of the fundamental value of the item goes up (i.e., when there is a reduction in its level of precision τ_v).

In the context of our motivating framework, managers of competing stores update their beliefs about v_1 by following the Bayes rule, after observing the new information revealed by store $Init$, $s_{1,Init}$. Then, the posterior belief of the manager of the competing store i^c about v_1, where $i^c \neq Init$, is given by:

$$v_{1,i^c}|s_{1,Init} \sim N(E_{i^c}[v_1], 1/\tau_{i^c}) \tag{5}$$

where $E_{i^c}[v_1]$ and τ_{i^c} are the expected value and precision of the posterior belief of the manager of competing store i^c at $t = 1$, respectively. Naturally, the values of $E_{i^c}[v_1]$ and $1/\tau_{i^c}$ depend on the amount of attention the manager of store i^c pays to learning the signal $s_{1,Init}$.

Information theory defines the amount of information learned from the signal $s_{1,Init}$ by the manager of the store i^c, $Inf_{i^c}(v_1; s_{1,Init})$, as the decline in the entropy due to the learning process:

$$\begin{aligned} Inf_{i^c}(v_1; s_{1,Init}) &\equiv H(v_1) - H(v_1|(i^c, s_{1,Init})) \\ &= \frac{1}{2}\ln\left(\frac{\tau_{i^c}}{\tau_v}\right). \end{aligned} \tag{6}$$

In this motivating framework, we use a logarithmic association of $Inf_{i^c}(v_1; s_{1,Init})$ with the amount of attention used in the learning process of each manager:

$$Inf_{i^c}(v_1; s_{1,Init}) = \frac{1}{2}\ln(1 + a_{i^c,Init}). \tag{7}$$

Here, $a_{i^c,Init}$ is the amount of attention used by the manager of store i^c in learning new information from the price change of store $Init$, where $a_{i^c,Init}$ is larger than zero, and thus the value of the term $\ln(1 + a_{i^c,Init})$ is always positive.

We assume that the amount of attention used in the learning process by the manager of store i^c becomes greater, the shorter is the distance from that store to the information source. This assumption is a shortcut, used to reflect the fact that store managers face frictions in the learning process, in that they are not completely attentive to the information revealed by competitors, but the amount of attention they devote to learning is larger when the new information concerns nearby competitors. This assumption is based on the empirical evidence suggesting that geographical proximity reduces the effort involved in obtaining new information, and that there are important economic benefits from learning about the nearby market environment, as previously mentioned in the literature review (see Section 2).

We make this simplification since the stylized learning model described in this section only serves as a motivating framework. We recognize such a stylized learning model is far from perfect. However, the objective of this motivating framework not to propose a new theoretical model of learning attention. Instead, our main objective is providing insights concerning the mechanisms for the nearby wake-up call explanation for retailer price reactions, and presenting the intuition behind the measure that serves as main dependent variable in our empirical strategy.

We incorporate this learning bias into our stylized model by assuming that the amount of attention used for learning, by the manager of store i^c, $a_{i^c,Init}$, is a decreasing function of the geographical distance between store i^c and the source of new information. Thus, $a_{i^c,Init}$ is given by:

$$a_{i^c,Init} = A(Dist_{i^c,Init}) \quad where \quad \frac{\partial A(Dist_{i^c,Init})}{\partial Dist_{i^c,Init}} < 0, \tag{8}$$

where $A(\cdot)$ is a function that depends on the distance between the stores i^c and $Init$, $Dist_{i^c,Init}$, with $0 \leq A(\cdot) \leq \tau_\varepsilon/\tau_v$. For instance, we can assume that $A(Dist_{i^c,Init}) = \tau_\varepsilon/\tau_v e^{-\varphi Dist_{i^c,Init}}$, where φ is a parameter that measures the attention sensitivity to distance (which might differ, for example, depending on how essential is the item and/or the size of the store $Init$ that implements the initial price change).[8]

Using Bayesian updating, the posterior belief of the manager of store i^c about v_1 is characterized in the following proposition:

PROPOSITION 1: *The posterior belief of the manager of store i^c about the fundamental value of the item at $t = 1$ is given by $v_{1,i^c}|, s_{1,Init} \sim N(E_{i^c}[v_1], 1/\tau_{i^c})$ with*

$$E_{i^c}[v_1] = \bar{v}_{i^c} + (s_{1,i^c} - \bar{v}_{i^c})\frac{\tau_\varepsilon e^{-\varphi Dist_{i^c,Init}}}{\tau_v + \tau_\varepsilon e^{-\varphi Dist_{i^c,Init}}} \quad and \quad \tau_{i^c} = \tau_v + \tau_\varepsilon e^{-\varphi Dist_{i^c,Init}}. \tag{9}$$

Proof: See online appendix (A).

Then, the price set for the item by store i^c at $t = 1$ is

$$p_{1,i^c} = c_{i^c} + E_{i^c}[v_1] = c_{i^c} + \bar{v}_{i^c} + (s_{1,Init} - \bar{v}_{i^c})\frac{\tau_\varepsilon e^{-\varphi Dist_{i^c,Init}}}{\tau_v + \tau_\varepsilon e^{-\varphi Dist_{i^c,Init}}}. \tag{10}$$

Consequently, Proposition 1 and expression (10) show that the amount of attention used to learn by the manager of store i^c affects the manager's expected value regarding v_1, and thus the price of the item at $t = 1$ in store i^c.

8. Nevertheless, similar results are obtained when we adopt other functional forms where $\partial A(Dist_{i^c,Init})/\partial Dist_{i^c,Init} < 0$, such as $A^\circ(Dist_{i^c,Init}) = \tau_\varepsilon/(\tau_v(1 + \varphi^\circ Dist_{i^c,Init}))$, amongst others.

3.1. Empirical implication

We now derive a testable implication in relation to the nearby wake-up call explanation, which is a consequence of Proposition 1 and expression (10). In particular, we can observe at $t = 1$ that the price $p_{1,Init}$ of store $Init$ that moves first (see equation (3)) and the price p_{1,i^c} of the competing store i^c (see equation (10)) are more homogeneous. This is because $p_{1,Init}$ and p_{1,i^c} have a *common* factor, $s_{1,Init}$, as the manager i^c is learning from the information signal revealed in the new price of store $Init$.

Moreover, the shorter is the distance between i^c and $Init$, $Dist_{i^c,Init}$, the stronger is the influence of the common factor on p_{1,i^c}. Thus, price p_{1,i^c} moves closer to price $p_{1,Init}$ as the distance $Dist_{i^c,Init}$ decreases. It is useful to analyze some extreme cases to understand the intuitions behind the association between $Dist_{i^c,Init}$ and the extent to which p_{1,i^c} approaches $p_{1,Init}$. On the one hand, in the case where the distance between i^c and $Init$ is very small and thus $Dist_{i^c,Init} \to 0$, the manager of store i^c fully learns the information disclosed in the new price of store $Init$, where

$$p_{1,i^c} = c_{i^c} + \bar{v}_{i^c} + (s_{1,i^c} - \bar{v}_{i^c})\frac{\tau_\varepsilon}{\tau_v + \tau_\varepsilon}. \tag{11}$$

In this case, when we compare equations (3) and (11), $p_{1,Init}$ and p_{1,i^c} have exactly the same common factor, $s_{1,Init}\tau_\varepsilon/(\tau_v + \tau_\varepsilon)$. On the other hand, in the case where the distance between i^c and $Init$ is very large and thus $Dist_{i^c,Init} \to \infty$, the manager of store i^c does not learn from the information revealed by store $Init$. Then, $p_{1,i^c} = c_{i^c} + \bar{v}_{i^c}$. In this second case, $p_{1,Init}$ and p_{1,i^c} do not share the common factor that is generated from learning the same information signal that is disclosed in $p_{1,Init}$.

We can write an expression to measure how p_{1,i^c} converges to $p_{1,Init}$, $WakeUpConv_{i^c,Init}$, when the value of $Dist_{i^c,Init}$ decreases:

$$
\begin{aligned}
WakeUpConv_{i^c,Init} &= |p_{1,i^c} - p_{1,Init}| \\
&= \left| c_{i^c} - c_{Init} + \bar{v}_{i^c} - \bar{v}_{Init} + (s_{1,Init} - \bar{v}_{i^c}) \left(\frac{\tau_\varepsilon e^{-\varphi Dist_{i^c,Init}}}{\tau_v + \tau_\varepsilon e^{-\varphi Dist_{i^c,Init}}} \right) \right. \\
&\quad \left. -(s_{1,Init} - \bar{v}_{Init}) \left(\frac{\tau_\varepsilon}{\tau_v + \tau_\varepsilon} \right) \right|.
\end{aligned} \tag{12}
$$

We can now derive the following empirical implication in relation to the expected value of $WakeUpConv_{i^c,Init}$, which is a consequence of the nearby wake-up call explanation.

EMPIRICAL IMPLICATION: *The expected value of how price p_{1,i^c} of competing store i^c at $t = 1$ approaches price $p_{1,Init}$ of store $Init$ that moves first, $E[WakeUpConv_{i^c,Init}]$, is*

$$
\begin{aligned}
E[WakeUpConv_{i^c,Init}] &= E[|p_{1,i^c} - p_{1,Init}|] \\
&= \left\{ \frac{2}{\pi} \left(\frac{2}{\tau_c} + \frac{\tau_v^2}{\tau_h} \left(\frac{1}{\left(\tau_v + \tau_\varepsilon e^{-\varphi Dist_{i^c,Init}}\right)^2} + \frac{1}{(\tau_v + \tau_\varepsilon)^2} \right) \right. \right. \\
&\quad \left. \left. + \frac{\tau_v \tau_\varepsilon \left(1 - e^{-\varphi Dist_{i^c,Init}}\right)^2}{(\tau_v + \tau_\varepsilon)\left(\tau_v + \tau_\varepsilon e^{-\varphi Dist_{i^c,Init}}\right)^2} \right) \right\}^{\frac{1}{2}},
\end{aligned} \tag{13}
$$

where $\partial E[WakeUpConv_{i^c,Init}]/\partial Dist_{i^c,Init} > 0$ meaning that, after a price change in store $Init$, the updated prices of nearby competitors are expected to be closer to the new price of the first-moving store. Proof: See online appendix (A).

Figure 1 illustrates this empirical implication, showing that $E[WakeUpConv_{i^c,Init}]$ decreases as $Dist_{i^c,Init}$ diminishes, where $E[WakeUpConv_{i^c,Init}]$ measures the expected value of the absolute difference between p_{1,i^c} and $p_{1,Init}$. Furthermore, this figure shows that the positive relationship between $E[WakeUpConv_{i^c,Init}]$ and $Dist_{i^c,Init}$ is weaker when the attention sensitivity to the distance from the information source, φ, is lower.

[Insert Figure 1 here]

4. Empirical implementation

In this section, we empirically assess the nearby wake-up call explanation for competitive price reactions. To do so, we firstly describe how we identify an initial price change in a store and the price reactions of its competitors. We then describe the data used in the empirical implementation and, finally, we present the empirical strategy used in our study, which is based on the motivating framework of Section 3.

4.1. Identification of initial price changes and price reactions of competitors

We consider a local retail market where different stores compete with each other. Let $p_{t,i,j}$ be the price at date t in store i for item j. [9] The geolocation of store i is given by G_i, which is a vector including its latitude and longitude coordinates. In the empirical strategy, we firstly need to define an *initial price change* decided by a store. This initial price change is the wake-up call for competitors in the retail market, inducing them to re-assess the fundamentals of a given item by learning from the information revealed in the new price of the store that moves first. Therefore, afterwards, we need to define the *price reactions* of store competitors that are triggered by the *initial price change*.

Initial price changes. Suppose that store $Init$, which is part of the retail chain $chain_{Init}$, updates at date t the price of the item j. We classify this price update as an *initial price change* if three conditions are met. First, no other stores that are part of other retail chains (i.e., not retail chain $chain_{Init}$), within a radius of Rad km around the geolocation of store $Init$, G_{Init}, update the price of the item j at date t. This helps us to mitigate endogeneity issues related to the effect of items' price increases or reductions due to pricing strategies of brand managers of producers, which should generate initial price changes in stores from different retail chains simultaneously.

9. We use a similar notation to that in the motivating learning model of Section 3.

Second, store $Init$ does not report any other price change *after* date t in the period between $t+1$ and $t+\Delta_{Eval}$, with $\Delta_{Eval} \geq 1$, for the item j. This condition prevents the inclusion of transitory price changes due to excess inventory or items that are close to expiry. It is important to notice, as explained below, that the period between $t+1$ and $t+\Delta_{Eval}$ will also be used as the evaluation period to examine the *price reactions* of competitors.

Third, subsequent to the date $t+\Delta_{Eval}$, a new price change in any store, for the item j, within the Rad km radius (around G_{Init}), is considered a new *initial price change*, only after Δ_{CoolD} additional calendar days (or equivalently, $t+\Delta_{Eval}+\Delta_{CoolD}$ calendar days after the immediately previous initial price change for the item j). Therefore, there is a cool-down period, Δ_{CoolD}, in which any further price changes are not considered in our analysis. The objective of the cool-down period is to have a clean identification of initial price changes in stores and the respective price responses of competitors.[10]

Price reactions. After the *initial price change* in store $Init$ for the item j, suppose that the competing store i^c belonging to retail chain $chain_{i^c}$ (where $chain_{i^c}$ is different to $chain_{Init}$) decides a price change for the same of the item j. We classify this price change in competing store i^c as part of a *price reaction* if three conditions are met. First, store i^c has a geolocation, G_i, within a Rad km radius around the geolocation of store $Init$, G_{Init}. This is to avoid noisy price responses that are beyond the retail market of competition of store $Init$ that implements the *initial price change*. Second, the price change in store i^c for the item j is observed *after* the date t (of the initial price change), in the period between $t+1$ and $t+\Delta_{Eval}$, with $\Delta_{Eval} \geq 1$. Indeed, on the one hand, we want to avoid endogeneity issues due to initial price change and price responses of competitors being simultaneously observed. On the other hand, there needs to be a maximum time span, $t+\Delta_{Eval}$ after the initial price change at t, during which price changes of competitors are considered to be part of

10. It may happen that, at date t, two (or more) stores of the *same* retail chain, $chain_{Init}$, update the price of the item j, where the geographical distance between those stores is less than Rad, and they also meet the three conditions described above. In this case, we randomly select one of these stores (which are from the same retail chain) to be the store with the initial price change, while the other stores are excluded from the analysis.

a price reaction. This helps to excluding noisy, far in the future price changes that are not likely to be reactions to the initial price change in store $Init$ at date t. Third, store i^c does not report any other price change in the period between t and $t+\Delta_{Eval}$ for the item j. This condition contributes to eliminating price responses related to transitory price changes (like in the case of initial price changes).[11]

Having defined *initial prices changes* and competitive *price reactions*, we can now write an expression for the main variable of the testable empirical implication regarding the nearby wake-up call explanation, which was described in the motivating framework in Section 3.1. Specifically, we calculate an adjusted version of equation (12), which controls for the impact of the price levels:

$$WakeUpConvAdj_{t,i^c,Init,j} = \frac{|p_{t+\Delta_{Eval},i^c,j} - p_{t,Init,j}|}{p_{t,Init,j}} \tag{14}$$

where $p_{t,Init,j}$ is the *initial price change* at date t in store $Init$ for the item j, while $p_{t+\Delta_{Eval},i^c,j}$ is the *price reaction* between $t+1$ and $t+\Delta_{Eval}$ of the competing store i^c for the same item, as described above.

Expression (14) is similar to equation (12) in the motivating framework in Section 3.1, but there are some differences. Firstly, expression (14) is an *adjusted* measure, which takes into account the heterogeneity of price levels when we consider different items (which are part of diverse product categories). This is not the case in equation (12), since in the motivating framework we assumed (for simplicity) a single item. Secondly, unlike in equation (12), the price change of store $Init$ and the price response of store i^c are not simultaneously observed in expression (14). This is to mitigate endogeneity issues due to simultaneity, as explained above. Thirdly, to reduce the noise of price

11. Similarly to the initial price changes, there is a possibility that two (or more) stores of the *same* retail chain $chain$ have price responses (after the initial price change) for the item j, and also meet the three conditions described above for being considered part of a price reaction. In this case, again, we randomly select one of these stores as the representative price response of the retail chain $chain$. Indeed, while stores within the same retail chain may adjust their prices simultaneously, we want to avoid overweighting the price reactions of retail chains that have several stores located in a retail market.

changes that are implemented by stores located outside the retail market, store i^c (with price $p_{i^c,j}$) has a geolocation, G_i, within the Rad km radius around the geolocation of store $Init$, G_{Init}.

4.2. Data

We use unique daily price data for grocery sales in medium and large supermarkets across different regions of France.[12] The data contain prices at the store-barcode level. Therefore, in this daily price dataser, each single item has a barcode, which reflects a unique combination of product-brand-volume(weight)-packaging.[13] The data also include, for each store, the address (from which we determined the latitude and longitude coordinates), as well as the retail chain to which it belongs.

We focus on the one thousand most widely sold items, which include items belonging to the product categories food and beverages (77%), personal care products (13%), household equipment and routine maintenance (6%), and recreation and culture (4%). The data span the period from October 2011 to September 2012. Thus, the price data were not affected by the expansion of online grocery shopping after 2015, which further strengthened during the COVID pandemic period (see Wang, Kim, Holguín-Veras, and Schmid, 2021; Chang and Meyerhoefer, 2021; Xu and Saphores, 2022).

Based on these data, we calculate the main dependent variable used in our empirical analysis, that is, the value of $WakeUpConvAdj_{t,i^c,Init,j}$ as described in equation (14). Note that $WakeUpConvAdj_{t,i^c,Init,j}$ compares the prices of exactly the same item, and not simply similar items belonging to a product category.[14] We also compute the main explanatory variable, $Dist_{i^c,Init}$,

12. In France, almost 80% of grocery sales take place in medium and large supermarkets (see Anderton et al., 2011).
13. The daily price data were collected by the company Prixing, to provide a price comparison tool (based on a mobile app and website). Prices were web-scraped from supermarkets offering a '$click\&collect$' service, where consumers shop online from the website page of a particular supermarket and then collect their shopping at the store or a drive-through facility. Note that, in the dataset, the price for an item in a given store is the same that consumers would actually pay in the brick-and-mortar store on the date that the data were collected. This is important due to the potential differences between online and offline prices (see, e.g., Cavallo, 2017).
14. In other words, the dataset allows to compare day by day the price of an item in two near-by stores. For instance, the price of a Coca-Cola zero, one liter bottle, and not only generically a zero sugar soda.

which is the geographical distance between store $Init$ that implements the initial price change and the competing store i^c that has a price response.

We calculate $WakeUpConvAdj_{t,i^c,Init,j}$ and $Dist_{i^c,Init}$ by following the empirical strategy described in Section 4.3. Suppose that, at date t, store $Init$ with geolocation G_{Init} modifies the price of item j. We set the evaluation period, in terms of observing a potential price reaction in a given store i^c, to one calendar week (i.e., $\Delta_{Eval} = 7$ calendar days). This is because one week is sufficient time for competing stores to update their prices, but sufficiently short to avoid observing other initial price changes under normal conditions. In addition, the choice of one week as the evaluation period allows us to mitigate the effect of promotional pricing strategies on some specific week days. This is because, as explained in Section 4.3, we eliminate observations where potential competitors report any other price change in the evaluation period, to mitigate the impact of transitory price changes on our empirical analysis. We set the cool-down period to three calendar days (i.e., $\Delta_{CoolD} = 3$ calendar days). Thus, if store $Init$ modifies the price of item j at date t (and we evaluate a potential price reaction between $t+1$ and $t+7$ calendar days), then a new initial price change in store $Init$ (or any of its competitors) for the same item is only considered after $t+7+3$ calendar days.

We define the retail market of store $Init$, where we examine potential price reactions of store $Init$'s competitors, as the area within a 5 km radius around the geolocation of store $Init$, G_{Init} (i.e., $Rad = 5$ km). Indeed, 5 km corresponds to a frictionless travel time of 10 minutes at 30 km/h, which is the typical speed limit in many French urban areas (although the real travel time would be much longer due to traffic lights, traffic congestion, and the time spent searching for a parking space, among other factors).[15]

Figure 2 shows all the geographical areas of evaluation (where we have observations) across the whole country, while Table 1 reports summary statistics for the main variables of interest. Figure

15. As a robustness check, we also use a 2.5 km radius and a 10 km radius. The findings of these unreported analyses are qualitatively similar to the results presented here, and available upon request.

2 suggests that the geographical areas of evaluation are rather representative in terms of their geographical distribution across France and are located in 21 out of the 22 regions in France.[16] Table 1 shows that the average value of the absolute difference between the updated prices of competitors and the new price of the store that moves first is 6.7%, while the average distance between the first price mover and its competitors is around 3 km.

[Insert Figure 2]

[Insert Table 1]

4.3. Empirical strategy

The stylized model, described in the motivating framework, provides a testable empirical implication about the nearby wake-up call explanation: after an initial price change, the updated price of nearby competitors is closer to the new price of the store that moved first (see Section 3.1). To test this empirical implication, we use an IV approach based on the following specification:

$$WakeUpConvAdj_{t,i^c,Init,j} = \alpha_0 + \alpha_1 Dist_{i^c,Init} + Controls + FEs + \epsilon_{t,i^c,Init,j}. \quad (15)$$

Here, the dependent variable is $WakeUpConvAdj_{t,i^c,Init,j}$, which conveys how price responses react to the new price of the store that moves first. The main explanatory variable is the geographical distance, $Dist_{i^c,Init}$, between store $Init$ that decides the initial price change and competing store i^c that has a price reaction.

We include several control variables ($Controls$) and fixed effects (FEs). Control variables relate to demographic characteristics of the retail market.[17] More specifically, we control for the population's income in the areas where stores are located, at a municipality level. To control for potential

16. Note that some of the 22 regions of France that existed during our sample period were then merged by the French government in 2016, resulting in the current 13 French regions.

17. Variables concerning demographic features of the geographical area of competition are obtained from the *Institut National de la Statistique et des Études Économiques* (INSEE) of France.

differences between urban and rural areas, we include a dummy variable that equals one if the store that has a price reaction is in an urban area (at a municipality level), and zero otherwise.[18]

Several fixed effects control for unobserved variables that might affect our results. Firstly, we absorb unobserved time-varying variables that might affect the empirical analysis, such as periods of sales, differences in the items' demand due to weather conditions, and/or other seasonal effects that might affect the price of items. In order to control for these unobserved market dynamics, we incorporate week fixed effects.

Moreover, we absorb the time-invariant heterogeneity related to store characteristics, in terms of the store size and the retail chain to which a store belongs. This is because, on the one hand, the size of a store is related to its market power in the local market. On the other hand, different retail chains might have explicit (or implicit) internal policies dictating how they react to changes in the competitive environment. Thus, we include store-size fixed effects and retail chain fixed effects (for both the stores deciding the initial price changes and the stores exhibiting price responses).

Furthermore, we absorb the time-invariant heterogeneity across items belonging to the same product categories. This is important because store managers might be more alert to price changes of some specific strategic product categories. Thus, we include fixed effects for product category, defined accordingly to the European Classification of Individual Consumption According to Purpose (ECOICOP).[19] These fixed effects correspond to the five-digit level of the ECOICOP, which is the most disaggregated level of this product category classification.[20] Last but not least, we include region fixed effects to absorb the time-invariant heterogeneity at the regional level. For instance,

18. Additionally, in some specifications we control for market concentration, using the HHI based on the number of stores per retail chain in the retail market.

19. ECOICOP is based on COICOP (Classification of Individual Consumption according to Purpose), a reference classification published by the United Nations Statistics Division. For more details on the product classification developed by the United Nations Statistics Division to classify and analyze individual consumption expenditures, see https://unstats.un.org/unsd/class/revisions/coicop_revision.asp.

20. ECOICOP is consistent with the UN version at four digits and is harmonized and developed by Eurostat at five-digit levels.

stores located in regions with an abundance of an item might have a different price reaction (e.g., stores in regions close to the sea will have access to a great amount of sea food) with respect to stores in regions where the same item is scarce.

To estimate the empirical specification (14), we use an IV approach, which accounts for potential endogeneity issues induced by omitted variables and the reflection problem (see Manski, 1993). Similarly to Olivares and Cachon (2009) and Habte and Holm (2022), we use as an instrument the population density at a municipality level. Here, the assumption underlying the exclusion restriction is that the distance between competing stores (the explanatory variable) should decrease as the population density increases. However, after applying data filters to avoid endogeneity issues, and after including all controls and fixed effects, the population density *per se* does not *directly* affect the competing price reactions (the dependent variable), but the population density is related to the competing price reaction *through* the reduced distance between competing stores. Therefore, equation (15) is estimated using two-stage least squares (2SLS), where $Dist_{i^c,Init}$ is instrumented with population density.

5. Empirical results

The theoretical framework that provides insights on the nearby wake-up call explanation for competing price reactions has an the empirical implication. The main objective of this section is to test it. Section 5.1 starts with an analysis of the price responses under the nearby wake-up call explanation. Afterward, in Section 5.2, we perform a validity analysis.

5.1. Prices responses under the nearby wake-up call explanation

Table 2 presents the estimation of the IV regression analysis, which is described in Section 4.3. Columns 1-2 (3-4, respectively) report results for the sub-sample where the store that moves first

has a negative (positive, respectively) initial price change. Columns 5-6 exhibit the estimates for the complete sample (i.e., including negative and positive initial price changes).

[Insert Table 2 here]

Table 2 shows that, after an initial price change, the updated price of nearby competitors is closer to the new price of the first-moving store. For instance, in column 6, the variable $Dist$ displays a significant coefficient of 0.046. This implies that a one-standard-deviation reduction in the variable $Dist$ results in an average decrease in the variable $WakeUpConvAdj$ of 0.059, which captures how price responses move towards the new price of the store that moves first. This 0.059 decrease is equivalent to an 88% decline relative to the average value at 0.067 of the variable $WakeUpConvAdj$.[21]

The results reported in Table 2 are consistent with the empirical implication of the motivating framework (see Section 3.1). Indeed, our stylized learning model implies that, after an initial price change (a wake-up call), nearby competitors are more attentive to the information revealed by the store with the new price, which increases the homogeneity of prices between the first price mover and its nearby competitors.

Interestingly, in the case of negative initial price changes, Table 2 shows a stronger effect of distance on how prices move in response to the new prices of the stores that move first, with respect to the case of positive price changes, once FE are absorbed. Indeed, the coefficient for the case of negative initial price changes reported in the column 2 is larger than the one for positive initial price changes reported in column 4 (0.063 versus 0.028). This asymmetric effect of distance on the variable $WakeUpConvAdj$ is in line with studies that examine whether store managers tend to follow competitors' price reductions more than competitors' price increases (e.g., Dickson and Urbany, 1994; and Shin, 2004).

21. The F-statistic of the first-stage regressions reported in Table 2 shows that the IV strategy pass the weak instrument tests (see, e.g., Stock, Wright, and Yogo, 2002).

5.2. Validity analysis of the nearby wake-up call explanation

A natural question arises: how do we know that, following an initial price change (a wake-up call), nearby competitors are more attentive to learning the information disclosed by the store with the new price than distant competitors? In spite of the fact that the nearby wake-up call explanation is based on a stylized model under attention frictions in the agents' learning process, we cannot offer a definite answer to this question. This is because learning dynamics and agents' information sets are not directly observable.

Nevertheless, to indirectly address this question, we develop a set of hypotheses (which we empirically test) to investigate how prices of competitors respond to an initial price change under different scenarios. These hypotheses rely on previous literature related to attention drivers and the effects of geographical proximity on information flows. This validity analysis can provide some insights into whether the nearby wake-up call explanation is consistent with market dynamics in terms of competitors' price responses.

Our first hypothesis is based on previous work highlighting that agents should be more attentive to learning new knowledge when the economic benefits derived from this new information outweigh the opportunity costs of diverting attention away from other activities (see, e.g., Peng and Xiong, 2006; and Mondria and Quintana-Domeque, 2013). In this context, mistakes in price setting for essential items (e.g., due to insufficient attention paid to learning the information revealed in competitors' price changes) might lead to larger economic losses, as these items represent an important part of stores' sales. Thus, after an initial price change in a item that is essential for consumers, competitors should be more attentive to the new information revealed by the new price, regardless of the distance they are from the information source. Consequently, we can write our first hypothesis:

Hypothesis 1: *In the case of essential items, the geographical distance will have a reduced impact on how competitors' prices react to the new prices set by first-moving stores.*

We test Hypothesis 1 by extending the baseline specification in equation (15) to incorporate the marginal effects of the geographical distance, when price reactions involve essential items. The model specification becomes:

$$WakeUpConvAdj_{t,i^c,Init,j} = \alpha_0 + \alpha_1 Dist_{i^c,Init} + \alpha_2 Dist_{i^c,Init} \cdot DUM(Essent) + Controls + FEs + \epsilon_{t,i^c,Init,j}, \tag{16}$$

where $DUM(Essent)$ is a dummy variable that takes a value equal to one when the price response involves an essential item, and zero otherwise.

We use two ways to classify a item as more essential for consumers than others. First, we exploit the weights of product categories (to which the items belong) used in calculating the French Consumer Price Index (CPI) during the same period as our empirical analysis, which are calculated by the *Institut National de la Statistique et des Études Économiques* (INSEE) of France. This is because the CPI's weighting of a product category reflects its relative importance in terms of the total household consumption. In equation (16), the dummy variable $DUM(Essent) = DUM(Essent_{CPI})$ equals one if the price response involves items in the upper quartile of the data in terms of their French CPI weights, and zero otherwise. Second, we use the number of observation for a given item in different supermarkets across the country. Indeed, observing an item in a large number of supermarkets is a proxy for the importance of this item for households. Consequently, in equation (16), the dummy variable $DUM(Essent) = DUM(Essent_{\#Obs})$ equals one when the price reactions compromise items in the upper quartile in relation to the number of observations in the dataset, and zero otherwise.

Tables 3 and 4 report the outcomes of the specification described in equation (16), which is used to test Hypothesis 1. In line with this first hypothesis, in the case of essential items, these tables

show an attenuated effect of the geographical distance on how competitors update their prices in response to the new price of a store that decides an initial price change.

[Insert Table 3 here]
[Insert Table 4 here]

The second hypothesis is grounded in the literature emphasizing that the level of attention used to learn new knowledge is influenced by the attributes of the information source (see, e.g., Wolff, Jarodzka, and Boshuizen, 2021). For instance, price responses of competitors should differ depending on the size of the store implementing the initial price change. Indeed, on the one hand, since large stores are relevant players in business activity within their area of competition, a manager should be more attentive to the actions of managers in large stores due to reputational concerns if they are compared relative to their relevant peers (Chevalier and Ellison, 1999). On the other hand, and similarly to the arguments used for Hypothesis 1, mistakes in price setting (stemming from a failure to learn from the new prices of a large store) can lead to significant losses, given that large stores are major competitors and can readily attract consumers away. Therefore, we expect that, following an initial price change decided by a *large* store, competitors should be more attentive to any knowledge disclosed in this new price, independently of their distance from the first-moving store. Thus, we can write our second hypothesis:

Hypothesis 2: *The geographical distance should have a reduced influence on how competitors adjust their prices in relation to the first price mover, if the initial price change is implemented in a large store.*

We extend the baseline specification in equation (15) to test this second hypothesis. In this model extension, we include marginal effects of the geographical distance when price reactions are triggered by an initial price change in a large store, which is written as follows:

$$\begin{aligned} WakeUpConvAdj_{t,i^c,Init,j} = \alpha_0 + \alpha_1 Dist_{i^c,Init} + \alpha_2 Dist_{i^c,Init} \cdot DUM(Large_{FirstMover}) \\ + Controls + FEs + \epsilon_{t,i^c,Init,j}. \end{aligned} \tag{17}$$

Here, $DUM(Large_{FirstMover})$ is a dummy variable that equals one when the price reactions follow an initial price change originated in a large store, and zero otherwise.

Table 5 reports the estimates of the analysis to test Hypothesis 2, corresponding to the specification described in equation (17). These estimates provide evidence of a weaker relationship between geographical distance and competitors' price adjustments in response to an initial price change when the initial price change occurs in a large store, which is consistent with the second hypothesis.

[Insert Table 5 here]

As a robustness check of Hypothesis 2, in Table B1 of the appendix, we also show that geographical distance has a reduced influence in the case of *small* stores competing with the supermarket that implemented an initial price change. This result is in line with Hypothesis 2. Indeed, if the managers of *small* stores are evaluated relative to their peers, they should be more attentive to the actions of managers in other stores due to reputational concerns. In addition, errors in price setting made in *small* stores, due to failing to learn from the new prices of competitors, can result in substantial losses, as competitors can easily attract consumers away from small stores. Consequently, following an initial price change, competitors in small stores should closely monitor any information revealed in a new price, regardless of their distance from the information source.

Our third hypothesis relates to the probability of price reactions. As previously explained, managers of competing stores should be more attentive when they are closer to the source of information. This is due to the fact that geographical proximity reduces the costs associated with acquiring new information, and because it is economically advantageous to understand local market conditions. In this sense, an extensive literature supports the idea that the strength of information flow increases with proximity to the information source (see Jaffe, Trajtenberg, and Henderson, 1993; Audretsch and Feldman, 1996; and Eriksson, 2011). Therefore, we hypothesize that, following an initial price change, the likelihood of subsequent price reactions (the probability of competitors' wake-ups) increases as the average distance of competitors from the store initiating the price change decreases.

Hypothesis 3: *The probability of price responses (the probability of competitors' wake-ups) rises as there is a reduction in the competitors' average distance from the store with the initial price change.*

We test this third hypothesis using the specification reported in expression (18). In this specification, $PrWakeUp_{t,Init,j}$ is the proportion of price reactions in competing stores after an initial price change in store $Init$ at date t for item j, among all the competing stores within a Rad km radius around the geolocation of store $Init$.

$$PrWakeUp_{t,Init,j} = \alpha_0 + \alpha_1 MDist_{Init} + \alpha_2 MDist_{Init} \cdot DUM(\cdot) + Controls + FEs + \epsilon_{t,i^c,Init,j}, \quad (18)$$

where $MDist_{Init}$ is the average distance between store $Init$ (i.e., the first price mover) and the competing stores in its retail market, while $DUM(\cdot)$ corresponds the dummy variables used to test Hypotheses 1 and 2 (see equations (16) and (17), respectively).

Table 6 presents the outcomes of the specification used to test Hypothesis 3. The first two columns of this table show that the likelihood of price reactions, or competitors' wake-ups, increases as the average distance between the competitors and the store that initiated the price change decreases, which is in line with Hypothesis 3. Furthermore, columns 3-8 of Table 6 show that the negative relationship between the probability of price reactions and the average distance of the competitors from the store initiating the price change is less pronounced for essential items and when the initiating store is large. Thus, the results in columns 3-8 are also consistent with the first and second hypotheses.

[Insert Table 6 here]

Our fourth and last hypothesis examines the potential impact of market concentration, defined as a high density of stores belonging to the same retail chain within a specific competitive geographical area. Indeed, there is evidence that market concentration can significantly modify the competitive environment in retail markets (see, e.g., Asplund and Friberg, 2002; Smith, 2004; Barros, Brito, and

Lucena, 2006; Allain, Chambolle, Turolla, and Villas-Boas, 2017). One might think that the distance variables (between the store initiating the price change and its competitors) used in our study could proxy market concentration. We acknowledge this concern, but it is important to clarify a key point. As outlined in the description of the data filters used in our analysis to mitigate endogeneity issues, the geographical distance considered in our study does not include all stores of a retail chain. Instead, we randomly select only one store per retail chain to calculate the geographical distance between the store initiating the price change and its competitors. This alleviates concerns regarding the possible link between market concentration and this geographical distance. Hence, we hypothesize the following:

Hypothesis 4: *The geographical distance still has an impact on how competitors update their prices in response to the new price set by the first-moving store, even after controlling for market concentration.*

We test this fourth hypothesis by extending the specification in expression (15) to include a market concentration measure in our empirical analysis. Specifically, we include the HHI, which is based on the number of stores per retail chain within the competitive geographical area, as follows:

$$\begin{aligned} WakeUpConvAdj_{t,i^c,Init,j} = \alpha_0 + \alpha_1 Dist_{i^c,Init} + \alpha_2 Dist_{i^c,Init} \cdot DUM(\cdot) \\ + \alpha_3 HHI_{Init} + Controls + FEs + \epsilon_{i^c,j}. \end{aligned} \tag{19}$$

Here, HHI_{Init} is the Herfindahl–Hirschman Index within the area of competition whose center is the geolocation of store $Init$ that makes the initial price change, and $DUM(\cdot)$ reflects the dummy variables used to test Hypotheses 1 and 2.

Table 7 shows the analysis related to the fourth hypothesis, which is described in the specification of equation (19). This table presents evidence supporting Hypothesis 4. Even after controlling for market concentration, geographical distance continues to influence how competitors' updated prices align with the new price set by the first-moving store. Additionally, this table shows that the geo-

graphical distance still has a reduced effect on how competitors adjust their prices in response to an initial price change, in the case of essential items and when the change occurs at a large store, which is consistent with Hypotheses 1 and 2.

[Insert Table 7 here]

6. Final remarks

We offer and empirically test a new explanation for competitive price reactions: the nearby wake-up call. We structure our empirical analysis around a motivating learning framework. The intuition behind the motivating model is that a price change of an item in a given store serves as wake up call to competitors, prompting them to reevaluate the fundamentals of the item by learning the information revealed by the updated price. This learning process requires a certain amount of their limited attention, which could be used for other important responsibilities that are part of the retail business per se. In this environment, nearby competitors allocate more attention to learning new fundamental information, due to the large economic benefits and reduced costs of learning information that is geographically proximate. We show evidence supporting the nearby wake-up call explanation through unique daily price data that include stores' geolocations across France, providing various validity analyses and robustness checks.

To conclude, it is important to notice that the methodological approach used in our paper is simple and intuitive. Most importantly, our study opens the door to a future research agenda on the nearby wake-up call explanation. For instance, interesting avenues for future studies include examining whether an initial price change generates price responses from competitors in related items, and analyzing potential price reactions across different brands of the same product category.

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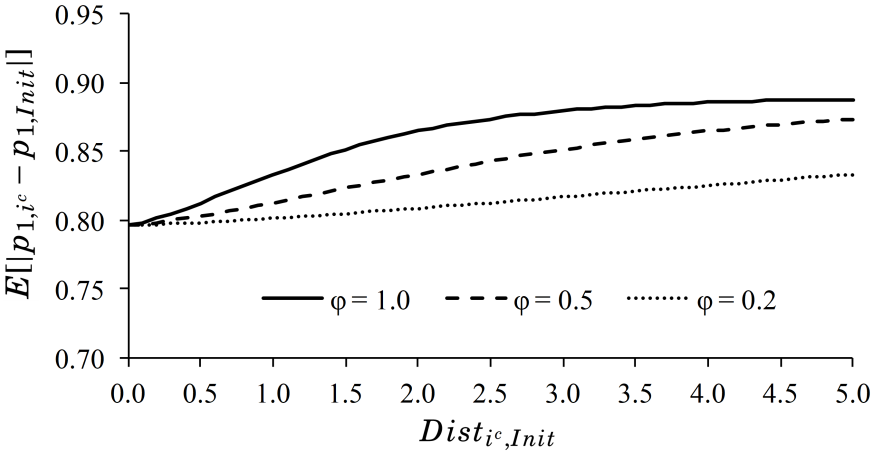


Figure 1: The effect of geographical proximity on how the updated prices of competitors converge to the new price of the store that moves first

Notes: We assume that $\tau_c = 5$, $\tau_h = 10$, $\tau_\varepsilon = 1$, $\tau_v = 3$, while $Dist_{i^c,Init}$ and φ change. In this plot, we assume that $A(Dist_{i^c,Init}) = \tau_\varepsilon/\tau_v e^{-\varphi Dist_{i^c,Init}}$ to keep this plot as simple as possible; however, similar results are obtained when we use other functional forms with $0 \leq A(\cdot) \leq \tau_\varepsilon/\tau_v$ and $\partial A(\cdot)/\partial Dist_{i^c,Init} < 0$.

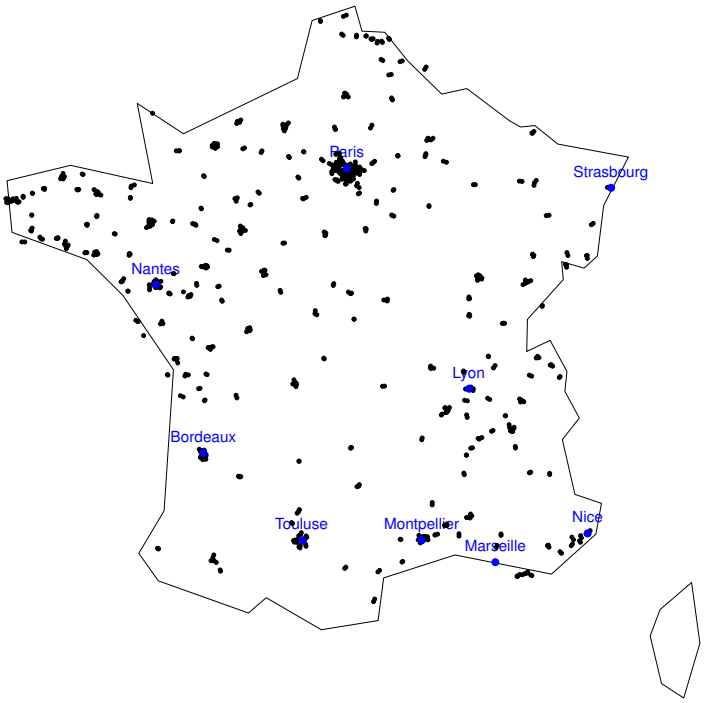


Figure 2: Geographical areas of evaluation across the whole country

Notes: This figure illustrates retail markets where an initial price change serves as a wake-up call to managers of competing stores, prompting them to re-assess the item's fundamentals by learning from the information revealed in the new price of the store that moves first.

Table 1: Summary statistics

	Summary statistics					
	Count	Mean	Median	St. dev.	Skewness	Kurtosis
$WakeUpConvAdj$ (when initial price changes are negative)	77,206	0.065	0.036	0.083	4.906	133.995
$WakeUpConvAdj$ (when initial price changes are positive)	64,440	0.069	0.047	0.072	4.576	162.288
$WakeUpConvAdj$ (total)	141,646	0.067	0.041	0.087	4.816	145.671
$Dist$ (competitors' distance from the store that moves first), km	141,646	2.999	3.123	1.286	−0.218	1.857

Notes: The variable $WakeUpConvAdj$ describes how prices of competitors compare to the new price of the store that moved first, once they have reacted to the initial price change, as described in equation (14). The variable $Dist$ represents the geographical distance between the store that decides an initial price change and the competing stores located in the same retail market that react to the initial price change.

Table 2: Price responses under the nearby wake-up call explanation

	Instrumental variable regression analysis Dependent var.: $WakeUpConvAdj$					
	Init. price change neg.		Init. price change pos.		All Init. price changes	
$Dist$	0.103^{***}	0.063^{***}	0.103^{***}	0.028^{***}	0.102^{***}	0.046^{***}
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Store-size F.E. (first price mover)	No	Yes	No	Yes	No	Yes
Store-size F.E. (competing stores)	No	Yes	No	Yes	No	Yes
Ret. chain F.E. (first price mover)	No	Yes	No	Yes	No	Yes
Ret. chain F.E. (competing stores)	No	Yes	No	Yes	No	Yes
Week F.E.	No	Yes	No	Yes	No	Yes
Product category (coicop5) F.E.	No	Yes	No	Yes	No	Yes
Region F.E.	No	Yes	No	Yes	No	Yes
Std. errors clusterized	No	Yes	No	Yes	No	Yes
F-stat first-stage	934.6^{***}	130.2^{***}	237.2^{***}	93.50^{***}	1094^{***}	167.4^{***}
Observations	77,206	77,206	64,440	64,440	141,646	141,646

Notes: The variables $WakeUpConvAdj$ and $Dist$ were described in the notes of Table 1. This analysis includes several controls and fixed effects, described in Section 4.3. Standard errors are reported in square brackets and are clustered at the municipality, week and product category levels. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 3: Prices responses under the nearby wake-up call explanation for essential items based on their weights in the construction of the consumer price index

	Instrumental variable regression analysis Dependent var.: $WakeUpConvAdj$					
	Init. price change neg.		Init. price change pos.		All Init. price changes	
$Dist$	0.107^{***}	0.070^{***}	0.104^{***}	0.031^{***}	0.104^{***}	0.052^{***}
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$Dist \cdot DUM(Essent_{CPI})$	-0.021^{***}	-0.059^{***}	-0.019^{***}	-0.026^{***}	-0.020^{***}	-0.044^{***}
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Store-size F.E. (first price mover)	No	Yes	No	Yes	No	Yes
Store-size F.E. (competing stores)	No	Yes	No	Yes	No	Yes
Ret. chain F.E. (first price mover)	No	Yes	No	Yes	No	Yes
Ret. chain F.E. (competing stores)	No	Yes	No	Yes	No	Yes
Week F.E.	No	Yes	No	Yes	No	Yes
Product category (coicop5) F.E.	No	Yes	No	Yes	No	Yes
Region F.E.	No	Yes	No	Yes	No	Yes
Std. errors clusterized	No	Yes	No	Yes	No	Yes
F-stat first-stage	906^{***}	116.7^{***}	238.6^{***}	79.96^{***}	1074^{***}	144.4^{***}
Observations	77,206	77,206	64,440	64,440	141,646	141,646

Notes: The variables $WakeUpConvAdj$ and $Dist$ were described in the notes of Table 1. The dummy variable $DUM(Essent_{CPI})$ equals one if the price responses involve items in the upper quartile of our sample in terms of their French CPI weights of their respective product categories, and zero otherwise. This analysis includes diverse controls and several fixed effects, as described in Section 4.3. Standard errors are reported in square brackets and are clustered at the municipality, week and product category levels. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 4: Price responses under the nearby wake-up call explanation for essential items based on the number of observations in the dataset

	Instrumental variable regression analysis Dependent var.: $WakeUpConvAdj$					
	Init. price change neg.		Init. price change pos.		All Init. price changes	
$Dist$	0.126^{***}	0.152^{***}	0.131^{***}	0.068^{***}	0.126^{***}	0.113^{***}
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$Dist \cdot DUM(Essent_{\#Obs})$	-0.040^{***}	-0.140^{***}	-0.042^{***}	-0.063^{***}	-0.041^{***}	-0.105^{***}
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Store-size F.E. (first price mover)	No	Yes	No	Yes	No	Yes
Store-size F.E. (competing stores)	No	Yes	No	Yes	No	Yes
Ret. chain F.E. (first price mover)	No	Yes	No	Yes	No	Yes
Ret. chain F.E. (competing stores)	No	Yes	No	Yes	No	Yes
Week F.E.	No	Yes	No	Yes	No	Yes
Product category (coicop5) F.E.	No	Yes	No	Yes	No	Yes
Region F.E.	No	Yes	No	Yes	No	Yes
Std. errors clusterized	No	Yes	No	Yes	No	Yes
F-stat first-stage F-stat first-stage	752.6^{***}	84.80^{***}	176.2^{***}	55.38^{***}	855.5^{***}	113.0^{***}
Observations	77,206	77,206	64,440	64,440	141,646	141,646

Notes: The variables $WakeUpConvAdj$ and $Dist$ were described in the notes of Table 1. The dummy variable $DUM(Essent_{\#Obs})$ equals one when the price reactions compromise items in the upper quartile in relation to the number of observations in the dataset, and zero otherwise. This analysis includes several controls and fixed effects, described in Section 4.3. Standard errors are reported in square brackets and are clustered at the municipality, week and product category levels. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 5: Price responses under the nearby wake-up call explanation after initial price changes made by a large retail store

	Instrumental variable regression analysis Dependent var.: $WakeUpConvAdj$					
	Init. price change neg.		Init. price change pos.		All Init. price changes	
$Dist$	0.108^{***}	0.063^{***}	0.085^{***}	0.029^{***}	0.098^{***}	0.047^{***}
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$Dist \cdot DUM(Large_{FirstMover})$	-0.022^{***}	-0.059^{***}	-0.018^{***}	-0.027^{***}	-0.020^{***}	-0.044^{***}
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Store-size F.E. (first price mover)	No	Yes	No	Yes	No	Yes
Store-size F.E. (competing stores)	No	Yes	No	Yes	No	Yes
Ret. chain F.E. (first price mover)	No	Yes	No	Yes	No	Yes
Ret. chain F.E. (competing stores)	No	Yes	No	Yes	No	Yes
Week F.E.	No	Yes	No	Yes	No	Yes
Product category (coicop5) F.E.	No	Yes	No	Yes	No	Yes
Region F.E.	No	Yes	No	Yes	No	Yes
Std. errors clusterized	No	Yes	No	Yes	No	Yes
F-stat first-stage	854.5^{***}	150.4^{***}	354.4^{***}	94.16^{***}	1154^{***}	181.1^{***}
Observations	77,206	77,206	64,440	64,440	141,646	141,646

Notes: The variables $WakeUpConvAdj$ and $Dist$ were described in the notes of Table 1. The dummy variable $DUM(Large_{FirstMover})$ equals one if the price reactions are the consequence of an initial price change that originated in a large store, and zero otherwise. This analysis includes several controls and fixed effects, described in Section 4.3. Standard errors are reported in square brackets and are clustered at the municipality, week and product category levels. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 6: Probability of competing price responses under the nearby wake-up call explanation

	Instrumental variable regression analysis Dependent var.: $PrWakeUp$							
	All Init. price changes							
$MDist$	-0.065^{***}	-0.057^{***}	-0.066^{***}	-0.064^{***}	-0.074^{***}	-0.134^{***}	-0.068^{***}	-0.044^{***}
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$MDist \cdot DUM(Essent_{CPI})$			0.008^{***}	0.054^{***}				
			[0.000]	[0.000]				
$MDist \cdot DUM(Essent_{\#Obs})$					0.017^{***}	0.126^{***}		
					[0.000]	[0.000]		
$MDist \cdot DUM(Large_{FirstMover})$							0.014^{***}	0.038^{***}
							[0.000]	[0.000]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
Store-size F.E. (first price mover)	No	Yes	No	Yes	No	Yes	No	Yes
Ret. chain F.E. (first price mover)	No	Yes	No	Yes	No	Yes	No	Yes
Week F.E.	No	Yes	No	Yes	No	Yes	No	Yes
Product category (coicop5) F.E.	No	Yes	No	Yes	No	Yes	No	Yes
Region F.E.	No	Yes	No	Yes	No	Yes	No	Yes
Std. errors clusterized	No	Yes	No	Yes	No	Yes	No	Yes
F-stat first-stage	7756^{***}	306.6^{***}	7667^{***}	271.9^{***}	6376^{***}	336.9^{***}	8053^{***}	580.6^{***}
Observations	1,516,987	1,516,987	1,516,987	1,516,987	1,516,987	1,516,987	1,516,987	1,516,987

Notes: The variable $PrWakeUp$ reflects the proportion of price reactions in competing stores after an initial price change, while $MDist$ is the average distance between the first price mover and competing stores within the local retail market. The variables $DUM(Essent_{CPI})$, $DUM(Essent_{\#Obs})$ and $DUM(Large_{FirstMover})$ were described in the notes of Tables 3, 4 and 5, respectively. Standard errors are reported in square brackets and are clustered at the municipality, week and product category levels. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 7: Price responses under the nearby wake-up call explanation after controlling for market concentration

	Instrumental variable regression analysis Dependent var.: $WakeUpConvAdj$							
	All Init. price changes							
$Dist$	0.135^{***}	0.093^{***}	0.137^{***}	0.100^{***}	0.171^{***}	0.257^{***}	0.130^{***}	0.059^{***}
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.002]	[0.000]	[0.000]
$Dist \cdot DUM(Essent_{CPI})$			-0.025^{***}	-0.084^{***}				
			[0.000]	[0.000]				
$Dist \cdot DUM(Essent_{\#Obs})$					-0.055^{***}	-0.237^{***}		
					[0.000]	[0.002]		
$Dist \cdot DUM(Large_{FirstMover})$							-0.027^{***}	-0.054^{***}
							[0.000]	[0.000]
HHI	0.143^{***}	0.142^{***}	0.138^{***}	0.130^{***}	0.155^{***}	0.177^{**}	0.140^{***}	0.034^{**}
	[0.000]	[0.003]	[0.000]	[0.004]	[0.000]	[0.011]	[0.000]	[0.019]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
Store-size F.E. (first price mover)	No	Yes	No	Yes	No	Yes	No	Yes
Store-size F.E. (competing stores)	No	Yes	No	Yes	No	Yes	No	Yes
Ret. chain F.E. (first price mover)	No	Yes	No	Yes	No	Yes	No	Yes
Ret. chain F.E. (competing stores)	No	Yes	No	Yes	No	Yes	No	Yes
Week F.E.	No	Yes	No	Yes	No	Yes	No	Yes
Product category (coicop5) F.E.	No	Yes	No	Yes	No	Yes	No	Yes
Region F.E.	No	Yes	No	Yes	No	Yes	No	Yes
Std. errors clusterized	No	Yes	No	Yes	No	Yes	No	Yes
F-stat first-stage	536.1^{***}	21.26^{***}	534.3^{***}	19.88^{***}	402.1^{***}	12.32^{***}	608.8^{***}	60.81^{***}
Observations	141,646	141,646	141,646	141,646	141,646	141,646	141,646	141,646

Notes: The variables $WakeUpConvAdj$ and $Dist$ were described in the notes of Table 1. The variables $DUM(Essent_{CPI})$, $DUM(Essent_{\#Obs})$ and $DUM(Large_{FirstMover})$ were described in the notes of Tables 3, 4 and 5, respectively. The variable HHI is the Herfindahl–Hirschman Index within the retail market of the store that decided the initial price change (the center is its geolocation). Standard errors are reported in square brackets and are clustered at the municipality, week and product category levels. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Online Appendix

A. Technical proofs

Proof of Proposition 1: From equations (6) and (7), we can obtain that $\tau_{i^c} = \tau_v + \tau_\varepsilon e^{-Disti^c,Init}$ when $a_{i^c,Init} = A(Dist_{i^c,Init}) = \tau_\varepsilon/\tau_v e^{-\varphi Dist_{i^c,Init}}$. Then, by again applying the Bayes rule in relation to the expected value of the posterior belief of the manager of store i^c at $t = 1$, we have:

$$E_{i^c}[v_1] = \bar{v}_{i^c} + (s_{1,i^c} - \bar{v}_{i^c})\frac{\tau_\varepsilon e^{-\varphi Dist_{i^c,Init}}}{\tau_v + \tau_\varepsilon e^{-\varphi Dist_{i^c,Init}}}. \tag{20}$$

Q.E.D.

Proof of Empirical Implications: Proof has two parts: (i) to get the expression for $E[|p_{1,i^c} - p_{1,Init}|]$; and (ii) to show that $\partial E[|p_{1,i^c} - p_{1,Init}|]/\partial Dist_{i^c,Init} > 0$. In terms of part (i), we need to obtain the expectation of the absolute value of $p_{1,i^c} - p_{1,Init}$. We can write $p_{1,i^c} - p_{1,Init}$ as:

$$p_{1,i^c} - p_{1,Init} = c_{i^c} - c_{Init} + \bar{v}_{i^c} - \bar{v}_{Init} + (s_{1,Init} - \bar{v}_{i^c})\left(\frac{\tau_\varepsilon e^{-\varphi Dist_{i^c,Init}}}{\tau_v + \tau_\varepsilon e^{-\varphi Dist_{i^c,Init}}}\right) - (s_{1,Init} - \bar{v}_{Init})\left(\frac{\tau_\varepsilon}{\tau_v + \tau_\varepsilon}\right) \tag{21}$$

Thus, equation (21) shows that $E[p_{1,i^c} - p_{1,Init}] = 0$ since $E[c_{i^c} - c_{Init}] = 0$, $E[\bar{v}_{i^c} - \bar{v}_{Init}] = 0$, $E[s_{1,Init} - \bar{v}_{i^c}] = 0$, and $E[s_{1,Init} - \bar{v}_{Init}] = 0$. In addition, by using that $\bar{v}_{i^c} = \bar{v} + h_{i^c}$ and $\bar{v}_{Init} = \bar{v} + h_{Init}$, we can re-write equation (21) as:

$$\begin{aligned} p_{1,i^c} - p_{1,Init} = {} & c_{i^c} - c_{Init} + (\bar{v} + h_{i^c})\left(\frac{\tau_v}{\tau_v + \tau_\varepsilon e^{-\varphi Dist_{i^c,Init}}}\right) - (\bar{v} + h_{Init})\left(\frac{\tau_v}{\tau_v + \tau_\varepsilon}\right) \\ & + s_{1,Init}\left(\frac{\tau_\varepsilon e^{-\varphi Dist_{i^c,Init}}}{\tau_v + \tau_\varepsilon e^{-\varphi Dist_{i^c,Init}}} - \frac{\tau_\varepsilon}{\tau_v + \tau_\varepsilon}\right). \end{aligned} \tag{22}$$

Equation (22) shows that all random variables on the right side of this expression are independent and normally distributed. Thus, $p_{1,i^c} - p_{1,Init}$ is normally distributed with variance:

$$Var(p_{1,i^c} - p_{1,Init}) = \frac{2}{\tau_c} + \frac{\tau_v^2}{\tau_h}\left(\frac{1}{\left(\tau_v + \tau_\varepsilon e^{-\varphi Dist_{i^c,Init}}\right)^2} + \frac{1}{(\tau_v + \tau_\varepsilon)^2}\right) + \frac{\tau_v \tau_\varepsilon \left(1 - e^{-\varphi Dist_{i^c,Init}}\right)^2}{(\tau_v + \tau_\varepsilon)\left(\tau_v + \tau_\varepsilon e^{-\varphi Dist_{i^c,Init}}\right)^2} \tag{23}$$

Given that $p_{1,i^c} - p_{1,Init}$ is normally distributed with mean zero, the value of $|p_{1,i^c} - p_{1,Init}|$ follows a half normal distribution. Thus, we can obtain $E[|p_{1,i^c} - p_{1,Init}|]$ by using the mean of a half normal distribution. Therefore:

$$\begin{aligned} E[WakeUpConv_{i^c,Init}] = {} & E[|p_{1,i^c} - p_{1,Init}|] \\ = {} & \left\{\frac{2}{\pi}\left(\frac{2}{\tau_c} + \frac{\tau_v^2}{\tau_h}\left(\frac{1}{\left(\tau_v + \tau_\varepsilon e^{-\varphi Dist_{i^c,Init}}\right)^2} + \frac{1}{(\tau_v + \tau_\varepsilon)^2}\right)\right.\right. \\ & \left.\left. + \frac{\tau_v \tau_\varepsilon \left(1 - e^{-\varphi Dist_{i^c,Init}}\right)^2}{(\tau_v + \tau_\varepsilon)\left(\tau_v + \tau_\varepsilon e^{-\varphi Dist_{i^c,Init}}\right)^2}\right)\right\}^{\frac{1}{2}}, \end{aligned} \tag{24}$$

In terms of part (ii), using equation (24), the proof follows from calculating $\partial E|p_{1,i^c}-p_{1,Init}|]/\partial Dist_{i^c,Init}$, which is always larger than zero. Similarly, we can also obtain $\partial E[|p_{1,i^c}-p_{1,Init}|]/\partial\varphi$, whose value is also larger than zero. Q.E.D.

B. Price responses under the nearby wake-up call explanation when the responses are observed in small stores

Table B1: Price responses under the nearby wake-up call explanation when the responses are observed in small stores

	Instrumental variable regression analysis Dependent var.: $WakeUpConvAdj$					
	Init. price change neg.		Init. price change pos.		All Init. price changes	
$Dist$	1.457^{***}	0.546^{***}	1.222^{***}	0.158^{***}	1.418^{***}	0.337^{***}
	[0.000]	[0.001]	[0.000]	[0.001]	[0.000]	[0.000]
$Dist\cdot DUM(Small_{CompetingStores})$	-1.453^{***}	-0.535^{***}	-1.220^{***}	-0.155^{***}	-1.415^{***}	-0.330^{***}
	[0.000]	[0.001]	[0.000]	[0.001]	[0.000]	[0.000]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Store-size F.E. (first price mover)	No	Yes	No	Yes	No	Yes
Store-size F.E. (competing stores)	No	Yes	No	Yes	No	Yes
Ret. chain F.E. (first price mover)	No	Yes	No	Yes	No	Yes
Ret. chain F.E. (competing stores)	No	Yes	No	Yes	No	Yes
Week F.E.	No	Yes	No	Yes	No	Yes
Product category (coicop5) F.E.	No	Yes	No	Yes	No	Yes
Region F.E.	No	Yes	No	Yes	No	Yes
Std. errors clusterized	No	Yes	No	Yes	No	Yes
F-stat first-stage	38.95^{***}	11.25^{***}	14.48^{***}	21.74^{***}	47.25^{***}	21.98^{***}
Observations	77,206	77,206	64,440	64,440	141,646	141,646

Notes: The variables $WakeUpConvAdj$ and $Dist$ were described in the notes to Table 1. In this table, the dummy variable $DUM(Small_{CompetingStores})$ equals one if the price responses are observed in small stores, and zero otherwise. This analysis includes diverse controls and several fixed effects, as described in Section 4.3. Standard errors are reported in square brackets and are clustered at the municipality, week and product category levels. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.