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ABSTRACT

Restaurant Prices and the Minimum Wage*

We examine the effect of the minimum wage on restaurant prices. We contribute to both the study of economic impact of the minimum wage and to the micro patterns of price stickiness. For that purpose, we use a unique dataset of individual price quotes collected to calculate the Consumer Price Index in France and we estimate a price rigidity model based on a flexible $(S;\ s)$ rule. We find a positive and significant impact of the minimum wage on prices. The effect of the minimum wage on prices is however very protracted. The aggregate impact estimated with our model takes more than a year to fully pass through to retail prices.

JEL Classification: E31, D43, L11

Keywords: price stickiness, minimum wage, inflation, restaurant prices

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1 Introduction

The economic effects of the minimum wage are at the heart of a long-lasting controversy. Recent and influential works by Katz and Krueger (1992) and Card and Krueger (1994) have revived this controversy. Focusing on US fast-food restaurants, in which employees paid at the minimum wage are a substantial part of the labor force, they find little evidence of an effect of the minimum wage on employment. Neumark and Wascher (2000) have disputed their result. Using payroll data, they found evidence of a negative employment effect. Card and Krueger (2000) have subsequently challenged this result by using the same payroll data. Although most of the controversy has focused on the impact of the minimum wage on employment (Brown, 1999), changes in the minimum wage may have an impact on prices as well. However, evidence on the price effect of the minimum wage is relatively scant for the moment (Lemos, 2008). In the case of fast-food restaurants, available evidence include papers by Card and Krueger (1994) and by McDonald and Aaronson (2006).

The present paper uses individual price quotes and a microeconometric approach to assess the impact of the minimum wage on prices in restaurants in France. Like in the US, French restaurants are well suited for assessing the effect of minimum wage increases since the proportion of employees paid at the minimum wage is high in this industry (around 40%). Moreover, wage setting is not affected by collective bargaining in restaurants, because collective agreements are very scarce in this industry composed of very small firms. Our price dataset is unique and consists of thousands of monthly price quotes collected in restaurants between 1994 and 2003 by the French Statistical Institute (Insee, Paris) to compute the Consumer Price Index (see Baudry *et al.,* 2007, for an overall analysis of price stickiness using these data).

The contribution of our paper is twofold. First, we provide new estimates of impact of minimum wage increases on prices by using microdata. This approach was introduced by Katz and Krueger (1992) and Card and Krueger (1994) who used a difference-in-differences estimation strategy.[1] More recent studies have used panel data with a larger time-dimension. For instance,

[1] Since the minimum wage in France is binding at the national level, all firms are equally concerned. Thus there is no possibility to apply a difference-in-differences methodology requiring the existence of a valid control group.

using BLS data, McDonald and Aaronson (2006) find a positive and fast impact of the minimum wage on prices. Using the same type of data, our econometric strategy is however different since we build a microeconometric non-linear model which accounts both for the infrequency of price adjustments and the size of price changes. This strategy allows us to better capture delayed effects of the minimum wage on prices and to analyze the aggregation of non-linear pricing rules adopted by heterogenous agents.[2]

Our paper also adds to the empirical literature on price rigidity. Price rigidity is a crucial issue in macroeconomics. After a shock, macroeconomic dynamics typically depends on microeconomic features, like price-setting behaviour of the firms (see, for instance, Goodfriend and King, 1997). A recurrent challenge for economists is to understand the mechanisms underpinning the infrequency of price adjustments. In particular, price changes in the services sector are known to be rare. In the euro area and in the US, only 5.6% and 15% of service prices are respectively modified each month (compared with 15% and 25% for prices composing the overall CPI). Restaurant prices are a particularly sticky component of services, with respective frequencies of price changes of 4.7% and 9.0% (Bils and Klenow, 2004 and Dhyne *et al.*, 2006). Restaurant prices thus appear as an ideal item for assessing price rigidity models. In addition, industries with very sticky prices are of particular interest from a monetary policy perspective: Aoki (2001) shows that the optimal monetary policy should put more emphasis on stabilizing the inflation rate in the stickiest sectors. Some recent papers have looked at restaurant prices with a sticky price perspective. For instance, Gaiotti and Lippi (2005) and Hobijn *et al.* (2006) have proposed theoretical models to explain the pricing behaviour of restaurants during the euro cash changeover. Using microdata for European and Italian restaurants, they build and calibrate theoretical models to test different theoretical assumptions and provide some insights into the mechanisms underpinning the inflation peak at the euro cash changeover date. Goette *et al.* (2005) report some empirical evidence about the price adjustment of various items sold in

[2] Another possibility is to use aggregate sectoral data. Adopting this approach, Lee and O'Roarke (1999) find a significant effect of the minimum wage on prices. Aaronson (2001) uses time-series reduced-form equations for estimating the reaction of the price subindices of the CPI (in the U.S. and Canada) to an increase of the minimum wage. He obtains some evidence of a lagged and positive impact of minimum wage increases on prices.

Swiss restaurants. They show that the size of price changes does not respond to inflation while the key variable in the variability of inflation seems to be the frequency of price changes. Our contribution is to estimate a microeconometric model that links restaurant prices to costs. By contrast, many empirical studies of price adjustment approximate marginal cost using a sectoral inflation rate (see, for instance, Cecchetti, 1986, and Fougère *et al.*, 2007) or an unobserved synthetic factor (Dhyne *et al.*, 2007). Here, the large proportion of workers paid the minimum wage in French restaurants motivates our focus on the minimum wage as a relevant measure of firms' marginal cost. We are then able to determine to what extent observed price stickiness in this industry may result from cost stickiness.

Our main findings are the following. The minimum wage has a positive and significant impact on prices in restaurants, in line with the weight of low-wage labor in total costs. However, contrary to other studies, we exhibit a protracted impact of the minimum wage on prices. Changes in the minimum wage can take more than a year to pass through to retail prices. As a result, stickiness in restaurant prices is not just the mere reflection of stickiness in its main determinants.

The next section presents the dataset used as well as the main features of restaurant price adjustments in France. Section 3 presents our econometric model of price rigidity. Estimation results and an assessment of the overall fit of the model are presented in Section 4. In Section 5, we simulate the model to assess the aggregate effect of the minimum wage on prices. We compare the response obtained from these microsimulations with those obtained from a linear model estimated with aggregate data.

2 Data

2.1 Restaurant prices

2.1.1 Data sources

Our data are extracted from a longitudinal dataset of monthly price quotes collected by the French Statistical Institute (Insee, Paris) from July 1994 to February 2003 to compute the

Consumer Price Index (CPI). Each observation is the price of a specific item (here a menu or a course) in a particular outlet (here a restaurant). Prices are inclusive of all taxes. Along with the price level, an individual product code (the outlet and the product category), the year and the month of the record are also available; they allow us to follow the price of a product through time. Prior to estimation, some specific data treatments have been done. Due to holidays, "missing" prices are quite frequent. The French Statistical Institute (Insee, Paris) generally replaces them with the average price observed in other outlets in the same area. But this procedure may introduce some spurious price changes. Thus, we assume that the price does not change when the restaurant is temporarily closed. As the euro cash changeover is included in our observation period, we divide all prices recorded before 2002:1 by 6.55957, the official French franc/euro exchange rate. Details on data treatments are provided in Baudry *et al.* (2007) and Fougère *et al.* (2007).

Our analysis is focused on restaurant prices. We distinguish between traditional and fast-food restaurants, since the pricing strategy of these two types of outlets is markedly different, as shown below. Several types of items are observed in our dataset: hors d'œuvre, desserts, main course, wine, meals in traditional restaurants, and meals in fast-food restaurants. We choose to restrict our sample to full meals in traditional and fast-food restaurants since they are the most representative items, and because data on full meals are more systematically recorded in restaurants (while the other items may not be systematically reported). The meal in a traditional restaurant typically consists of a starter plus a main course or a main course plus a dessert. In fast-food restaurants, it consists of a hamburger, french fries and a soft drink. Prices in restaurants are always inclusive of service and value-added tax (VAT). Note that the VAT rate for take-away food is lower than for traditional restaurants (5.5% versus 19.6%). Our database contains 93,816 price quotes for the item "menu in a traditional restaurant", corresponding to 2,948 different restaurants, and 10,726 observations for the item "menu in a fast-food restaurant", corresponding to 448 different fast-food restaurants.

Figure 1 displays examples of actual price trajectories for a full meal price in traditional restaurants. Price changes do not occur continuously. This pattern is quite typical of sticky prices: long periods of price stability are interspersed with small or large price increases. In the following section, we document the main characteristics of price rigidity in traditional and fast-food restaurants.

[Figure 1]

2.1.2 Patterns of price rigidity

The frequency of price changes is generally considered as a good indicator of price rigidity (e.g. Bils and Klenow, 2004, Dhyne *et al.*, 2006). In our sample, restaurant prices and, to a lesser extent, fast-food prices are very rigid. On average, around 4% of traditional restaurant prices and 9.4% of fast-food prices are modified each month in France, compared to around 19% on average for all CPI price quotes (Baudry *et al.*, 2007). As a result, the duration of a price spell is on average equal to two years in restaurants and to less than one year in fast-food restaurants (see Table 1). This result is quite consistent with previous findings in the US and in the euro area. Using US data, MacDonald and Aaronson (2006) find that around 13% of restaurant prices change every two months, implying a monthly frequency of price changes equal to 6.5%. For the euro area, Dhyne *et al.* (2006) report a frequency equal to 4.7%. Owing to this apparently high degree of stickiness, restaurant prices seem to be a good candidate for the estimation of price rigidity models.

[Table 1] [Figure 3]

The infrequency of price changes is often explained by the existence of price adjustment costs. As noticed by Fisher and Konieczny (2006), these costs can be divided into three categories. First, some costs, called menu-costs, are associated with printing new menus or labels. The second category includes the costs of the decision-making process, e.g. collecting information, analyzing changes in the "optimal" nominal price in the absence of adjustment costs, and deciding the amount of the price change. The last type of costs could occur in the event of an unfavourable reaction from customers to price increases; these costs could be called "antagonization costs". In restaurants, these three types of costs are likely to be at stake. Note that in traditional restaurants, managers may choose a decrease in quantity or quality of food in their standard menu as a substitute to a price increase. This reaction would strengthen the case for antagonization costs with respect to price changes. Such a strategy is however not possible for standardized products like fast-food restaurant items, which may rationalize the higher degree of price stickiness in traditional restaurants.

Figure 3 displays the frequency of price changes over time for the two types of restaurants considered here. The frequency of price changes is quite stable over time, except in some specific months. In the case of traditional restaurants, the frequency of price changes has noticeable peaks in January and September, the frequency value being around 5% in these two months versus around 3% in other months.[3] In fast-food restaurants, the frequency of price changes displays less regular patterns. However, in January, February and July, around 10% of prices are modified, against less than 7% on average during the year.[4] Such seasonal price changes may result from the costs associated with the price-change decision. As documented by Zbaracki *et al.* (2004), adjusting prices is a long process which can last a whole year because managers have to collect information on competitors and monitor the cost developments. Moreover, as shown by Müller *et al.* (2009), the opportunity cost of adjusting prices may increase in some periods of the year in which managers face a higher store traffic (for example during holidays). So, managers may prefer revising their prices according to a discrete-time process (in specific periods of the year) rather than continuously (see Fisher and Konieczny, 2006, for some empirical evidence). In our case, January and September correspond to the re-opening of traditional restaurants after holidays. Price changes during these months would then be less costly.

2.1.3 The distribution of price changes

A specific feature of price changes in services is the low proportion of price decreases: 20% of price changes are decreases while this proportion is around 40% for the whole CPI (Baudry *et al.,* 2007). The degree of downward price rigidity is even higher in traditional restaurants: more than 90% of price changes are increases and only 10% are price decreases. Prices in fast-food

[3] This calculation does not take account of years 2002 and 2003, which have very specific patterns due to the impact of the euro cash changeover.

[4] This calculation does not take account of years 2002 and 2003. See the previous footnote.

restaurants also exhibit, though to a lesser extent, some nominal downward rigidity. In fast-food restaurants, 24% of price changes are price decreases. Two interpretations for nominal downward rigidity can be invoked. First, marginal costs may rarely decrease. Second, it could also be a consequence of customer antagonization costs: Rotemberg (2005) develops a model in which consumers may react negatively to price changes and Zbaracki *et al.* (2004) show the empirical relevance of these antagonization costs. A restaurant manager may thus be reluctant to reduce the price immediately if he/she expects that the price will rise again in the future, which implies that the adjustment cost will have to be paid again. Although it is unlikely that a price decrease would entail customer anger, one can assume that the prospect of future antagonization costs could prevent current price decreases.

[Table 2] [Figure 4]

The distribution of price changes is represented in Figure 4. While a simple menu-cost framework would suggest that, as price changes are rare, the size of price changes should be rather large, we observe that the proportion of small price changes is substantial. Around 25% of the price increases are smaller than 1.6% in traditional restaurants and smaller than 1.3% in fast-food restaurants (Table 2). We also note that the average size of a price decrease is larger than the size of a price increase (Table 2). The distribution of price changes is also characterized by a noticeable proportion of large price changes: in traditional restaurants 10% of price increases are larger than 8% (while 10% of price decreases are smaller than -13%). One possible interpretation is that, although customers may react more strongly to a large price increase than to small repeated price increases, some firms may prefer implementing large price changes because of fixed costs associated with price changes.

To sum up, large price decreases are common and small price increases are not rare. MacDonald and Aaronson (2006) observe similar patterns for US restaurant prices: the price change distribution is asymmetric, the proportion of small price changes is important, 12% of price changes are large (above 10%), and the average size of price increases is smaller, in absolute value, than the average size of price decreases.

2.2 Determinants of price changes

Our aim is to investigate determinants of price changes. Following Cecchetti (1986) and Ratfai (2006), we assume that the price adjusts infrequently to an unobserved optimal "frictionless" price which depends on the structure of costs and demand. This optimal price is typically defined by a mark-up over marginal costs. Our starting point is that, in restaurants, labor costs and input costs (food prices) are the main elements of marginal costs.

2.2.1 Labor costs and the minimum wage

We expect labor costs to be a major element of costs in restaurants. According to national accounts, the share of total compensation in costs is around 40% in traditional restaurants and 33% in fast-food restaurants (on average between 1997 and 2002). For fast-food restaurants, we can also use Parsley and Wei (2007)'s cost function estimation for Big Mac hamburgers (a standardized product) as another benchmark. They find that labor costs represent around 46% of total costs.

In French restaurants, most of the labor costs consist of the wages of employees paid the minimum wage. In restaurants and hotels, more than 40% of employees are paid the minimum wage (DARES, 2003). This ratio is particularly high as compared to the national proportion of employees paid the minimum wage, which lies between 12% and 15% over the observation period. Moreover, minimum wage increases may spill over to wages of employees above the minimum wage. Koubi and Lhommeau (2006) find that the elasticity for restaurants and hotels is estimated at 0.7 for wages lower than 1.1 times the minimum wage. This implies that a minimum wage increase is expected to indirectly but rapidly affect a wider share of labor costs in restaurants.

In France, the minimum wage (SMIC, Salaire Minimum Interprofessionnel de Croissance) is set a national level. It applies to all employees and types of firms, and minimum wage increases are binding. The minimum wage is raised each year in July according to a legal rule, which is based on the partial indexation to past inflation and to past wage growth. Besides these indexation procedures, the government may decide on a discretionary basis to amplify the raise.

Over the sample period, the minimum wage was mostly changed in July, except in 1996 when it was also increased in May. We observe some variability among the minimum wage increases over the period: most of the minimum wage increases were in the interval +1.2% to +4% (see Figure 2). Over the period, the minimum wage increases were on average higher than the overall wage growth. In parallel, the successive French governments implemented policies that consisted in reducing employer social security contributions on low wages. For instance, the employer social security contribution rate at the level of the minimum wage was brought from 24.8% to 12.0% in September 1995 and to 4.2% in January 2003.[5] The index for the labor cost at the minimum wage level that we use hereafter takes into account this rate.

[Figure 2]

Measuring wages and costs in the restaurant industry raises specific issues, which could bias the estimated impact of the minimum wage on labor costs. First, it is known that a fraction of restaurant employees are hired on the black market.[6] But we can assume that the wage level on the black market is proportional to the minimum wage level. Second, tips are not reported in the available price quotes. Tips are however a limited concern since a service charge is included in restaurant prices; thus tips may contribute to the incomes of employees, but they do not affect restaurant cost functions. They may affect restaurant decisions only indirectly, through the opportunity to offer a lower wage against the payment of tips. In addition, tips are optional and there is no standard convention or social norm in France as to their level. Our assessment is that tips are unlikely to bias our estimates.

2.2.2 Other costs, demand and specific events

Another obvious cost consists of food inputs. For fast-food restaurants, Parsley and Wei (2007) find that food inputs represent 31.6% of costs to produce a Big Mac hamburger. In this study, we use an aggregate price index to approximate the price of inputs, namely the producer price index

[5] Contribution rates are taken from OFCE (2003, table 1, page 230).

[6] Measuring the size of the black-market is extremely difficult. A recent study by the Central Agency of Social Security Organizations (ACOSS) estimates that illegal work accounts for around 12% of employees in hotels, cafés and restaurants in 2005.

of food over the sample period. We also incorporate a control variable to represent the demand level. More precisely, we use the volume of total sales in traditional and fast-food restaurants. These two monthly series are published by the French Statistical Institute (Insee, Paris).

Two changes in VAT rates occurred during the observation period. They may have had an impact on the pricing policy of restaurants. In August 1995, the standard VAT rate was raised from 18.6% to 20.6%, while in April 2000 it was lowered from 20.6% to 19.6%. We construct two dummy variables for these changes. These changes may have had non-trivial impact in presence of menu-costs. For instance, restaurants may cluster price changes planned otherwise at the time of the tax change. Consumers could also be more likely to accept a price rise at the time of a tax increase because the tax increase is a macro event observable by them. Note that the VAT rate for take-away food is 5.5%, so that fast-food restaurants are expected to be much less affected by changes in VAT. The standard fast-food restaurant policy is to post the same tax-included price for a given item, either for take-away or dine-in. In the case of fast-food restaurants, the relevant VAT rate is a weighted average of the regular and low rate.

Finally, a dummy variable for the euro cash changeover that occurred in January 2002, as well as two other dummies for the period just before and just after the introduction of the euro[7], are included. At the time of the euro cash changeover, all restaurants had to change their nominal price due to the currency conversion. As already noticed by Hobijn *et al.* (2006), who consider restaurants in the euro area, such an event forces firms to pay a menu cost, and then implies a clustering of price changes that would have taken place at other dates in the absence of the euro cash changeover. As a consequence many traditional restaurants choose to change their prices at this date or just before (see Figure 3). However, we can assume that the currency change did not affect the long-run price level in restaurants.

[7] The period before the euro cash changeover begins in September 2001 and ends in December 2001. The period after the euro introduction begins in February 2002 and ends in April 2002.

3 An econometric model of infrequent price changes

3.1 Theoretical background

Menu-cost models are the most standard theoretical approach to rationalizing infrequent price changes. Sheshinski and Weiss (1977) first showed that, in presence of menu-costs and of deterministic exogenous shock, the optimal price-setting behaviour of the firm has the form of an (S, s) rule. The essence of the (S, s) model is the existence of a "band of inaction": firms tolerate some deviation from their optimal frictionless price as long as this deviation is not too large. Dixit (1991) and Hansen (1999) then extended this basic model to allow for non-deterministic shocks, and they proved that the optimal behaviour may still be represented by an (S, s) rule. Note however, as discussed by Attanasio (2000), that a (S, s) policy is a solution to an optimal pricing problem in specific cases only.

In (S, s) models, the frictionless price is generally the price level that would be observed in the absence of any costs of adjustment. It can be derived in a straightforward way under the assumption of flexible prices. If we denote by P_{it}^* the optimal price set by a monopolistically competitive outlet i at date t, a standard result is that the optimal frictionless price is given by a markup over marginal costs MC_{it}, i.e. $P_{it}^* = k_i MC_{it}$. Assuming that the production function has two inputs, labor and food, maximizing profit under an isoelastic demand curve yields a log-linear expression for the optimal price, similar to that obtained, for instance, by Rotemberg (1982) and Cecchetti (1986):

$$p_{it}^* = a_i + bw_t + cq_t + dy_t \tag{1}$$

where w_t and q_t are the logarithms of costs of labor and food, respectively, and y_t is the demand level.

In the presence of adjustment costs, firms trade off between the opportunity cost of deviating from the optimal price (i.e. the foregone profit) and the adjustment cost. Under some conditions shown to be of the (S, s) type, the optimal adjustment rule is then to adjust the price only if the difference between the optimal price p_{it}^* and the price $p_{it-\tau}$ modified at period $t - \tau$ (where τ is the duration since the last price change), exceeds some threshold. We assume that when prices are reset they are set at the optimal frictionless price (up to a constant, like in the paper by Tsiddon, 1993). If the price was changed τ periods before, then $p_{it-1} = p_{it-\tau} = p^*_{it-\tau}$. The firm's pricing decision depends on the distance covered by p^*_{it} between dates $t-\tau$ and t (the date at which the price is observed). We denote this variable by $\Delta_\tau p^*_{it}$. If it exceeds a certain threshold C, the price is changed.[8] Allowing for error terms in the optimal price, or in the size of the band, the probability of a price change will depend on the cumulative change in p^*_{it} since the last price change.

The (S, s) model puts strong restrictions on the patterns of price adjustments. In particular, in a standard menu-cost model, the size of the price change will be the same for all price changes equal to C. Moreover, a large adjustment cost would imply infrequent and large price changes. This prediction is at variance with the prevalence of infrequent but small price changes observed in the data (see Figure 1).

To capture this pattern, we rely on time-varying menu costs following Dotsey *et al.* (1999). Under such an assumption the threshold fluctuates over time, as shown by Caballero and Engel (1999) in a model of investment decision. In our model, thus, the threshold is allowed to vary over time and across firms. Our specification is rather flexible. For instance, our model encompasses the Calvo model: when the threshold varies a lot, the model predicts a constant probability for a price change and can generate small price changes.

Overall, our approach is related to the adjustment hazard model elaborated by Caballero and Engel (1999). In such an approach, the probability of a price change is a function of the gap between the current price and a static frictionless optimal price. That gap is the relevant state variable, so that despite the fact that an optimization problem underlies the decision rule, no expectation term is explicitly present.

One additional specification issue is that, in restaurants, there could exist an alternative adjustment margin other than price. As noticed before, restaurants may choose to decrease quality or quantity rather than increase their prices. The existence of such an adjustment margin is expected to lower the value of the parameter b in equation (1), compared to a standard model

[8] In theoretical models (see, for instance, Sheshinski and Weiss, 1977), this threshold is shown to be an increasing function of the menu cost. However, in a reduced-form approach like ours, the adjustment cost cannot be measured since this function depends on structural parameters that cannot be identified .

in which this margin does not exist. Nevertheless, in our reduced-form approach, as far as w_t, q_t and y_t are exogenous covariates, the overall impact of the minimum wage on nominal prices is consistently estimated.[9]

3.2 The econometric model

Our econometric model encompasses the (S, s) specification and is related to some empirical models that have been previously set forth in the literature. For instance, Attanasio (2000) has put forward a flexible econometric specification for estimating (S, s) models applied to consumption of durables. More recently, in a price-setting context, Ratfai (2006) has proposed to estimate (S, s) models by using a probit specification, while Dhyne *et al.* (2007) have introduced stochastic bands.[10] On the methodological side, our distinctive feature is, with respect to the former, to estimate a model for the size of the price change. With respect to the latter, we allow for observed proxies of the marginal cost and potential asymmetry in the decision to change the price.

Let us denote p_{it} the price posted by restaurant i $(i = 1, ..., n)$ at date t, and $\Delta_\tau p^*_{i,t}$ the optimal price change.

In our a flexible (S, s) approach the decision rule is as follows:

$$\begin{array}{ll} \Delta_\tau p_{i,t} = \Delta_\tau p^*_{i,t} & \text{if } \Delta_\tau p^*_{i,t} > C^+_{it} \text{ or } \Delta_\tau p^*_{i,t} < C^-_{it} \\ \Delta_\tau p_{i,t} = 0 & \text{if } C^-_{it} < \Delta_\tau p^*_{i,t} < C^+_{it} \end{array}$$

Our econometric model is thus characterized by three processes, the optimal price change $\Delta_\tau p^*_{i,t}$, and the time-varying thresholds C^-_{it} and C^+_{it} associated with price decreases and price increases, respectively.

The optimal price change is specified as:

$$\Delta_\tau p^*_{i,t} = \beta_0 + \Delta_\tau X_{1,t}\beta_1 + u_i + \varepsilon^p_{i,t} \tag{2}$$

[9] For French CPI data, the French statistical institute (INSEE, Paris) discontinues the series whenever the nature of the product changes significantly, which limits the empirical case for such an adjustment margin.

[10] Ratfai (2006) studies the price of meat in Hungary, Dhyne et al.(2007) a wide range of consumer goods in France and Belgium. See also Sheshinski et al. (1981) for an early estimation of such models.

where $\Delta_\tau X_{1,t} = X_{1t} - X_{1,t-\tau}$ is the variation of covariates $X_{1,t}$ between dates t and $t - \tau$ (τ being the duration since the last price change) and (β_0, β_1) is a vector of parameters to be estimated.[11] The vector of covariates $X_{1,t}$ includes variables affecting the cost structure, especially the variation of the minimum wage level (our proxy for the variation of labor costs), of the food producer price index, of the aggregate demand either in traditional or fast-food restaurants, and of the VAT. All these variations are taken between dates $t - \tau$ and t. The term u_i captures the time-invariant characteristics of the restaurant that may affect the optimal price change, like differences in costs of price changes or in marginal costs.[12] It is assumed to be normally distributed with mean 0 and variance σ_u^2, and to be stochastically independent of the aggregate (macro) variations $\Delta_\tau X_{1,t}$. The random term $\varepsilon_{i,t}^p$ is a normally distributed idiosyncratic (white noise) shock with mean 0 and variance σ_p^2.

The time-varying thresholds are specified as

$$\begin{aligned} C_{it}^+ &= C^+ + X_{2,t}\beta_2^+ + v_i + \varepsilon_{i,t}^{c+} \\ C_{it}^- &= C^- + X_{2,t}\beta_2^- + v_i + \varepsilon_{i,t}^{c-} \end{aligned} \tag{3}$$

The time-varying threshold associated with price increases (respectively, price decreases) depends on a constant parameter C^+ (respectively C^-), and on $X_{2,t}$, a vector of time-dependent indicators, such as monthly dummies and euro cash changeover dummies[13]. The monthly dummies are incorporated because we observe that restaurant managers are more likely to revise their prices in January or September. This may reflect that the price-change decision may vary across months. Adjustment costs would then be lower during these months.[14] We also include

[11] Note the first date τ is not observed so that the first spell is not usable for estimation. We expect however the selection bias resulting from this omission to be small since we observe repeated spells for each restaurant.

[12] The random terms u_i could be correlated due to local or brand effects. Unfortunately, our data set contains no information on the location nor on the brand of restaurants.

[13] We assume that none of the determinants of the optimal price explains the band associated with the menu-costs.

[14] Woodford (2003) writes that "the main benefit of infrequent price changes is not lower menu costs, but reduction of the costs associated with information collection and decisionmaking. Obtaining this benefit necessarily means that the timing of the occasions upon which prices are reconsidered is largely independent of current market conditions; for example, firms often reconsider pricing policy at a particular time of year."

in the vector $X_{2,t}$ the dummy variable indicating the euro cash changeover that occurred in January 2002. At this date, all firms had to change their prices from francs to euros, and were thus forced to pay the menu costs, which gave them an incentive to cluster price changes at that date (Hobijn *et al.*, 2006). The vectors β_2^+ and β_2^- are slope parameters to be estimated. The term v_i captures the time-invariant characteristics affecting the menu cost of restaurant i. Finally, $\varepsilon_{i,t}^{c+}$ and $\varepsilon_{i,t}^{c-}$ are normally distributed random terms with mean 0 and respective variances σ_{c+}^2 and σ_{c-}^2. These shocks are shocks on the price-change decision, resulting from shocks on menu costs. Consistent with the theoretical models of random menu cost (e.g. Dotsey *et al.*, 1999), the menu cost shock is independent of the shock $\varepsilon_{i,t}^{p}$ on the optimal price.

The contribution to the likelihood function of a constant price at date t, given that the specific (random) characteristic is u_i, is thus:

$$
\begin{aligned}
l_{i,t}(u_i) \quad &= \Pr(\Delta_\tau p_{i,t} = 0) = \Pr(C_{it}^- < \Delta_\tau p_{i,t}^* < C_{it}^+) \\
&= \Pr\left[\varepsilon_{i,t}^{p} - \varepsilon_{i,t}^{c+} < C^+ + X_{2,t}\beta_2^+ + v_i - (\beta_0 + \Delta_\tau X_{1,t}\beta_1 + u_i)\right] \\
&\quad - \Pr\left[\varepsilon_{i,t}^{p} - \varepsilon_{i,t}^{c-} < C^- + X_{2,t}\beta_2^- + v_i - (\beta_0 + \Delta_\tau X_{1,t}\beta_1 + u_i)\right] \\
&= \Phi\left[\frac{C^+ + X_{2,t}\beta_2^+ + v_i - (\beta_0 + \Delta_\tau X_{1,t}\beta_1 + u_i)}{\sqrt{\sigma_{c+}^2 + \sigma_p^2}}\right] \\
&\qquad\qquad -\Phi\left[\frac{C^- + X_{2,t}\beta_2^- + v_i - (\beta_0 + \Delta_\tau X_{1,t}\beta_1 + u_i)}{\sqrt{\sigma_{c-}^2 + \sigma_p^2}}\right]
\end{aligned}
\tag{4}
$$

where Φ is the c.d.f of the Gaussian distribution. As idiosyncratic shocks on $\Delta_\tau p_{i,t}^*$ and C_{it}^- and C_{it}^+ are independent, this implies that $\mathrm{cov}(\varepsilon_{i,t}^{c+}, \varepsilon_{i,t}^{p}) = \mathrm{cov}(\varepsilon_{i,t}^{c-}, \varepsilon_{i,t}^{p}) = 0$, and that $V(\varepsilon_{i,t}^{c+} - \varepsilon_{i,t}^{p}) = \sigma_{c+}^2 + \sigma_p^2$ and $V(\varepsilon_{i,t}^{c-} - \varepsilon_{i,t}^{p}) = \sigma_{c-}^2 + \sigma_p^2$.

The contribution to the likelihood function of a price increase in restaurant i at date t, given that the specific (random) characteristic is u_i, is thus:

$$
\begin{aligned}
l_{i,t}(u_i) &= \frac{1}{\sigma_p}\phi\left(\frac{\Delta_\tau p_{i,t} - \beta_0 - \Delta_\tau X_{1,t}\beta_1 - u_i}{\sigma_p}\right) \times \Pr\left[\Delta_\tau p^*_{i,t} > C^+_{it} \mid \Delta_\tau p_{i,t} = \Delta_\tau p^*_{i,t}\right] \\
&= \frac{1}{\sigma_p}\phi\left(\frac{\Delta_\tau p_{i,t} - \beta_0 - \Delta_\tau X_{1,t}\beta_1 - u_i}{\sigma_p}\right) \\
&\quad \times\Phi\left[\frac{\beta_0 + \Delta_\tau X_{1,t}\beta_1 + u_i - (C^+ + X_{2,t}\beta_2^+ + v_i) + \Delta_\tau p_{i,t} - \beta_0 - \Delta_\tau X_{1,t}\beta_1 - u_i}{\sigma_{c+}}\right] \\
&= \frac{1}{\sigma_p}\phi\left(\frac{\Delta_\tau p_{i,t} - \beta_0 - \Delta_\tau X_{1,t}\beta_1 - u_i}{\sigma_p}\right) \times \Phi\left(\frac{-C^+ - X_{2,t}\beta_2^+ - v_i + \Delta_\tau p_{i,t}}{\sigma_{c+}}\right)
\end{aligned} \tag{5}
$$

where ϕ is the p.d.f of the Gaussian distribution. Let us remark that the correlation between the shocks of the two equations $\varepsilon^p_{i,t} - \varepsilon^{c+}_{i,t}$ and $\varepsilon^p_{i,t}$ is equal to

$$
\mathrm{corr}(\varepsilon^p_{i,t} - \varepsilon^{c+}_{i,t}, \varepsilon^p_{i,t}) = \frac{\sigma_p}{\sqrt{\sigma^2_{c-} + \sigma^2_p}}
$$

Price decreases are treated separately from price increases in order to take into account the asymmetry in price changes, which might reflect antagonization costs or other differences in the firm's pricing policy. The contribution to the likelihood function of a price decrease in restaurant i at date t, is very similar to the one for price increase.

$$
\begin{aligned}
l_{i,t}(u_i) &= \frac{1}{\sigma_p}\phi\left(\frac{\Delta_\tau p_{i,t} - \beta_0 - \Delta_\tau X_{1,t}\beta_1 - u_i}{\sigma_p}\right) \times \Pr\left[\Delta_\tau p^*_{i,t} < C^-_{it} \mid \Delta_\tau p_{i,t} = \Delta_\tau p^*_{i,t}\right] \\
&= \frac{1}{\sigma_p}\phi\left(\frac{\Delta_\tau p_{i,t} - \beta_0 - \Delta_\tau X_{1,t}\beta_1 - u_i}{\sigma_p}\right) \\
&\quad \times\Phi\left[\frac{-\beta_0 - \Delta_\tau X_{1,t}\beta_1 - u_i + C^- + X_{2,t}\beta_2^- + v_i - \Delta_\tau p_{i,t} + \beta_0 + \Delta_\tau X_{1,t}\beta_1 + u_i}{\sigma_{c-}}\right] \\
&= \frac{1}{\sigma_p}\phi\left(\frac{\Delta_\tau p_{i,t} - \beta_0 - \Delta_\tau X_{1,t}\beta_1 - u_i}{\sigma_p}\right) \times \Phi\left(\frac{C^- + X_{2,t}\beta_2^- + v_i - \Delta_\tau p_{i,t}}{\sigma_{c-}}\right)
\end{aligned} \tag{6}
$$

where ϕ is the p.d.f of the Gaussian distribution. As in the case of price increases, we have:

$$\mathrm{corr}(\varepsilon^{p}_{i,t} - \varepsilon^{c-}_{i,t}, \varepsilon^{p}_{i,t}) = \frac{\sigma_p}{\sqrt{\sigma^2_{c-} + \sigma^2_p}}$$

In traditional restaurants, price decreases are very scarce. For this type of outlet, we pool the occurrences of price decreases with those of no-changes. For fast-food restaurants, we allow β_0 to be different for price increases and for price decreases, since price decreases are difficult to capture with an equation similar to the one for price increases. This model closely proxies a model with two regimes of price changes. The first regime is the standard regime of price changes. The alternative one is characterized for instance by sales, i.e. large negative changes that cannot be captured by standard economic mechanisms. Besides, we set $u_i = w_i$ and $v_i = (1+\alpha)w_i$ where w_i is assumed to be normally distributed with mean 0 and variance σ^2_w.

The likelihood function for an i.i.d. sample of n restaurants is thus:

$$\ln L = \sum_{i=1}^{N} \ln \left(\int \prod_{t=1}^{T} l_{it}(w_i) \frac{\phi(w_i)}{\sigma_w} dw_i \right)$$

The maximization of this likelihood function is performed using the GAUSS software *maxlik* procedure. A Gauss-Hermite quadrature is used to approximate numerically the integral appearing in the log-likelihood function.[15] Formally our model is close to a Tobit type 2 model. So all parameters of the model are statistically identified (see Amemiya, 1984).

3.3 Identification issues

The model raises several identification issues that are discussed in this section. In particular, we argue that the model is able to disentangle the influence of the minimum wage on prices in spite of the seasonality affecting both of them.

A first concern is that the degree of variability in minimum wage increases is limited. The distribution of legal minimum wage changes, occurring each year in July, has a narrow support during the period we consider (see Figure 2). However, this is a limited concern *per se* since a discrete support does not impede identifiability. In addition, in our model, the right-hand

[15] We use 40 points of integration on the interval $[-10; 10]$.

side variable is the cumulative increase in the minimum wage since the last price change. This induces a much wider support and a higher dispersion (the distribution of this right-hand side variable is represented in Appendix A.1) and favors identification of the minimum wage effect on prices.

Second, a specific concern here is that minimum wage systematically increases every year in July. Using OLS time series regression to disentangle the effect of “minimum wage” changes from any seasonal “July” effect would be difficult because the identification would rely on: (i) the fact that the size of increase varies across years, (ii) there is one episode of increase in May and (iii) there are episodes of reduction in social security contribution.[16] However, here the relevant variable is the cumulative increase in the minimum wage since the last price change, which strongly reduces collinearity between seasonal dummies and the relevant labor cost variable. Indeed, in our data, while the correlation in the time dimension between the minimum wage increases and the July dummy variable is high (0.43 for traditional restaurants and 0.34 for fast-food restaurants), the correlation between spell-specific cumulative increases and dummies is only 0.15 for traditional restaurants and 0.18 for fast-food restaurants. Another identification issue comes from the fact that prices tend to change more frequently in September, suggesting either a seasonal menu cost or a two-month systematic lag. This latter hypothesis can be questioned by looking at our individual data since, for the average restaurant, the price duration is larger than one year and close to 2 years (see Table 1). This suggests that firms do not adjust two months after a minimum wage increase but more than one year after.

A last issue is related to parameter identification in bivariate sample selection models. Our model consists of two equations: one for the decision of price change and one for the size of the price change. A theoretical result is that the parameters of this class of models are identified without any restriction on the regressors. However, if exactly the same regressors appear in both equations, the model is still identified but the identification relies on functional form assumptions (Wooldridge, 2002). Here, we implement exclusion restrictions which strengthen the identification of the model. The first one is related to the euro cash change-over. Economic theory indeed strongly points out that a change in *numéraire* should not influence the long

[16] The comparison of our approach with time series linear regression is developped in details in section 5.

run real prices or the mark-up ratio and relative price levels. It is thus natural to exclude this variable from the size of price change equation. On the other hand, theory tells us that to the extent that the change in *numéraire* entails menu costs, it is very much predicted to influence the probability of a price change (as argued in Hobijn *et al.* 2006). We also argue that seasonality provides a relevant restriction: there exists some seasonality in menu costs (due to institutional factors like timing of holidays and accounting periods, see Müller *et al.* (2009), Woodford (2003) and Zbaracki *et al.* (2004), and our Section 2.1). This seasonality only affects the menu costs which play a role in the first equation only. Besides, since we control for demand, the price level should not be expected to depend *per se* on seasonality (see above our Section 2.1).

4 Empirical results

Table 3 reports estimation results for menus in traditional restaurants while Table 4 reports those for menus in fast-food restaurants. Parameter estimates associated with the estimation of $\Delta_\tau p^*_{i,t}$ (equation (2)) are displayed in the first column of these tables, while those associated with C^+_{it} and C^-_{it} (equation (3)) are displayed in the second and third columns of these tables.

[Tables 3 & 4]

4.1 Minimum wage effect

The effect of the minimum wage on restaurant prices is significant for both traditional and fast-food restaurants. A minimum wage rise increases the probability of a price increase in both traditional and fast-food restaurants, but it decreases the probability of a price decrease in fast-food restaurants. This result is in line with theoretical results of state-dependent pricing models. The minimum wage thus triggers a selection effect in restaurants that change their prices, which influences the dynamics of the pass-through (see the next section). The effect of the minimum wage on the size of the price change is noticeable. In traditional restaurants, after a 1% minimum wage increase, prices that change are increased by 0.08%. In fast-food restaurants, the elasticity of price increases with respect to the minimum wage is similar, since it is equal to 0.117. Estimates are less precise than those obtained for traditional restaurants;

this may be due to the sample size, which is substantially smaller for fast-food restaurants. We therefore cannot reject the assumption that the elasticity is the same in both types of outlets.

Using aggregate data for France, we are able to compare these results with benchmark estimates obtained from a proxy of the share of compensations of workers paid at the minimum wage in total restaurant costs (Table 5). According to available sources, the share of these labor costs in restaurant total costs lies between 33% and 46% in fast-food restaurants and is equal to 40% in traditional restaurants. The share of minimum wage compensations in the wage bill is approximately 32% in fast-food restaurants and 31% in traditional restaurants. Computing the effect of the minimum wage on costs as the product of these numbers, we find an elasticity between 0.10 and 0.15 for fast-foods and equal to 0.12 for traditional restaurants. Taking into account the share of black market labor (estimated to be 12%, see above), the range is lowered to values comprised between 0.09 and 0.13. If we now take into account potential spillover from minimum wage increases to other wages, we obtain 0.15 for traditional restaurants and a range of estimates between 0.13 and 0.18 for fast-food restaurants. Our econometric results are lower but consistent with these benchmark estimates.

[Table 5]

The estimated effects we obtain are somewhat higher than those found in previous studies on US data by Aaronson (2001), MacDonald and Aaronson (2006) or Aaronson and French (2007). These studies show that the cumulated effect of a 1% increase in the minimum wage on restaurant prices lies between 0.04% and 0.08%.[17] This gap between US and French results is explained by the lower share of labor costs in restaurants's total costs in the US (31% in full-service restaurants and 25% in limited-service restaurants,[18] versus 40% in traditional restaurants and 33% in fast-food restaurants in France) and the lower share of minimum wage compensations in the wage bill in the US (17% versus more than 30% in France; see Aaronson and French, 2007).[19]

[17] Using US input-output data, Lee and O'Roark (1999) find higher elasticities, between 0.08 and 0.12.

[18] See Aaronson and French, 2007.

[19] This is partly explained by the lower share of employees paid at the minimum wage in the United States (23% versus more than 40% in France; see Aaronson and French, 2007).

4.2 Effects of input prices and demand

As expected, food input prices have a significant and positive effect on the variations of the optimal price Δp^*. The elasticities of restaurant prices with respect to input prices are quite different for traditional and fast-food restaurants. They stand around 0.22 and 0.48 for traditional restaurants and fast-foods restaurants, respectively. Parsley and Wei (2007) find that the share of food input costs in total costs is around 32% for Big Mac hamburgers. Using national accounts, the share of intermediate consumption (which include food inputs) in total costs is around 60% in the restaurant industry. Our estimation results appear to fall in the range of these benchmark estimates.

We find that demand has also a positive impact on Δp^* in the case of fast-food restaurants, and a negative effect in the case of traditional restaurants. In the latter case this might reflect a counter-cyclical mark-up. Bils (1987) shows empirically that mark-ups could be counter-cyclical. Portier (1995) and Chatterjee *et al.* (1993) propose models of procyclical entry in which the addition of new firms during booms causes mark-ups to fall (Rotemberg and Woodford, 1999).

In traditional restaurants, the effect of a change in the VAT rate on Δp^* is asymmetrical.[20] A VAT increase has a strong positive effect, but a VAT decrease has a negative but smaller (in absolute terms) effect on Δp^*. The 2% increase in the VAT rate in 1995 is estimated to have triggered a price increase of 4.2%, whereas after the 1% reduction in the VAT rate in 2000, prices that were modified decreased by 1%.

Finally, we can remark that the estimates for the variance of idiosyncratic shocks associated with Δp^* are large (6.4 for traditional restaurants and 5.9 for fast food restaurants). This result may be linked to the recent findings on the importance of idiosyncratic shocks in state-dependent models to explain large price adjustments (Golosov and Lucas, 2007).

[20] Because the standard VAT rate is only marginally relevant in the case of fast-food restaurants we do not include it in the model. When including dummies for VAT changes, results are unaffected and these dummies are statistically non-significant.

4.3 Seasonality and the euro

We now discuss the effects of the variables that are assumed to affect only the decision to revise prices, but not the target price level. These variables are dummy variables indicating the specific months of the year and the euro cash changeover.

The effect of month dummies is quite consistent with the descriptive evidence that we have previously reported. In traditional restaurants, C^+ is lower in September, January and to a lesser extent May, than in other months, all other things being equal. This means that the probability of a price change is significantly higher during these months. In December, this probability is lower than in other months. In fast-food restaurants, managers are more likely to increase their prices in January, July Au gust and December and less likely to increase in October. They are more likely to decrease their prices at the end of the year. This might reflect the discrete-time nature of the price revision process in restaurants: specific periods of the year are more likely to be devoted to price-change decisions, because, during these periods, managers have more time to collect information or think about the "optimal" price change.

The effect of the euro cash-changeover is quite different for the two different items. Descriptive statistics show that, in traditional restaurants, price decreases are rarely observed during the euro cash changeover, while many prices increased just before and just after January 2002. Our estimation confirms this insight. For fast-food restaurants, the frequency of price changes increased in January 2002, but neither before nor after. Hobijn *et al.* (2006) propose a menu cost interpretation for the inflationary effect of the euro cash changeover in restaurants that can rationalize such a pattern. With fast-food restaurants data, the estimated effect on the frequency of price changes is rather symmetrical. Our estimates show that the probabilities of price increases and decreases rose simultaneously in January 2002, implying no overall inflationary effect.

The variances of idiosyncratic shocks on C^+ or C^- are much lower than those obtained for Δp^* (0.39 for traditional restaurants and 0.36 for fast food restaurants). Thus, seasonal variations appear to capture most of the variability in the adjustment costs as suggested by Woodford (2003) or Zbaracki *et al.* (2004).

4.4 Overall fit of the model

We now test the goodness of fit of our model by assessing its ability to match some aggregate moments of the data. More specifically, we compute three groups of indicators from the estimated model: the frequency of price changes, the size of price changes and the inflation rate. For this purpose, we run Monte Carlo simulations on the basis of our parameter estimates. Explanatory variables are taken at their sample values. More specifically, we simulate price trajectories and compare the aggregate results obtained with those observed. To obtain standard errors for simulated moments, we repeat the simulation exercise a number of times by drawing several sets of parameters from their estimated asymptotic distribution.[21]

[Table 6]

Results are presented in Table 6. Frequencies of price changes are slightly overestimated. For traditional restaurants, we obtain an overall frequency of 4.1%, whereas the frequency of price changes is only 4.2% in the data; for fast-food restaurants, the simulated frequency of price changes is equal to 10.5%, versus 9.4% in the sample. Standard deviations are quite small: around 0.1 percentage point for traditional restaurants and 0.3 percentage point for fast-food restaurants.

The average sizes of price changes are well replicated. The average sizes of price increases estimated with our model are equal to 3.4% in fast-food restaurants and 4.3% in traditional restaurants versus respectively, 3.3% and 4.3% in the sample. For price decreases in fast-food restaurants, the model slightly overestimates the size of price changes. Figure 5 displays the simulated and actual distributions of price changes for both items. First, the model captures the asymmetry of both distributions. However, our model, reflecting its similarity with a menu-cost model, fails to fully account for the share of small price changes observed in the data. One rationalization for small price changes has been put forward by Midrigan (2007) and relies on price setting behavior by a multiproduct firm. Assuming that a restaurant faces a fixed cost of reprinting the menu, any large deviation from the optimal price for one single item gives rise to a free opportunity to reset price for all items in the menu. In such circumstances, one may

[21] The Monte Carlo experiments are described in more detail in section 5.1.

observe small price changes of several items. Our model cannot capture such a rationalization for small price changes since we have sampled one item (the main menu) in each outlet. However the degree of within-outlet synchronization in price changes across items appears to be quite limited in our data which suggests that the multiproduct argument does not fully rationalize the occurrence of small price changes here.[22]

[Figure 5]

The estimated inflation rate, which is obtained by averaging price changes at each date, is rather well reproduced by our model. The average simulated monthly inflation rates are 0.171% and 0.166% in traditional and fast-food restaurants while the observed rates are respectively 0.134% and 0.135%.

5 Aggregate implications of the model

Our estimates are now used to examine the aggregate effects of minimum wage changes on the price level in restaurants. Due to the non-linearity of our model as well as the heterogeneity incorporated in our specification, the aggregate dynamics following a shock are non-trivial. We thus investigate them through simulations. We illustrate the implications of our model by comparing them with the predictions of a simpler, partial-adjustment linear model, which is fitted to aggregate data.

5.1 Assessing the impact of a minimum wage increase

The dynamic effect of a minimum wage increase on prices is assessed by conducting the following simulation experiment. First, as in section 4.4, we simulate individual price trajectories by inserting our estimates in the system of equations (2) - (3). Shocks $\varepsilon^{p}_{i,t}$, $\varepsilon^{C+}_{i,t}$, and $\varepsilon^{C-}_{i,t}$ are drawn from three i.i.d. normal distributions with mean 0 and variances equal to the estimated variances.

[22] For instance, among the restaurants for which the prices of three items are collected, the monthly frequency of a single price change is 4.8%; the frequency of two simultaneous price changes is 1.9%, and 1.0% for three simultaneous price changes.

Paths for covariates are identical to their sample trajectories. To obtain more accurate and smoother response functions, we simulate 40 trajectories for each actual sample trajectory. We then aggregate all these individual price trajectories to compute a single path for the price level. Second, we reiterate the experiment with the same set of random shocks, but now assume that the minimum wage is permanently above its baseline trajectory as from July 1998. Three different scenarios are considered, corresponding to increases of 1%, 2% and 5% respectively. Finally, we compare the alternative scenarios by computing differences in aggregate price levels between the benchmark and each alternative scenario. This exercise provides only partial equilibrium results, since we assume the exogeneity of the minimum wage with respect to restaurant prices, and we assume other covariates (producer prices, demand) to be unaffected by the shock on the minimum wage. We view these assumptions as reasonable approximations.[23]

[Table 7]

The main results of our simulation exercise are gathered in Table 7, as well as in Figures 6 and 7. Taking as a benchmark the case of a 1% increase, we observe that the long-run impact of the shock on the minimum wage is to raise the price level by 0.130% in fast-food restaurants and by 0.097% in traditional restaurants. These results are quite consistent with the estimated value of the parameter β_1 associated with the minimum wage. There appears a mild non-linearity, since the impact of a 5% shock is slightly lower than five times the impact of a 1% shock. The long-run impact of a minimum wage increase on restaurant prices is also in line with the one that we would recover using a simple benchmarking exercise based on national account statistics (see subsection 4.1).

[Figure 6]

A striking result is that the impact of the minimum wage change on restaurant prices is very protracted. For traditional restaurants, after 14 months, only half of the long-run response

[23] As a crude test, we run Granger causality tests and we reject that monthly inflation in restaurants causes overall monthly inflation and minimum wage changes. We also reject that minimum wage causes food input inflation. Non-causality between demand and restaurant prices cannot be fully rejected.

has been materialized. After two years, only 75% of the long-run effect is completed. In the case of fast-food restaurants, adjustment is faster but still very slow: the half-life of the shock is 6 months, and after 12 months, 75% of the effect has been materialized. This protracted adjustment means that, each month, only a small fraction of restaurants decides to revise their prices. Part of the adjustment operates at the extensive margin, a point illustrated by Figure 6. After a shock, the fraction of restaurants revising their price rises. By contrast, in Calvo's model, this fraction is constant. Since, here, the fraction of restaurants revising their price depends on covariates, the speed of adjustment varies with the size of the shock. Indeed, with a 1% shock on the minimum wage, the share of traditional restaurants adjusting their prices rises by 0.10 percentage point in the first month. These effects are larger in fast-food restaurants, the effect is 0.25 percentage point in the first month after a 1% minimum wage shock (Figures 6).

5.2 Comparison with linear aggregate models

We compare the results obtained above with those resulting from a linear time series model fitted to our aggregate data. One motivation for this exercise is provided by the methodology and results proposed by Aaronson (2001), who estimates a linear model of restaurant price indices to assess the impact of lagged, present and future values of the minimum wage on prices.[24] He finds a significant and rapid impact of the minimum wage on the prices set by different types of restaurants in the US and Canada.[25]

Tables 8 and 9 report the estimates of various autoregressive distributed lag (ARDL) models for fast-food and traditional restaurants respectively. The general specification is the following:

$$\overline{\Delta p}_t = c + \sum_{k=-F}^{K} \alpha_k \Delta w_{t-k} + \sum_{k=1}^{L} \theta_k \overline{\Delta p}_{t-k} + \sum_{j=1}^{J} \mu_j z_{j,t} + \varepsilon_t$$

where $\overline{\Delta p}_t$ is the sectoral inflation rate (computed as a simple average of individual price changes) and $z_{j,t}$ is a set of covariates (seasonal dummies, dummy variables for the euro cash changeover

[24] Wolfson and Belman (2004) use comparable time-series analysis at the industry level and find no significant effect of the minimum wage on employment in the US.

[25] The relation between the minimum wage and the overall CPI in France has been analyzed by L'Horty and Rault (2004) who estimate a VAR model.

period, the growth rates of demand and of food producer prices). We investigate various specifications, with and without seasonal dummies, and with various lags and leads of the minimum wage. In the case of traditional restaurants, results reported in Table 8 show that these covariates are often significant: the dummy variables corresponding to the VAT increase and to the euro area changeover period, as well as autoregressive terms, are systematically significant. The results are sensitive to the inclusion of seasonal dummies. The impact of the minimum wage is not clear-cut: only the second lag is systematically significant (see Table 8). The long-run effect of a permanent 1% increase in the minimum wage is estimated to be comprised between 0.015 and 0.148, i.e. somewhat lower than the effects obtained in the previous subsection by aggregating microeconomic behaviors.

Results for fast-food restaurants are reported in Table 9. Only a few variables appear to explain changes in the aggregate price level. When seasonal dummies are included, the contemporary effect of the minimum wage increase is significant but its lag has a negative sign. Overall, the estimated long-run impact of a variation in the minimum wage is very small. It is even negative under some specifications.

[Figure 7]

Thus, the predictions of the linear model are rather at variance with those obtained in previous microsimulations. To understand these differences, it should first be noted that the linear model does not disentangle strong seasonality effects from the effect of a change in the minimum wage (an expected problem since most changes in the minimum wage level occur in July, see section 3.3). Unlike what happens with US data (Aaronson, 2001), there are in France no geographical or within-year variations in the timing of minimum wage changes that would help for identification. Moreover, the above results illustrate the fact that a linear aggregate model may not adequately capture the protracted adjustment resulting from individual lumpy behaviors, a property analyzed by Caballero and Engel (2003). Micro estimates tend to point to slower adjustment than what macro estimates show. This is clearly suggested by the graphs in Figure 7. These graphs compare the impulse responses of a shock on the minimum wage for the two estimated models. For fast-food restaurants, the linear model predicts an immediate adjustment (to a long-run target close to zero). In the case of traditional restaurants, the aggregate linear model indicates that full adjustment is almost complete (90%) after 20 months, while reaching the same relative adjustment requires 35 months according to the aggregate micro process (see Table 7).

The analytical results obtained by Caballero and Engel (2003) help provide an understanding of our results. These authors examine the performance of a partial adjustment model fitted to aggregated data for measuring the speed of adjustment, when micro-level data are actually governed by a simple lumpy adjustment model, namely a constant hazard (Calvo-type) process. They show that the aggregate model is asymptotically able to capture the probability of adjustment embodied in the Calvo process (namely, when the number of firms N is large and the sample period T is long). However, when N and T are small or moderate, the speed of adjustment is overestimated by a linear aggregate model. In addition, the approximation provided by the linear partial adjustment model is particularly poor when the probability of adjustment is low. All these mechanisms appear to be present here, especially in the case of traditional restaurants, for which the probability of a price change is close to 5%.

Our empirical model is somewhat more complex than the analytical framework considered by Caballero and Engel (2003). For instance, our model contains an additional element of non-linearity. More precisely, our specification for the probability of a price change is able to respond to a deviation from the target variable (see equations (2) and (3)). Moreover, we have introduced several covariates as well as unobserved heterogeneity. As a consequence, the analytical results obtained by Caballero and Engel (2003) may not give a full picture of the mechanisms operating here. To further illustrate the relationship between lumpy adjustments at the individual level and aggregate dynamics in our set-up, we perform the following Monte Carlo experiment. We again use the model (2) and (3) as a data-generating process (DGP). We complete this DGP by estimating simple autoregressive processes for covariates, namely the demand variable as well as the producer price index for food. We also design a DGP for minimum wage changes in the following way: every month of July, the minimum wage increase is drawn randomly from a uniform distribution with support $[2\% - 5\%]$. This mimics the actual process for changes in the minimum wage. With this complete DGP, we are able to simulate trajectories of individual and aggregate prices for an arbitrary number of economic units N and time periods T. We then simulate trajectories both for the size of our sample ($T = 105$, $N = 2,948$ for traditional restaurants and $N = 448$ for fast-food restaurants) and for "large" T and N ($T = 1,000$, $N = 10,000$). In a further step, we use the artificial data thus generated to compute an aggregate price index, and use artificial aggregate data to estimate a linear model. This exercise, which is in the spirit of that conducted by Attanasio (2000), provides us with the asymptotic predictions of a linear approximated model when the DGP is given by the individual lumpy adjustment process.[26]

Results are provided in Tables 10 and 11. First, these experiments confirm that, with a small sample, it is difficult to recover the effects of a minimum wage increase when using the linear aggregate specification.[27] For both types of restaurants, the simulated mean impact (0.09 in traditional restaurants and 0.10 in fast-food restaurants) are quite consistent with the DGP parameters but these estimates are associated with very high standard deviations (0.211 for traditional restaurants and 0.165 for fast-food restaurants).[28] The pseudo-true values derived with a large sample ($T = 1,000$ and $N = 10,000$) are close to the true elasticity.

Second, we confirm that the aggregate model dramatically overestimates the adjustment speed, as can be inferred for example from the sum of the autoregressive parameters. In respectively fast-food restaurants and traditional restaurants, the sum of the AR parameters is equal to 0.40 and 0.77 in the model fitted to actual data and to 0.66 and 0.82 in the Monte Carlo "small sample" case. By contrast, in the Caballero-Engel set-up, we would expect this persistence parameter to be close to $1 - \lambda$, where λ is the frequency of price changes. In restaurants, the frequency ranges between 5 and 10% (see Table 6). Note that the bias partly vanishes in the asymptotic simulations, where the sum of the autoregressive parameters is equal to 0.86 for

[26] In accordance with the econometrics of misspecified models, the probability limits of the parameters can be labeled "pseudo-true values".

[27] The poor performance partly reflects the restriction to one specific class of time series models, namely ARDL models. As suggested by Caballero and Engel (2003), the performance of an aggregate model may be improved by incorporating, say, moving average terms in the model. We stick to the ARDL since it is the class of models used in the empirical studies of price pass-through.

[28] We run 200 simulations.

fast-food restaurants and 0.92 for traditional restaurants.

In sum, this exercise illustrates that a linear aggregate model is bound to be a poor approximation. Although the source of the imprecision is the non-linearity and the individual heterogeneity present in the underlying process, it is amplified by the limited size of the available sample.

6 Conclusion

In this paper, we have used a unique dataset of individual price quotes to assess the impact of the minimum wage on prices both in traditional and fast-food restaurants. Given that, in this sector, price changes are scarce, we have adopted an empirical model that features lumpy adjustment. Using this framework, we provide arguably better identified estimates of the impact of the minimum wage on prices.

We find that the minimum wage has a positive and significant impact on prices in traditional and fast-food restaurants. The estimated elasticity of prices with respect to the minimum wage is around 0.10 for both types of outlets. This impact is consistent with the share of minimum-wage compensations in total costs that can be estimated with macroeconomic data. This elasticity is higher than that found by MacDonald and Aaronson (2006) for the US. This presumably reflects the lower fraction of workers paid the minimum wage in U.S. restaurants (25% in the U.S. versus more than 40% in France).

Taking into account lumpiness in the microeconomic adjustment of prices, we exhibit such a protracted impact of the minimum wage on aggregate prices. The aggregate impact estimated with our model typically takes more than a year to pass through to retail prices. We show that such protracted impact is difficult to capture using aggregate data. In terms of price rigidity, our results indicate that, although one main reason for restaurant price stickiness is that one important determinant of the cost (namely, the minimum wage) changes infrequently, there is also a substantial degree of “intrinsic” stickiness. Price stickiness is not a mere reflection of cost stickiness. In addition, our results point to the crucial role of non-linearity and individual heterogeneity in inflation dynamics.

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8 Tables and figures

Table 1: Monthly frequency of price changes (%)

	Sample size	Price changes	Price increases	Price decreases	Implied average price duration
Traditional restaurants	93,816	4.16	3.80	0.36	24.04
Fast-food restaurants	10,726	9.41	7.07	2.34	10.63

Note: the implied average price duration (in months) is calculated as the inverse of the monthly proportion of price changes.

Table 2: Size of price changes (%)

		Sample size	Δp_{90}	Δp_{75}	Δp_{50}	Δp_{25}	Δp_{10}	Δp_{av}
Traditional restaurants	Δp^-	340	-13.36	-8.54	-3.95	-1.30	-0.26	-6.09
	Δp^+	3,909	8.00	5.25	3.18	1.65	0.30	4.34
Fast-food restaurants	Δp^-	269	-7.55	-5.09	-2.78	-0.95	-0.55	-3.74
	Δp^+	844	5.88	3.66	2.82	1.29	0.34	3.35

Note: In the calculations, price changes equal to zero are not taken into account. Price increases Δp^+ and decreases Δp^- are considered separately. Δp_{90} is the 90th percentile of the distribution; Δp_{75} is the 75th percentile of the distribution; Δp_{50} is the median of the distribution; Δp_{25} is the 25th percentile of the distribution; Δp_{10} is the 10th percentile of the distribution; Δp_{av} is the average price change.

Table 3: Parameter estimates: traditional restaurants

$\Delta_\tau p^*_{i,t}$			C^+_{it}		
Notation	Covariate	Estimate	Notation	Covariate	Estimate
β_0	Constant	-10.072 (0.320)	β_2^+	January	1.624 (0.137)
β_1	Food PPI	0.225 (0.037)		February	1.989 (0.126)
	Min. wage	0.080 (0.015)		March	1.817 (0.119)
	Demand	-0.114 (0.023)		April	1.961 (0.137)
	VAT increase	4.210 (0.315)		May	1.744 (0.118)
	VAT decrease	-0.990 (0.500)		June	1.907 (0.139)
				July	1.913 (0.148)
				August	1.919 (0.147)
				September	1.615 (0.151)
				October	2.008 (0.132)
				November	2.101 (0.124)
				December	2.512 (0.158)
				Pre Euro	-1.111 (0.177)
				Euro	-3.368 (0.488)
				Post Euro	-1.366 (0.192)
σ_w		0.452 (0.019)	α		-1.139 (0.194)
σ_p		6.382 (0.144)	σ_c		0.390 (0.040)

Value of the log-likelihood function =-8.231

Sample size: 93,816

Table 4: Parameter estimates: fast-food restaurants

$\Delta_\tau p^*_{i,t}$			C^+_{it}			C^-_{it}		
Notation	Covariate	Estimate	Notation	Covariate	Estimate	Notation	Covariate	Estimate
β_0^+	Constant	-8.266 (0.319)	β_2^+	January	0.470 (0.172)	β_2^-	January	-1.256 (0.002)
β_0^-	Constant	10.308 (0.369)		February	0.713 (0.168)		February	-1.002 (0.002)
β_1	Food PPI	0.479 (0.066)		March	1.011 (0.199)		March	-0.860 (0.002)
	Min. wage	0.118 (0.031)		April	1.043 (0.163)		April	-1.465 (0.002)
	Demand	0.246 (0.048)		May	0.795 (0.156)		May	-1.380 (0.002)
				June	0.784 (0.188)		June	-1.319 (0.002)
				July	0.468 (0.127)		July	-1.319 (0.002)
				August	0.418 (0.132)		August	-1.266 (0.002)
				September	0.602 (0.135)		September	-0.713 (0.002)
				October	1.153 (0.207)		October	-1.102 (0.002)
				November	1.024 (0.180)		November	-0.468 (0.002)
				December	0.138 (0.126)		December	-0.460 (0.003)
				Euro	-1.139 (0.358)		Euro	0.967 (0.005)
σ_w		0.571 (0.057)	α^+		1.389 (0.146)	α^-		0.047 (0.004)
σ_p		5.948 (0.170)	σ_{c+}		0.360 (0.076)	σ_{c-}		0.001 –

Value of the log-likelihood function = -11.0061

Sample size: 10,726

Table 5: Effects of a 1% minimum wage increase on prices: benchmark estimates

Firm size	Wage level	(1)	(2)	(3)	(4)	(5)	(6)
Traditional restaurants	Min. wage	0.12	0.40	0.31	1	0.11	0.11
	1.1× Min. wage	0.12	0.40	0.17	0.7	0.04	0.15
Fast-food restaurants	Min. wage	0.12	0.33	0.32	1	0.09	0.09
(Assumption 1)	1.1× Min. wage	0.12	0.33	0.17	0.7	0.03	0.13
Fast-food restaurants	Min. wage	0.12	0.46	0.32	1	0.13	0.13
(Assumption 2)	1.1× Min. wage	0.12	0.46	0.17	0.7	0.05	0.18

Note: Column (1) reports the share of workers in the black market for hotels and restaurants (ACOSS, 2006). Column (2) reports the share of labor cost in total cost (Assumption 1: French national sectoral accounts (1997-2002); Assumption 2: Parsley and Wei, 2007). Column (3) reports the share of the minimum wage compensations in the wage bill (DARES and French national sectoral accounts (1997-2002)). Column (4) gives the elasticity of wages just above the minimum wage with respect to minimum wage increases (Koubi and Lhommeau, 2006). Column (5) gives the effect of the minimum wage increase on total cost, *i.e.* col.(5) = (1-col(1)) × col.(2) × col.(3) × col. (4). Column (6) is the cumulated sum of the lines of column (5).

Table 6: Goodness of fit

		Size of price changes		Frequency of price changes		
	Inflation	Increase	Decrease	Increase	Decrease	Total
Traditional restaurants						
Simulated	0.171	4.257	−0.408	4.044	0.101	4.145
	(0.004)	(0.061)	(0.037)	(0.082)	(0.019)	(0.086)
Observed	0.134	4.336	-6.086	3.797	0.363	4.160
Fast-food restaurants						
Simulated	0.166	3.358	−3.243	7.640	2.869	10.510
	(0.012)	(0.079)	(0.077)	(0.256)	(0.168)	(0.300)
Observed	0.135	3.346	-3.739	7.070	2.335	9.405

Note: Numbers in brackets are standard deviations.

Table 7: Simulation results

	(1)	(2)	(3)	(4)	(5)
Traditional restaurants	1%	0.097	14	26	34
		(0.017)			
	2%	0.193	14	25	34
		(0.034)			
	5%	0.471	13	24	33
		(0.081)			
Fast-food restaurants	1%	0.130	6	12	19
		(0.032)			
	2%	0.257	6	12	18
		(0.063)			
	5%	0.623	5	11	18
		(0.147)			

Note: Numbers in brackets are standard deviations. Column (1) is the size of the shock on the minimum wage at t. Column (2) reports the cumulated impact after 57 months. Column (3) reports the duration (in months) corresponding to half of the total cumulated impact. Column (4) reports the duration (in months) corresponding to 75% of the total cumulated impact. Column (5) reports the duration (in months) corresponding to 90% of the total cumulated impact.

Table 8: Linear model estimated with aggregate data (traditional restaurants)

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.124**	0.052**	0.044**	0.094**	-0.008	0.044
Min. wage$_{t+3}$			-0.007*			0.002
Min. wage$_{t+2}$			0.003			-0.080
Min. wage$_{t+1}$			-0.005			0.015
Min. wage$_{t}$	-0.011**	-0.009**	0.004	-0.009	-0.003	-0.003
Min. wage$_{t-1}$	-0.002	0.001	0.000	-0.003	0.003	0.012
Min. wage$_{t-2}$	0.014**	0.017**	0.020**	0.013**	0.019**	0.008
Min. wage$_{t-3}$	-0.001	0.000	0.000	-0.001	-0.001	-0.012
Min. wage$_{t-4}$	0.000	-0.003	-0.004	0.009	0.008	-0.043**
Min. wage$_{t-5}$	-0.001	-0.003	-0.002	0.002	-0.002	-0.009
Min. wage$_{t-6}$	0.013**	0.014**	0.011**	0.005	0.005	-0.011
Inflation$_{t-1}$		0.130*	0.127*		0.198**	0.171**
Inflation$_{t-2}$		0.263**	0.268**		0.217**	0.240**
Inflation$_{t-3}$		0.202**	0.216**		0.331**	0.216**
Producer prices	0.009	0.005	0.019	0.007	0.001	0.016
Demand	0.004	0.005	0.007**	0.006	0.003	0.008
VAT increase	0.059	0.066	0.110	0.074	0.114**	0.115**
VAT decrease	-0.015	-0.049	-0.033	0.011	-0.004	-0.015
Pre Euro	0.139**	0.091**	0.100**	0.156**	0.088**	0.141**
Euro	0.662**	0.573**	0.597**	0.581**	0.453**	0.545**
Post Euro	0.021	-0.153**	-0.152**	0.034	-0.183**	-0.140**
Month dummies	N	N	N	Y	Y	Y
R-squared	0.653	0.720	0.786	0.733	0.826	0.856
Long-term impact	0.012	0.043	0.049	0.016	0.118	0.148

Note: statistical significance levels: **: 5%, *: 10%.

Table 9: Linear model estimated with aggregate data (fast-food restaurants)

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.136**	0.088**	0.090**	0.130	0.046	0.002
Min. wage$_{t+3}$			0.000			0.007
Min. wage$_{t+2}$			-0.016			-0.019
Min. wage$_{t+1}$			-0.014			-0.008
Min. wage$_{t}$	0.031*	0.036**	0.039**	0.035*	0.040**	0.044*
Min. wage$_{t-1}$	-0.032**	-0.036**	-0.046**	-0.037*	-0.041**	-0.062**
Min. wage$_{t-2}$	0.001	0.003	0.003	0.006	0.010	0.010
Mini. wage$_{t-3}$	0.015	0.023	0.020	0.005	0.017	0.015
Inflation$_{t-1}$		0.164	0.168		0.189*	0.198*
Inflation$_{t-2}$		0.182*	0.178*		0.199*	0.201*
Producer prices	0.051	0.045	0.057	0.079	0.070	0.069
Demand	0.009	0.008	0.007	0.013	0.003	-0.007
Euro	-0.091	-0.055	-0.051	-0.170	-0.157	-0.149
Month dummies	N	N	N	Y	Y	Y
R-squared	0.109	0.176	0.201	0.176	0.254	0.291
Long-term impact	0.015	0.039	-0.020	0.009	0.044	-0.023

Note: statistical significance levels: **: 5%, *: 10%.

Table 10: Aggregate results with simulated data (traditional restaurants)

	OLS - aggregate data $T = 105$ (1)	OLS - simulated data $T = 105, N = 2,948$ (2)	OLS - simulated data $T = 1,000, N = 10,000$ (3)
Min. wage$_t$	-0.003 (0.005)	0.006 (0.011)	0.004
Min. wage$_{t-1}$	0.003 (0.004)	0.004 (0.011)	0.005
Min. wage$_{t-2}$	0.019 (0.005)	0.003 (0.009)	0.002
Mini. wage$_{t-3}$	0.001 (0.005)	0.002 (0.012)	0.001
Min. wage$_{t-4}$	0.009 (0.005)	0.001 (0.012)	-0.001
Min. wage$_{t-5}$	-0.001 (0.005)	0.000 (0.011)	0.000
Min. wage$_{t-6}$	0.004 (0.005)	0.001 (0.012)	0.000
Inflation$_{t-1}$	0.174 (0.080)	0.343 (0.109)	0.508
Inflation$_{t-2}$	0.194 (0.088)	0.198 (0.109)	0.167
Inflation$_{t-3}$	0.298 (0.095)	0.158 (0.114)	0.161
Inflation$_{t-4}$	0.101 (0.075)	0.119 (0.100)	0.079
Month dummies	Y	Y	Y
Long-term impact	0.137	0.092 (0.211)	0.071

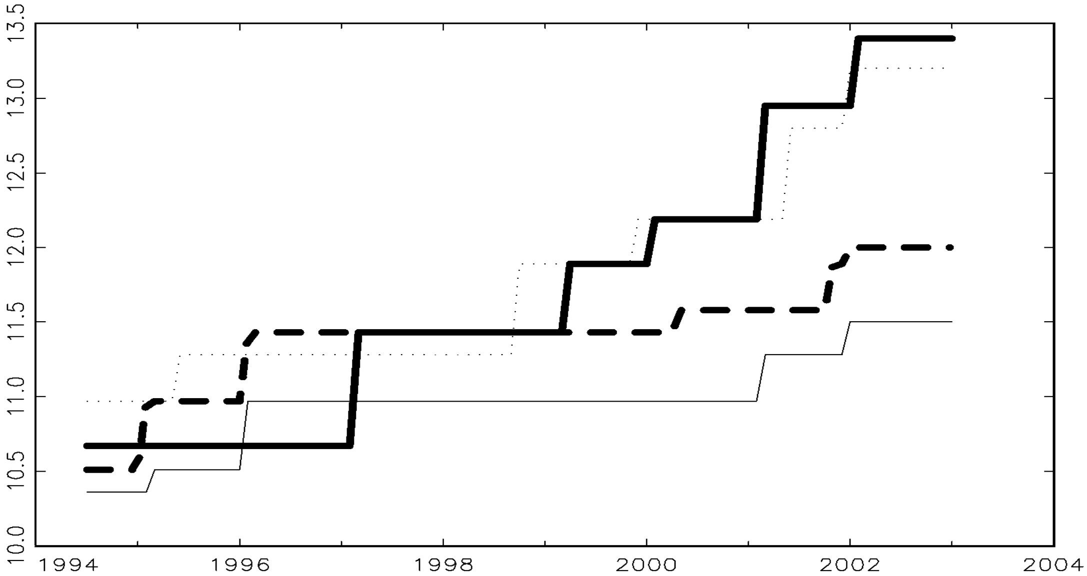
Note: Column (1) reports the OLS estimates obtained with actual aggregate data. Column (2) reports the OLS estimates obtained with aggregate simulated data and a small sample size ($T = 105$, $N = 2,948$). Here the probability of a price change is endogenous. Column (3) reports the OLS estimates with aggregate simulated data and a large sample size ($T = 1,000$, $N = 10,000$).

Table 11: Aggregate results with simulated data (fast-food restaurants)

	OLS - aggregate data $T = 105$ (1)	OLS - simulated data $T = 105, N = 448$ (2)	OLS - simulated data $T = 1,000, N = 10,000$ (3)
Min. wage$_t$	0.040 (0.019)	0.018 (0.034)	0.019
Min. wage$_{t-1}$	-0.040 (0.020)	0.009 (0.032)	0.000
Min. wage$_{t-2}$	0.010 (0.024)	0.003 (0.029)	0.000
Min. wage$_{t-3}$	0.016 (0.024)	0.002 (0.032)	-0.002
Inflation$_{t-1}$	0.184 (0.112)	0.327 (0.100)	0.775
Inflation$_{t-2}$	0.194 (0.115)	0.187 (0.100)	0.105
Inflation$_{t-3}$	0.022 (0.110)	0.145 (0.094)	-0.020
Month dummies	Y	Y	Y
Long-term impact	0.043	0.096 (0.165)	0.112

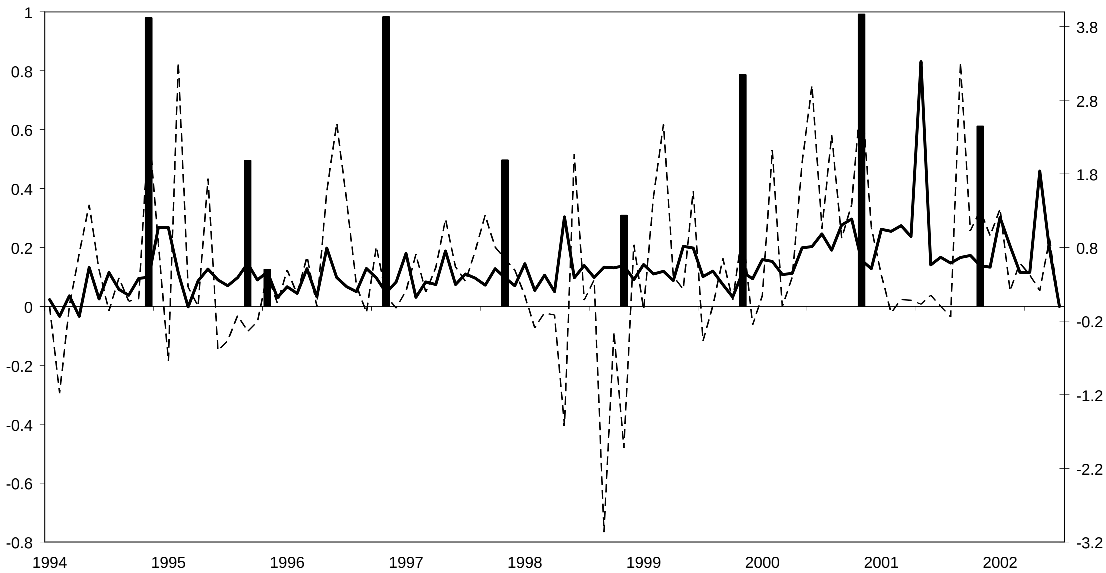
Note: Column (1) reports the OLS estimates obtained with actual aggregate data. Column (2) reports the OLS estimates obtained with aggregate simulated data and a small sample size ($T = 105$, $N = 448$). Here the probability of a price change is endogenous. Columns (3) reports the OLS estimates with aggregate simulated data and a large sample size ($T = 1,000,\ N = 10,000$).

Figure 1: Examples of price trajectories



Note: each line corresponds to a price trajectory for a menu in a restaurant, prices are expressed in euros.

Figure 2: Inflation in restaurants and fast-foods and minimum wage increases



Note: Solid line, left scale: monthly inflation in restaurants. Dashed line, left scale: monthly inflation in fast-food restaurants. Bars, right scale: monthly minimum wage increases.

Figure 3a: Frequency of price changes in traditional restaurants

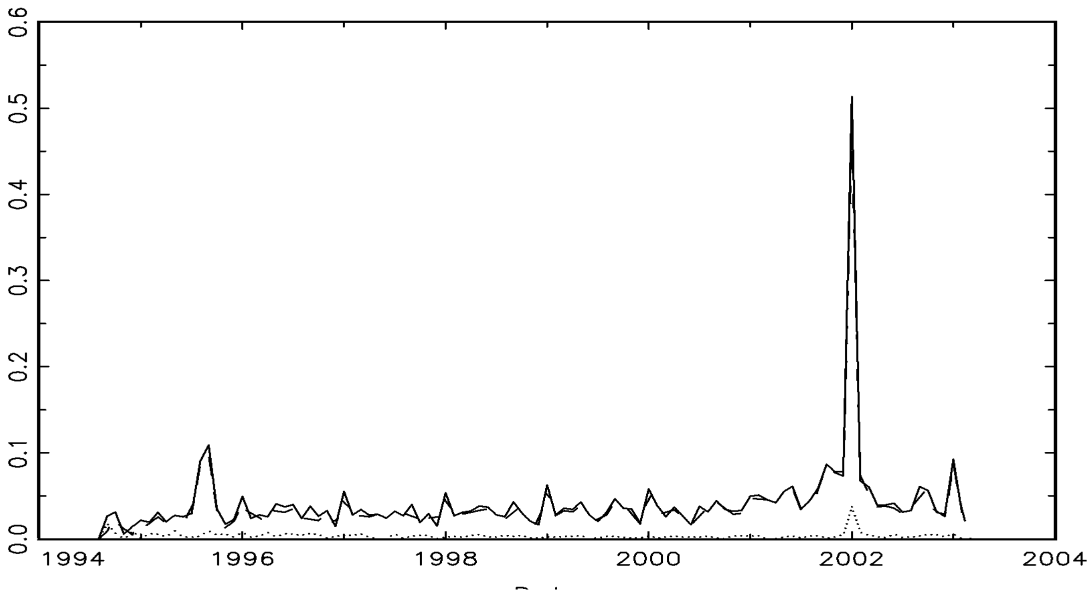
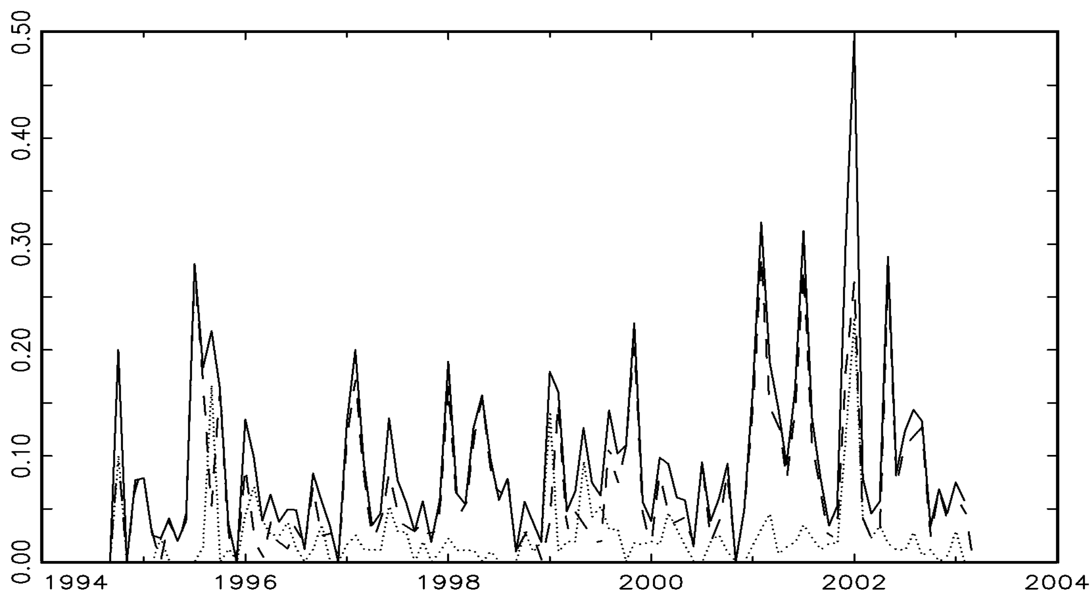
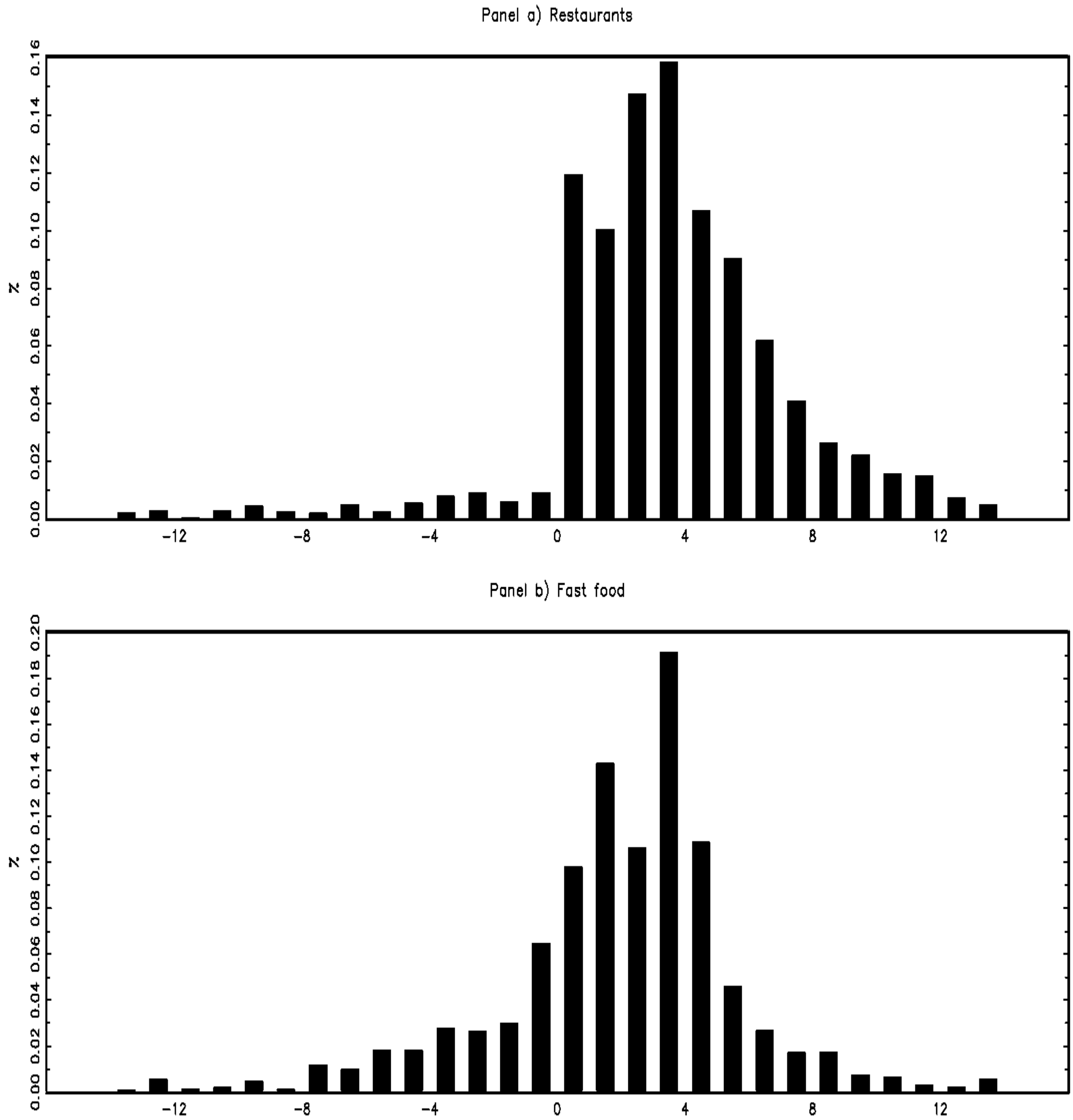


Figure 3b: Frequency of price changes in fast-food restaurants



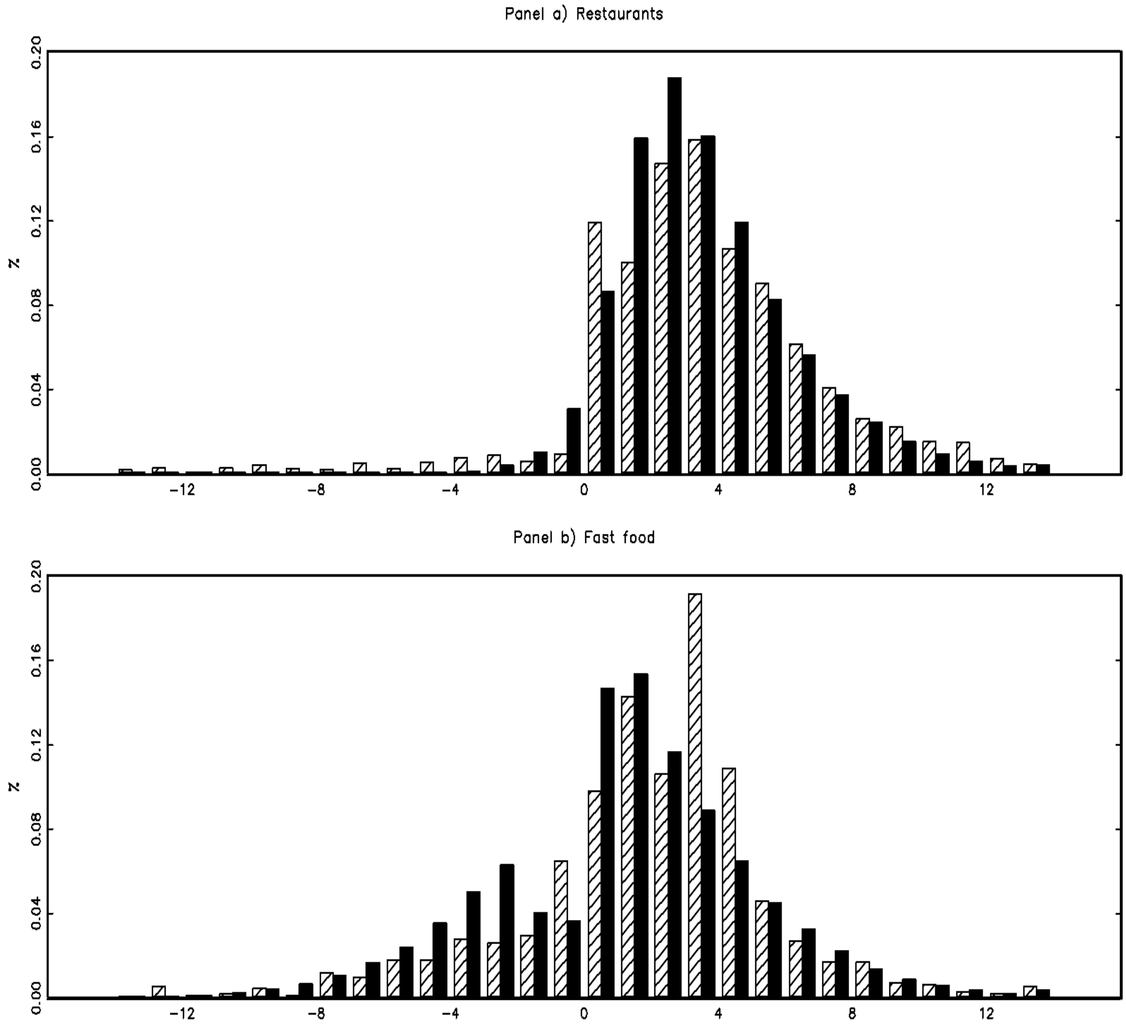
Note: Solid line: Frequency of price changes. Dashed line: Frequency of price increases. Dotted line: Frequency of price decreases

Figure 4: Distribution of price changes



Note: Price changes equal to zero are not taken into account.

Figure 5: Actual versus simulated price change distributions



Notes: Black bars: simulated price change distribution. Dashed bars: actual price change distribution.

Figure 6a: Impact of a minimum wage increase on the frequency of price changes in traditional restaurants

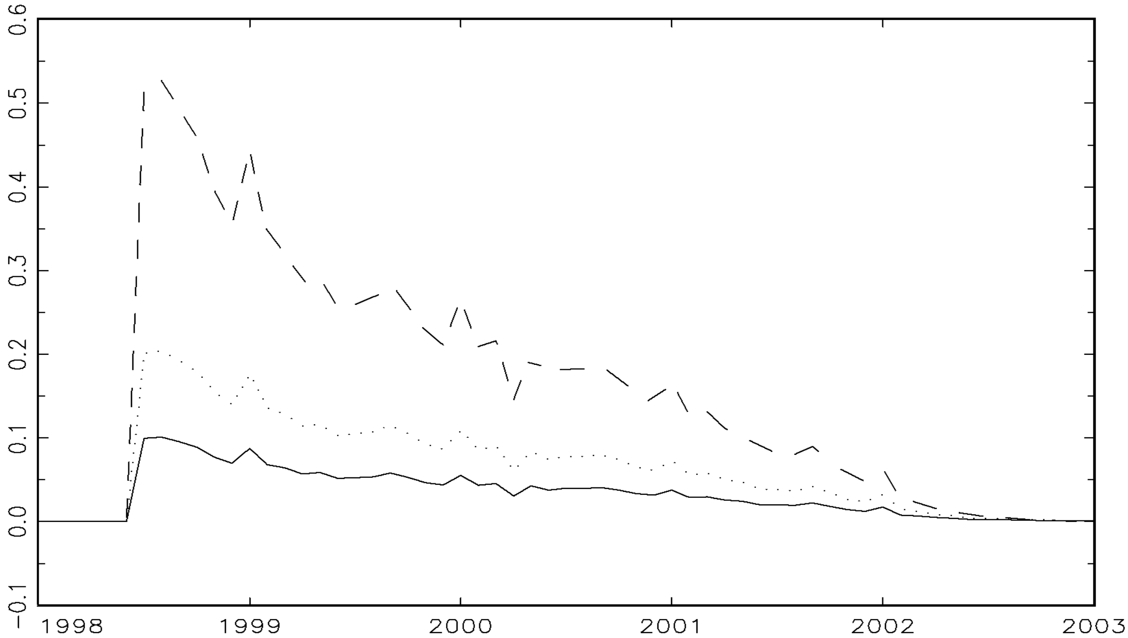
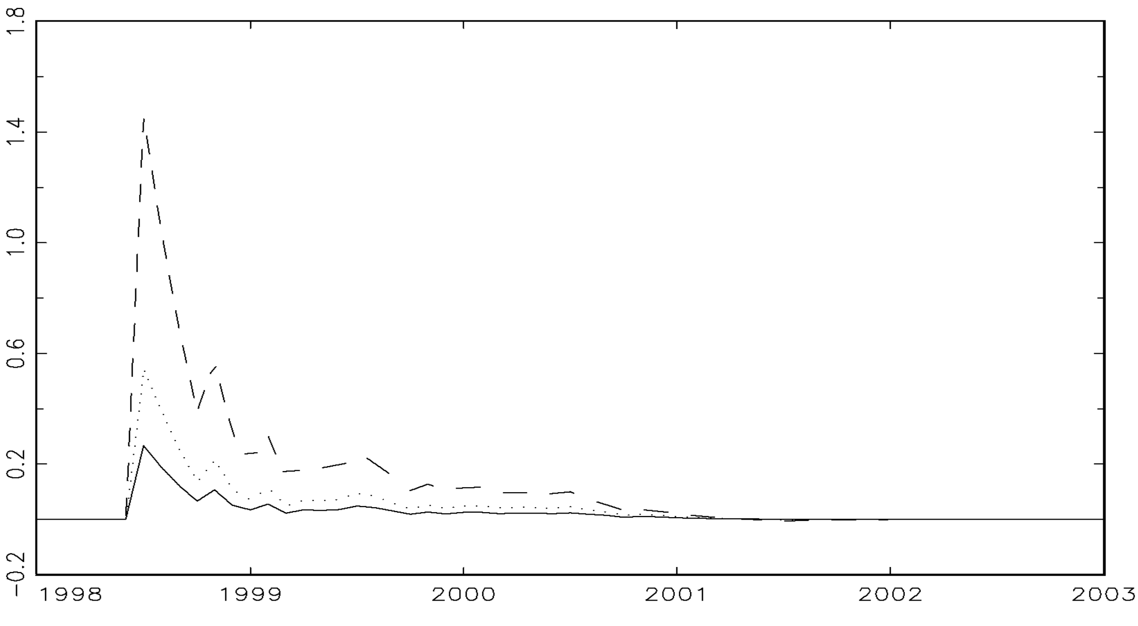


Figure 6b: Impact of a minimum wage increase on the frequency of price changes in fast-food restaurants



Note: Solid line: 1% increase. Dotted line: 2% increase. Dashed line: 5% increase

Figure 7a: Aggregate response to a minimum wage increase (traditional restaurants)

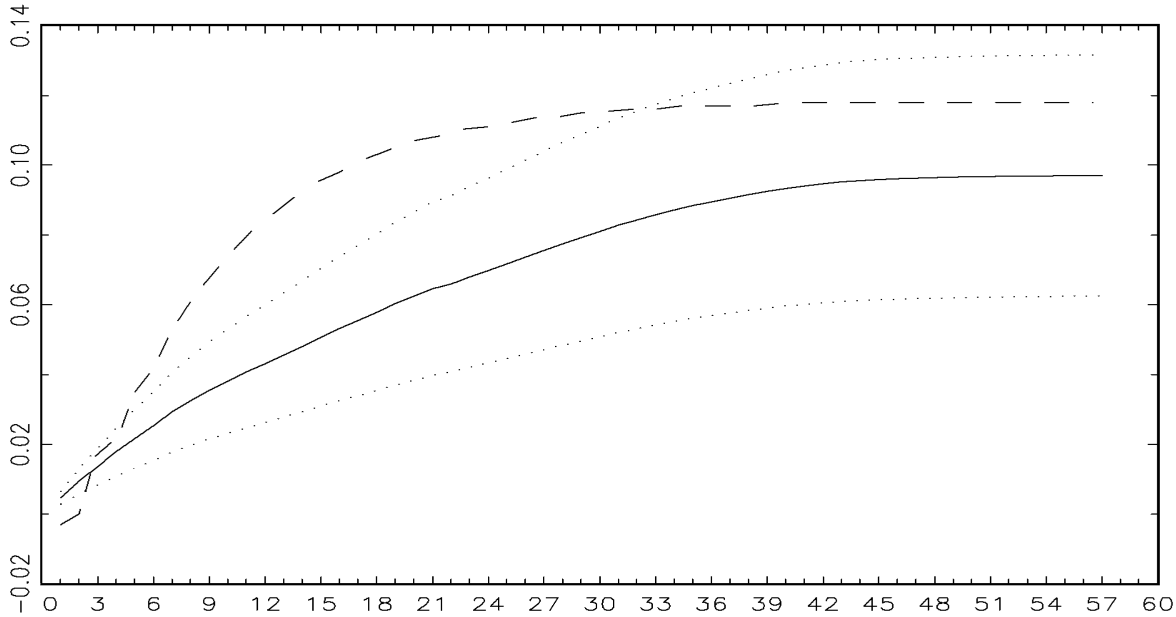
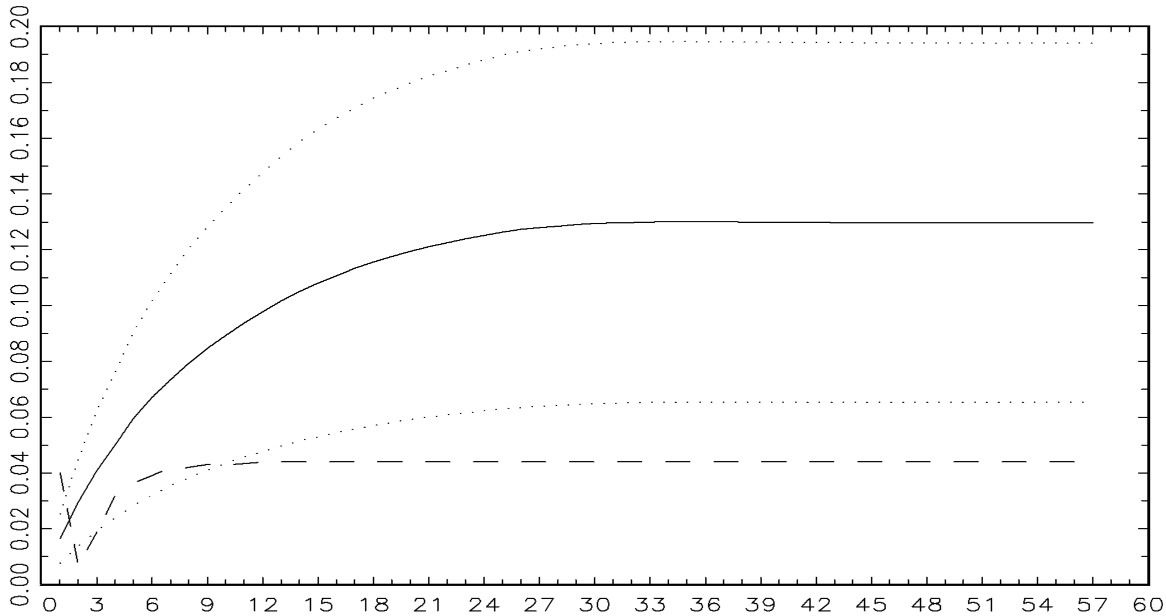


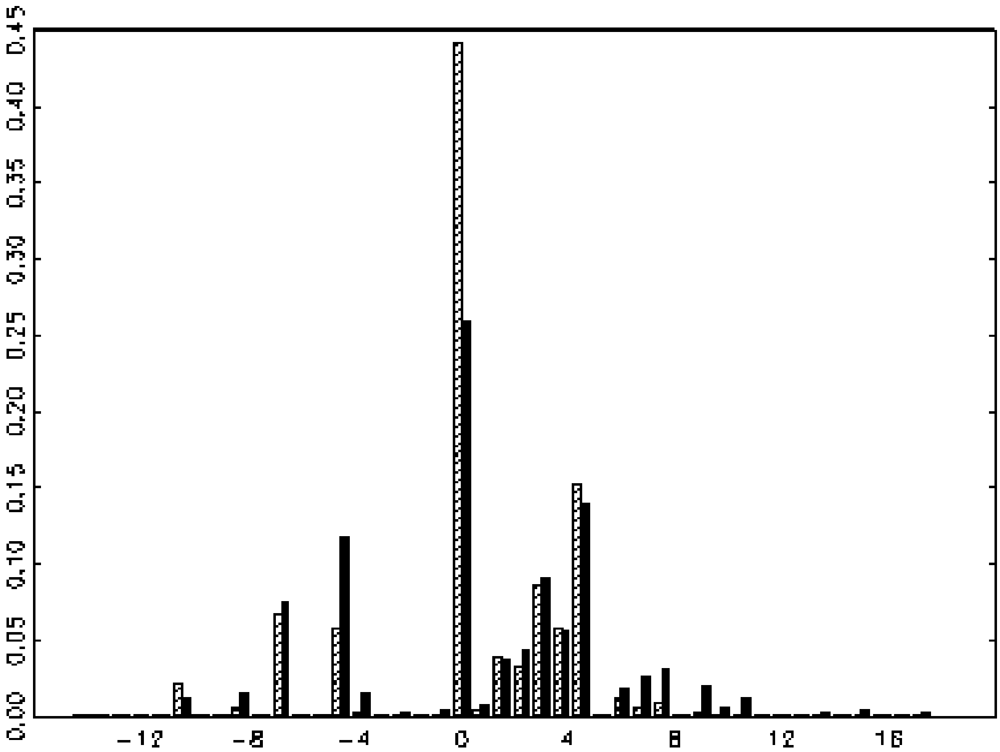
Figure 7b: Aggregate response to a minimum wage increase (fast-food restaurants)



Note: Solid line: simulated average aggregate response. Dotted line: bounds of the 95% confidence interval. Dashed line: response derived from the linear model estimated with aggregate data.

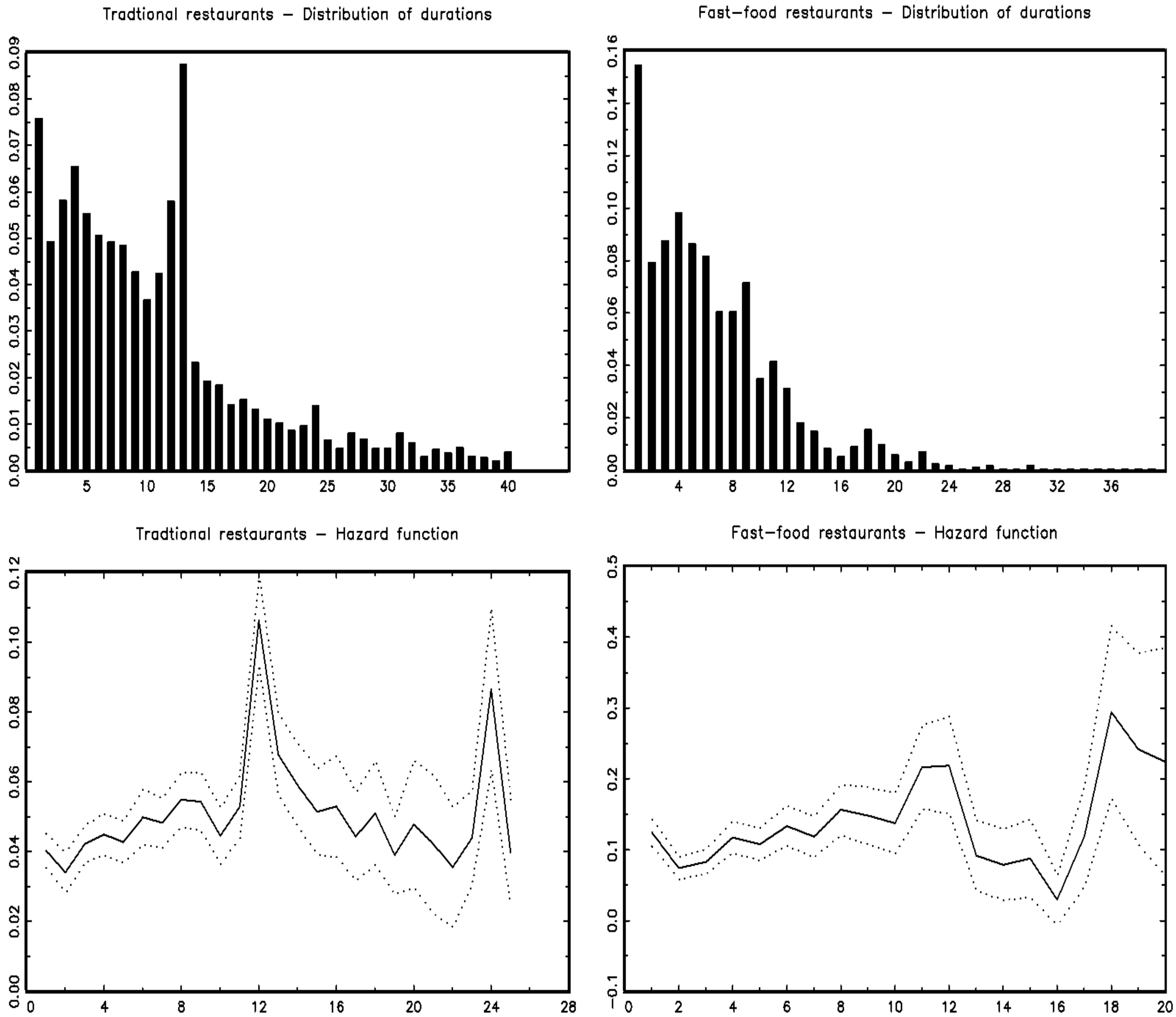
Appendix

Figure A1: Distributions of the cumulated minimum wage increase since the last price change



Note: black bars for traditional restaurants, dashed bars for fast-food restaurants. Decreases in employers' social contributions are included in labor cost at minimum wage.

Figure A2: Distributions of durations and hazard functions



Note: Hazard functions are estimated using a simple piecewise-constant duration model.