

# Food Banks and Retail Markups

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## Abstract

Food banks play a critical part in the food distribution system. In this paper, we examine the impact of food bank donations on retailer markups using data on donations and store-level productivity. We frame our empirical model of food bank donations and store-level markups as an example of quality-based price discrimination and find that stores that donate more food to the local food bank are able to charge higher markups—33% higher—after controlling for the well-known endogeneity problems. Our findings suggest that donations are not just charitable gestures by retailers but are in their own self-interests.

**Keywords:** food banks, food retailing, markups, price discrimination, production economics

**JEL classification:** D43, L13, M31

## 1. Introduction

In 2019, nearly 1 in 7 households in the USA relied on food banks to meet at least a portion of their food consumption needs (Feeding America, 2021). Food bank donations play an essential role in helping to alleviate food insecurity, but also provide an outlet for still-edible food that would otherwise go to waste, and may improve retailer profitability as well. In the absence of food banks, food retailers have to selectively discount perishable food prices on items that are near expiry, or pay waste disposal charges, so-called ‘tipping fees’, to discard these items into landfills. Donating food that is approaching its date of expiry also allows retailers to maintain the freshness of perishable foods on display, a form of quality-based price discrimination that can allow retailers to set higher prices than would otherwise be possible (Cohen, 2001;

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Leslie, 2004; McManus, 2007; Epple *et al.*, 2019; Richards and Hamilton, 2020). In this paper, we empirically examine the implications of food bank donations for retail markups using a unique data set that combines store-level production data with store-level food bank donations.

There are, at least, three mechanisms through which food bank donations can increase retail markups. First, it is at least theoretically possible for retailers to price dynamically, that is, to reduce the price of perishable items before they expire, thereby price discriminating between high-valuation and low-valuation consumers as a means of moving items off the shelf quickly (Tsiros and Heilman, 2005; Theotokis, Pramataris and Tsiros, 2012; Sanders, 2020).

Second, retailers typically pay fees to municipal waste departments for any organic items that are intended for disposal in a landfill (ReFed, 2018). The magnitude of these fees tends to vary by jurisdiction, but can be substantial, so donation allows retailers to avoid the high cost of discarding perishable food.

Third, by donating perishable food, retailers can improve the average quality of food on their shelves, using local food banks as something akin to a secondary market for food that is about to expire (Anderson and Ginsburgh, 1994; Chen, Esteban and Shum, 2013). In this way, retailers exercise quality-based price discrimination by increasing the average quality on the shelf, thereby raising prices, and accepting a zero price (or a small positive price through tax deductions) by moving lower-quality produce to the food bank.

We examine the relationship between donations and store-level markups using a structural model of firm production under imperfect competition (De Loecker and Warzynski, 2012). Researchers in marketing and industrial organisation typically frame problems concerning retailer performance and profitability from a demand-side perspective (see e.g. Chintagunta, 2002; Ellickson, Misra and Nair, 2012; Arcidiacono *et al.*, 2016; Richards, Hamilton and Yonezawa, 2018); however, food retailers typically sell thousands of products, which makes analysing profitability at the entire store level fundamentally intractable from the demand-side perspective. We depart from this literature following Hall (1986) by developing an approach that allows us to estimate firm- and industry-level markups using data on the value of output, retailer expenditures on key inputs, and the responsiveness of output to changes in the use of variable inputs. If firms are perfectly competitive, then there should be no difference in the input–expenditure share of revenue and the elasticity of output with respect to that input. Conversely, under imperfect competition, there is no guarantee that this relationship will hold, and the gap that results is attributed to the markup over marginal cost. This approach allows us to estimate retail markups indirectly by inferring the size of the difference between a variable input’s expenditure share in sales revenue, weighted by the output elasticity, relative to a unit benchmark. De Loecker (2007, 2011b), De Loecker and Warzynski (2012), and Curzi, Garrone and Olper (2021) use this approach to examine the impact of a firm’s export status on markups, while De Loecker (2011a) provides more detail on how this empirical framework applies to more general questions in empirical industrial organisation. To the

best of our knowledge, our paper is the first to use this approach to estimate markups for retailers at the individual store level.

With this approach, however, we cannot formally test which of the three mechanisms described above is likely the most important pathway for food bank donations to influence markups. Because our method only infers markups from the departure of the labour elasticity of output from labour's expenditure share in revenue, it cannot discern price effects from cost effects. A production-side approach to estimating market power focuses on markups over variable costs of production or, more intuitively, the dollar amount of sales attributable to the next worker, relative to the dollar amount of compensation paid to the worker.

Among the three mechanisms above, we know that food bank donations cannot do anything to reduce worker compensation, as they either reduce fixed costs of operation (lower tipping fees) or raise the dollar value of output to the marginal worker (reduce price discounting and generate higher prices). Furthermore, we know that retailers seek to avoid profit-reducing discounts (Tsiros and Heilman, 2005; Theotokis, Pramataris and Tsiros, 2012) or image-destroying produce that lies on the shelf past expiry (Matsa, 2011; Sanders, 2020) so we can rule out price discounting. Therefore, we focus on the latter effect, or the ability of retailers to use quality-based price discrimination to raise prices, and increase the level of sales for any given number of workers, thereby increasing apparent labour productivity.

Our empirical strategy controls for two key threats to identification: The potential endogeneity of labour inputs and of donations themselves. Without controlling for these two sources of endogeneity, a reduced-form model of donations and store revenue shows that donations increase store sales at the expense of store-level markups. After controlling for these two sources of endogeneity, we find that donations reduce store-level sales, but increase markups.

This finding is intuitive. If food banks serve as a mechanism for stores to raise in-store food quality and charge higher unit prices, then we would expect to observe higher markups and lower sales volumes among retailers. Our approach to controlling for these two sources of endogeneity represents an important methodological advance in the markup-estimation literature, as previous empirical research relies on panel data and within-firm variation in markups over time to identify the existence of market power. Our method, however, is appropriate for static, cross-sectional data.

We find that food bank donations increase retail markups substantially relative to the no-donation case. Indeed, gross markups average 283 per cent for non-donating stores, and 376 per cent for donating stores, a 33 per cent premium.<sup>1</sup> Our counterfactual simulations show that total store sales, measured in dollars, are higher by 1 per cent for every 50 per cent increase in donations.

1 Note that these markups are relatively high, because they refer to variable markups, or the difference between price and marginal cost, and do not take into account fixed costs. Food retailers are high fixed-cost operations, so these markups are necessary to cover fixed costs (Ellickson, 2007).

We interpret this finding as evidence in support of our hypothesis that food bank donations allow retailers to increase the quality of perishable items on their shelves, allowing them to raise retail margins while avoiding costly alternatives such as discounting or discarding food items with depreciated freshness.

Our findings contribute to the relatively sparse literature on the economic role of food banks, the empirical literature on food retailing and the more general literature on estimating markups using the production-side data approach. Despite the broad economic importance of food banks (Prendergast, 2017; Gundersen and Ziliak, 2018), we know very little about the role of food banks in the food supply chain and the motive for retailers to create a secondary food market through their own donation channels. Our model and our empirical findings show that food banks may be more important for food retailers than previously thought, and donations are not merely charitable donations, but in retailers' self interests.

Our empirical model of the effect of maintaining a secondary market for food on retail pricing is the first we know of to adopt a markup-based, production-side empirical approach. While Lazarev (2013) and Chen, Esteban and Shum (2013) estimate empirical models in which they test for the impact of secondary markets on the prices set in the primary market, we approach this problem in a fundamentally different way and, in so doing, show how to estimate pricing effects in multiproduct markets served by vendors that sell thousands of items at once that jointly contribute to the overall store-level markup. Unlike much of the firm-level literature on estimating markups using production data that relies on the panel nature of their data (De Loecker and Warzynski, 2012), we exploit data from individual retail stores in a static empirical setting and demonstrate how markups can be estimated using input variation across firms, and not within firms over time.

In the next section, we provide some background on our model of price discrimination and the impact of secondary markets for food on store-level markups. In the third section, we provide more detail on our empirical approach and explain how it differs from the more usual production-side approach to estimating markups. We describe our data in the fourth section and the details on our identification strategy in light of the clear endogeneity of both store labour and donations. We present and interpret our estimation results in a fifth section, including some counter-factual simulations that demonstrate the impact of donations on store-level profitability. We conclude in the final section and offer some guidance for future research on both food banks' role in the food supply chain and for future applications of markup estimation in the retail sector.

## 2. Theoretical model of food donations and markups

In this section, we provide a brief review of the production approach to estimating firm-level markups and describe how we intend to use this approach to test for the impact of food bank donations on store-level profitability. Because

we approach this problem from a production perspective, we do not directly address the specific mechanisms involved in quality-based price discrimination (Verboven, 2002; Leslie, 2004; McManus, 2007), but rather focus our attention on the ultimate effect of the practice on firm- (or store- in our case) level markups. Given that consumers' perceptions of product quality are formed over literally hundreds of different products in any retail food environment, our approach provides a reasonable and viable alternative.

## 2.1. Production-side estimation of markups

The empirical approach to estimating markups in imperfectly competitive industries is well-understood, so our review is brief. De Loecker (2011a; 2011b) and De Loecker and Warzynski (2012) explain the basic approach to estimating markups, and therefore market power, using minimal production data, and output prices. In contrast to the 'new empirical IO' method (Bresnahan, 1989), this approach does not require the analyst to estimate demand, even in a multiproduct environment in which substitution opportunities would otherwise seem to limit pricing power. Rather, the approach relies on an observation by Hall (1986) that '...firm  $i$ 's share of expenditures on labor in total sales is only equal to the share of expenditures in total costs if the price  $p_i$  equals the marginal cost  $c_i$ '. Any departure is due to market power, for whatever reason.

Empirically, our approach relies on the existence of at least one variable production input that does not have adjustment costs that confound the relationship between its revenue share and output elasticity. We treat labour as the adjustable variable input, which implies markups derived from minimising cost with respect to variable inputs, conditional on observed values of fixed, or quasi-fixed, inputs of

$$\left( \frac{\partial f(w_{it})}{\partial w_{it}} \right) \frac{w_{it}}{y_{it}} = \varepsilon_w = \frac{p_{wit}w_{it}}{\lambda_{it}y_{it}}, \quad (1)$$

for firm  $i$  in time period  $t$ , where  $w_{it}$  is the amount of the variable input,  $p_{wit}$  is its price,  $y_{it}$  is the amount of output, from a production surface  $f(w_{it})$ ,  $\varepsilon_w$  is the output elasticity with respect to labour, and  $\lambda_{it}$  is the Lagrange multiplier associated with the cost-minimisation problem. We interpret  $\lambda_{it}$  as the marginal cost of production.

Recognising that the markup  $mu_{it} = p_{it}/\lambda_{it}$ , we substitute this definition into the cost-minimisation solution above to obtain:

$$\varepsilon_w = mu_{it} * s_w, \quad (2)$$

where  $p_{y_{it}}$  is the output price and  $s_w$  is the labour-expenditure share of firm revenue. Intuitively, an input's output elasticity is equal to the markup multiplied by the ratio of the input's expenditure share of the total revenue. Thus, all that is required to estimate markups is an estimate of the output elasticity for one variable input, combined with its revenue share. In our case, we have

store-level data for each of the key variables noted above, which allows us to apply this approach at the individual store level of a retail chain, rather than at the firm level.

In our model, we argue that food bank donations allow food retailers to practice quality-based price discrimination by removing lower-quality perishable products from the shelf before the retailer either discards them, a practice associated with tipping fees, or else clears the inventory through selective price discounting. By leaving a higher-quality selection of fresh products on the shelf, the donating retailer is able to set higher prices by charging a quality premium on the products that remain on the shelf. Implicitly, therefore, if donations remove lower-quality, lower-value produce prior to either discounting or donating, then the marginal productivity of labour, all else constant, will be higher for retail stores that donate relative to non-donating stores. In terms of the simple markup story above, our hypothesis implies

$$\left( \frac{\partial f(w_{it})}{\partial w_{it}} \Big|_{d_{it} > 0} \right) \frac{w_{it}}{y_{it}} = \varepsilon'_w > \varepsilon_w.$$

It follows that donating ( $d_{it} > 0$ ) retailers will enjoy higher markups relative to non-donating retailers when the labour share of revenue remains constant.

Our theoretical predictions reflect the labour-intensive nature of inventory-management practices at food retailers. [Matsa \(2011\)](#) argues that the absence of stock-outs, and hence careful inventory management, is the key measure of service quality among food retailers. Restocking shelves is the most labour-intensive activity in any modern food retailer, so there is a direct connection to maintaining quality items on the shelf and the marginal productivity of labour. Retailers that rotate perishable items out frequently and ensure that only the best-quality items are displayed during critical shopping times will be able to charge higher prices than retailers who simply let items deteriorate while on display, perhaps discounting them before throwing them out. Empirically, therefore, we expect to find a positive relationship between donations and the marginal productivity of labour that reflects a greater attention to fresh-food quality by donating retailers. We describe how inventory management enables quality-based price discrimination next.

## 2.2. Quality-based price discrimination

Recall that we cannot directly test whether any of the mechanisms that may lead markups to vary with food bank donations dominates the others. While the economic motives that underlie the price-discounting and tipping-fee explanations are clear, the third mechanism (price discrimination) is more subtle, and perhaps more interesting. In this regard, our analysis considers the role of food banks as a secondary market for perishable food. In this sense, food banks provide an outlet for buyers with low valuations for freshness and other aspects of

retail food quality, allowing retailers the ability to practice quality-based price discrimination by selecting both the volume and the quality of perishable food to donate from the back of the store.<sup>2</sup>

It is well understood that a monopoly seller of a durable good may benefit from an active secondary market when consumers have heterogeneous preferences for the ‘newness’ of a product (Anderson and Ginsburgh, 1994; Johnson, 2011). When transaction costs associated with acquiring used products are substantial, as would be the case when procuring food from a food bank is time-consuming or when there is social stigma attached to receiving donated food, retailers have the ability to extract rents from the secondary market by controlling the quality of donated food products that are transacted in the secondary market. This practice can allow retailers to ‘upgrade’ the freshness of their food products and raise retail prices to higher-valuation buyers that remain in the primary market.

Retailers, however, are generally not monopoly sellers. Chen, Esteban and Shum (2013) extend the logic of Anderson and Ginsburgh (1994) to show that the emergence of a secondary market can enhance profits in oligopoly settings. In their model, suppliers of durable goods with secondary markets are subject to a *substitution effect*, in which new goods compete with used goods on the secondary market, and an *allocative effect* associated with segmenting buyers in the market between high-valuation and low-valuation groups. Their analysis demonstrates that secondary markets raise retail profits when the durability of goods is ‘low’ and transaction costs of participating in the secondary market are ‘high’—characteristics that are likely to be satisfied in the case of retail food donations.

Much of the secondary markets literature relies on durability as the basis for intertemporal pricing strategies. However, secondary markets also exist for highly perishable items with similar properties as fresh food, for instance tickets to live performances (Leslie and Sorensen, 2013), live sporting events (Sweeting, 2012) and airline fares (Lazarev, 2013). The empirical insights from these markets show that allowing resale markets to emerge increases vendor profitability, while improving the allocative efficiency of the ticket-distribution system. Our aim in this study is to empirically examine whether food donations by retailers serve to increase retail markups and enhance retail profits.

Our theory rests on the implicit assumption that retail markets consist of segments of high-valuation and low-valuation consumers. While it is tempting to think of the retail food market as consisting of one group that always goes to supermarkets, and another uniquely served by food banks, such an outcome is not, in fact, the case. Instead, Caswell, Yaktine and National Research Council (2013) show that food-bank clients tend to regard their status as transitory, using food banks to tide them over between regular visits to

2 Richards and Hamilton (2020) show that retailers use a similar practice upstream, in their purchases from fresh-produce suppliers, in order to segment the downstream market for food of random quality.

supermarkets.<sup>3</sup> Because consumers purchase food frequently, and households have many different food needs, the primary and secondary markets for food provide a mechanism to shift marginal consumers between the two markets and raise retail prices by controlling the quality of food donations, which in turn enhances the quality of food items available in the secondary market.

We explain how we test the implications of this theory in the next section.

### 3. Empirical model of donations and markups

In this section, we describe our empirical approach to estimating the impact of food-bank donations on store-level markups. We begin with a brief overview of our markup estimation approach and, given that it is relatively new to the empirical industrial organisation literature, we compare this approach to the more usual, demand-side method. We then describe our specific application in more detail and our extension of the [Akerberg, Caves and Frazer \(2015\)](#) estimation method that is appropriate for cross-sectional data, unlike the panel approach developed by others in this literature.

#### 3.1. Method overview

Estimating markups from a production perspective offers a number of benefits relative to traditional, demand-side, empirical industrial organisation estimates ([De Loecker, 2011b](#)). First, we do not require the specification and estimation of a potentially large-scale demand system in order to capture the full range of product–demand interactions. If the accuracy of demand-side markup estimates is conditioned on the quality of own- and cross-price elasticity estimates, then analysts are forced to make very strong separability assumptions in retail data to exclude the many possible interactions within the store. For example, if the question concerns markups in yogurt, and the model describes the consideration set of a typical consumer, it is unlikely that the top 30 products purchased accurately represent the larger consideration set ([Mehta, Rajiv and Srinivasan, 2003](#); [Koulayev, 2014](#); [De los Santos and Koulayev, 2017](#)).

Second, our method accounts for errors in measuring store-level prices in a direct way ([De Loecker and Warzynski, 2012](#)). Because production-side estimate typically employ revenue-based measures of outputs, our instruments control for the resulting errors in store-level price measurements.

Third, demand-side markup estimates tend to impose a particular interaction game among sellers in order to infer the extent of market power, or at least departure from the maintained form of the game ([Villas-Boas, 2007](#)). Although there are examples of menu-type approaches that seek to examine which form of game among sellers is most appropriate ([Gasmi, Laffont and Vuong, 1992](#)), these models nevertheless test among restrictive solutions for equilibrium prices.

<sup>3</sup> Gundersen, Engelhard, and Hake (2017) summarise the 2014 Hunger in America data from Feeding America and note the high percentage of survey respondents who report the temporary nature of food bank support. While their data do not make this point directly, the implication that food bank support is transitory is clear.

Fourth, our model captures store-level factors that may influence markups that demand-side models simply would not be able to capture. While we do not suggest that markup estimation using the Hall (1986)-type approach is ideal for all retail applications, it is indeed well-suited to the case at hand, and other empirical problems that are intractable from a demand-side perspective. That said, the empirical application we describe next departs from the method described in [De Loecker and Warzynski \(2012\)](#) in several, important ways that are unique to food-retail settings.

### 3.2. Empirical model

Estimating markups in a production framework typically requires panel data ([De Loecker, 2011a](#); [De Loecker and Warzynski, 2012](#)). While there is nothing in the theoretical derivation of equilibrium markups that requires panel data, identifying labour-productivity parameters using methods developed in the empirical production-economics literature (Olley and Pakes, 1996; [Levinsohn and Petrin, 2003](#), [Akerberg, Caves and Frazer, 2015](#)) relies on a fundamental assumption that the unobserved productivity process that affects output, and hence equilibrium input–employment decisions, is a Markov process. Without panel data, therefore, researchers are left with the problem of identifying labour productivity with unobserved, cross section shocks to productivity.

We overcome this problem using a two-stage, control-function approach similar in nature to [Akerberg, Caves and Frazer \(2015\)](#), but amenable to estimation in cross-sectional data. In fact, our empirical approach contributes to the literature on markup estimation as there are many interesting economic problems that cannot be answered by either traditional demand-side markup-estimation data (retail scanner data) or census data that are typically used to estimate markups from a production perspective. Store-level data are generally not observed for retail outlets, but many of the most interesting questions regarding store conduct are simply irrelevant when the data are aggregated up to the firm level. Our approach retains the consistency and simplicity of the [Akerberg, Caves and Frazer \(2015\)](#) approach, but we argue that it is more relevant to problems in empirical industrial organisation as it can be applied to a far wider set of interesting questions.

Based on the markup-estimation approach introduced by Hall (1986), [De Loecker and Warzynski \(2012\)](#) and others, the fundamental objective of the empirical model is to estimate the output elasticity of a variable input—here assumed to be labour. While a seemingly simple task, estimates of the marginal productivity of labour are bedeviled by the endogeneity issues described in [Levinsohn and Petrin \(2003\)](#) and [Akerberg, Caves and Frazer \(2015\)](#). Therefore, we adopt a variation on their approach to estimate the output elasticity of labour, and store-level markups. In general, our application of their approach consists of two steps. In the first step, we invert the demand for an intermediate input, and obtain a non-parametric expression for expected output, for any set of production parameters. In the second step, we adjust output for this

unobserved productivity shock, and control for the endogeneity of labour, and donations in our setting, using control functions (CFs).<sup>4</sup>

In the first stage, we begin by specifying a parametric function for store-level output that consists of one variable input (or at least one free of adjustment costs), and at least one state variable. The essence of the Olley and Pakes (1996) and Levinsohn and Petrin (2003) approach is to use the demand for this state variable as a proxy for the unobserved productivity shock, on the assumption that productivity is governed by something other than observed variable inputs. In our application, we assume a simple Cobb–Douglas production function for store  $i$  in period  $t$  in labour ( $w_{it}$ ) and two state variables ( $k_{1it}, k_{2it}$ ), so our production surface is written:<sup>5</sup>

$$y_{it} = \beta_0 + \beta_w w_{it} + \beta_{k1} k_{1i} + \beta_{k2} k_{2i} + \beta_z \mathbf{z} + \omega_{it} + \eta_{it}, \quad (3)$$

where all variables are in logs;  $y_{it}$  is store-level revenue (deflated by a price index for retail grocery stores); labour  $w_{it}$  is the number of full-time equivalent workers employed by store  $i$  in year  $t$ ;  $k_{1i}$  is the size of store  $i$ , and is assumed to be time-invariant, as is  $k_{2i}$ , which is the number of checkouts in store  $i$ ;  $\mathbf{z}_{it}$  represents a vector of variables that may explain the productivity of store  $i$ ;  $\omega_{it}$  is a Hicks-neutral productivity shock, unobservable to the econometrician, and assumed to be correlated with the labour input; and  $\eta_{it}$  is a purely random error term, uncorrelated across firms and time.<sup>6</sup>

In our empirical model, we assume  $k_1$  forms the proxy variable for unobserved productivity and  $k_2$  is the state variable as we can more readily model the demand for store size than the infrastructure in the store. Because our two measures of the level of capital investment in each store are, by definition, time-invariant, our data amount to repeated cross-sectional output observations for our sample stores, rather than the panel used by others in this literature (Akerberg, Caves and Frazer, 2015: for example). This is the key difference between our approach and the usual way of estimating these models, as we rely on cross-sectional variation in  $k_1$  to identify unobserved productivity shocks, rather than time-varying intermediate inputs. We elaborate on this distinction below. The vector  $\mathbf{z}$ , meanwhile, consists of dummy variables indicating whether the store sells gas and/or liquor, the level of food bank donations, and an interaction term between the level of donations and labour input. These elements of  $\mathbf{z}$  allow us to test our core hypothesis, namely the effect of donations on store output, and on the marginal productivity of the labour input. We return to this interpretation in more detail below.

- 4 We depart from Akerberg, Caves and Frazer (2015) in this second step, because the Markov assumption for unobserved productivity requires panel observations for individual stores, something that is not consistent with our data.
- 5 De Loecker and Warzynski (2012) assume a translog production function, but we adopt a different approach to including firm-level variability in markups (random parameters), and the translog is simply not tenable without data similar to their firm-level panel.
- 6 De Loecker (2011b) and De Loecker and Warzynski (2012) discuss the role of deflating observed revenue by an aggregate price index to arrive at a physical measure of output. As in their approach, our instrumental-variables procedure corrects for the store-level error induced by this approach, and our findings are invariant to this deflation procedure.

Our approach is a static analog to the [Akerberg, Caves and Frazer \(2015\)](#) method in that we rely on their two key assumptions: (i) a scalar unobservable and (ii) monotonicity in the proxy variable.<sup>7</sup> These assumptions are necessary as they mean we are able to invert the demand function for the proxy variable and express the unobserved productivity of firm  $i$  as an unknown function of the proxy and state variables, as well as other factors that may explain inter-store differences in productivity. Specifically, the demand for  $k_{1i}$  by store  $i$  is written as:

$$k_{1i} = h(k_{2i}, \omega_{it}, \mathbf{z}_{it}), \quad (4)$$

where we do not necessarily assume that all elements of  $\mathbf{z}_{it}$  are purely exogenous. The monotonicity and scalar-unobservable assumptions then allow us to write the unobserved productivity shock for firm  $i$  at time  $t$  as the inverse of the demand function for  $k_{1i}$ , or:

$$\omega_{it} = h^{-1}(k_{1i}, k_{2i}, \mathbf{z}_{it}) = g(k_{1i}, k_{2i}, \mathbf{z}_{it}), \quad (5)$$

where the  $g(\cdot)$  function essentially indexes the productivity of firm  $i$ . In the first stage of the estimation procedure, we then substitute the expression for  $\omega_{it}$  back into the production function in (3) to arrive at an expression for the output of firm  $i$  that depends only on observables, and purely random factors:

$$y_{it} = \beta_0 + \beta_w w_{it} + \beta_{k1} k_{1i} + \beta_{k2} k_{2i} + g(k_{1i}, k_{2i}, \mathbf{z}_{it}) + \eta_{it}. \quad (6)$$

Whereas  $\beta_w$  is identified in the first stage in [Olley and Pakes \(1996\)](#) and [Levinsohn and Petrin \(2003\)](#), we follow [Akerberg, Caves and Frazer \(2015\)](#), who argue that the labour in this stage is fundamentally unidentified and is instead a deterministic function of the other variables in the production function.

Our first stage, therefore, consists of an unknown production function of capital and labour inputs,  $\psi(w_{it}, k_{1i}, k_{2i}, \mathbf{z}_{it})$ , which we estimate using non-parametric methods. For this purpose, we follow [Levinsohn and Petrin \(2003\)](#) and estimate a locally weighted regression model, which allows us to find expected values of production,  $\psi$ , for any parameter vector,  $\beta$ , and form a control function,  $CF_{it}$ , by calculating the residuals from this first-stage, non-parametric regression.

In the second stage, we introduce our assumption that underlies the data-generating process for productivity and our point of departure from [Akerberg, Caves and Frazer \(2015\)](#). While they assume productivity follows a Markov process, and so can be written as a function of lagged values of itself and a random error term, the Markov assumption is simply not viable in our data. And, we would argue that there are many cases in which this assumption is

<sup>7</sup> In our case, monotonicity implies  $\partial k_{1i} / \partial \omega_{it} > 0$ , which [De Loecker and Warzynski \(2012\)](#) argue holds under a wide range of underlying models of imperfect competition, including the Bertrand-Nash price rivalry typical of supermarket retailers. In such case, monotonicity is necessary to invert the demand function for store-level capital.

either not supported by the available data or rather too strong an assumption to actually take to the data with any degree of confidence that it is true. Therefore, we make an alternative assumption that productivity instead represents store-specific deviations from more general, cross-section patterns across rival stores.

Because individual stores, particularly within the large chains in our data, tend to change very little over time, we argue that the primary driver of productivity differences among stores are idiosyncratic factors, such as managerial skill, location or local preferences, that are better represented by cross-sectional differences from industry-mean productivity. Mathematically, our cross-sectional productivity process is captured by the CF estimated below,  $CF_i$ , so that the productivity process for firm  $i$  is given by:

$$\omega_{it} = CF_i(\bar{\omega}_t) + \xi_{it},$$

where  $\bar{\omega}$  represents industry-mean productivity. Therefore, in the second stage we begin by removing the value of  $CF_{it}$  from observed levels of output and writing the result as a function of labour, capital and a new unobservable term that represents store-level deviations from industry-average productivity:

$$y_{it} - CF_{it} = y_{it}^* = \beta_0 + \beta_w w_{it} + \beta_{k1} k_{1i} + \beta_{k2} k_{2i} + \beta_z \mathbf{z} + \xi_{it} + \eta_{it}, \quad (7)$$

where we have substituted in the value of the CF from the previous expression, and assume the independence of the remaining unobservable,  $\eta_{it}$ .

As [Akerberg, Caves and Frazer \(2015\)](#) observe, however, the labour input from this expression is likely to be correlated with  $\xi_{it}$ , so they then form moment conditions between this composite error term and the instruments in their model—lagged values of labour and the capital input—and estimate with Generalised Method of Moments. In our static analog to their approach, our theoretical model suggests that both labour and donations are likely to be correlated with store-level deviations from industry-average productivity, so we estimate CFs for both the labour input and donations. As we explain in the Data section, our instrument for store-level labour inputs consists of market-level wages for employers in the retail food industry, while our instrument for donations consists of address-specific commercial real estate (CRE) prices. With this two-stage, control-function approach, we are then able to consistently estimate the marginal productivity of labour (and the output elasticity), and the remaining parameters of the production function.

In addition to the two assumptions that underlie the estimation procedure above, we add another in order to account for any unobserved heterogeneity that remains after estimating the two-stage CF described above. That is, we assume each of the core production-function parameters is randomly distributed over the stores in our data set. By estimating a random-parameters version of the production surface described above, we account for not only variability in productivity, but deeper-level heterogeneity that affects labour

and capital productivity more generally, independent of any underlying productivity process. Because some of the unobserved heterogeneity among stores is simply due to factors that we literally cannot observe, we allow for variability in markups across stores, which can be accommodated in our data without sacrificing degrees of freedom as in [De Loecker and Warzynski \(2012\)](#). Specifically, the use of store-level data allows us to implicitly account for factors such as in-store merchandising, store-level managerial quality and the intensity of local competition that are not directly observed in our data.

Using a random parameters approach also allows the labour elasticity of output to vary across stores in our data, without the need to adopt the translog production function used by [De Loecker and Warzynski \(2012\)](#). While the translog production-function approach is more flexible than ours in the traditional, algebraic sense, it is less flexible econometrically as it imposes a strict, highly parameterised, functional form on the model. Our approach eliminates the need for these parametric restrictions.

#### 4. Data and identification strategy

Our primary data set consists of store-level observations of production and input employment, food bank donations, census-block measures of the economic environment surrounding each store, and markups. Specifically, our store-level retail attribute data are from Nielsen/TDLinx, which provides detailed estimates of annual store-level store volume (measured in terms of dollar sales), number of employees, and a variety of proxy measures for the amount of capital employed at the store level: size of the store (in square feet), the number of checkouts and whether the store offers services besides just grocery sales. Our sample period, consistent with our donation data below, is from 2009 through 2018.

Second, our donations data are unique, and particularly well-suited to the purposes at hand. Our food-bank data capture donations at the store level from stores that belong to five large, national grocery chains, to a regional, Feeding-America-affiliated food bank in the Midwest United States. Reported in standard form, the donation data are derived from ‘donor source reports’ (DSRs) provided by the food bank. Although the DSR data are reported at the transaction level, we aggregate up to an annual basis to match the annual observations from our TDLinx store-attribute data. Donations are reported on a category-by-category basis, for several different categories of perishable and non-perishable products, but our hypothesis rests on the assumption that donations affect the perception of quality on a store level, so we need not use the category-level variation in our data.<sup>8</sup> In total, we have 993 annual observations

<sup>8</sup> The DSR classifies retail donations by both category and item description, and the food bank is responsible for receipting retail food donations. Due to the considerable variation in the category-item description linking, we cannot be confident that the receipted volume by category is truly accurate. Therefore, we choose not to compare category-level donations across retailers. In consultation with the food bank, we map item descriptions to a condensed list of six categories.

from 128 unique stores, from 5 different chains, over a 10-year time period in an unbalanced-panel data structure.<sup>9</sup>

We provide detail on our DSR data in [Table 1](#). From the data in this table, it may appear as though donations are small in absolute volume. Clearly, the relative importance of donations to a store's operations is a key measure of the prominence of donation as an active strategy to improve quality and profit according to the mechanism we describe here. However, the TDLinX data that form our primary data set only report volumes in terms of total-store dollar sales. Fortunately, we have access to store-level Nielsen scanner data for perishable-category sales (i.e. bakery, dairy, meat, produce and deli) for a similar sample of stores. From that sample, we know that average category sales, expressed in pounds, is about 6,840 pounds per week, or 356,000 pounds per year. Donations for the sample of stores in that data are roughly the same as in our current sample of stores, so we believe that the relative amounts are also approximately comparable, at least for summary purposes. Therefore, these data imply that the donation amounts in the current sample likely amount to approximately 14.0 per cent of annual perishable-item sales. Given the attention paid to minimising 'shrink,' or unintentional inventory loss, by food retailers, donating this much perishable food represents a substantial amount of lost revenue, so there must be some expectation of a commensurate gain.

Third, we recognise that applying the production approach to estimating markups requires only data on store revenue, variable input employment, employment of a proxy input and compensation for the variable input (in order to arrive at an expenditure-share variable that we measure by store). The TDLinX data contain measures for all of these variables, except for labour compensation. For this purpose, we rely on the US BLS QCEW data. As the name suggests, the QCEW is a census of all employers on a quarterly basis, for each county, state and North American Industry Classification System (NAICS) (grocery stores = 4,451) industry. We know the exact location of each store, so assume each store manager pays local, prevailing wages for employees in the supermarket sector.

Using the maximum level of spatial granularity of the QCEW data, we merge the TDLinX and QCEW data at the county level in order to capture as nearly as possible the local variation in wage expense among our sample of grocery stores, yet still maintaining the market-wage nature of the data necessary for its exogeneity. In total, there are 35 counties represented by the stores in our data, so labour expense varies considerably among our sample stores (35 counties times 10 years = 350 points of variation, see [Table 1](#)). Although total wage compensation in reality is likely to differ substantially from the amount implied by our strategy, ours is likely a better measure of the variable component of labour cost as employees that earn above this wage are likely to be

<sup>9</sup> Our data form an unbalanced panel because some stores open, others close, and some do not meet the greater than or equal to 25 receipted donations (per year) threshold that we require to meet the definition of a 'regular donating' store.

**Table 1.** Summary of Retail Markup Estimation Data

Variable	Source	Units	Mean	Std. Dev.	Minimum	Maximum	N
Output	TDLinx	\$/,000/wk	674.1188	236.0014	225.0	1,475.0	993
Store size	TDLinx	,000 sq.ft.	64.5700	26.7144	25.0	140.0	993
Employees	TDLinx	#	130.8077	104.2897	0.0	380.0	993
Checkouts	TDLinx	#	13.1390	10.3086	0.0	48.0	993
Donations	DSR	,000 lbs./yr	49.9869	64.4014	2.0	460.9	993
Donations	DSR	#/yr	60.4471	32.7505	25.0	196.0	993
Gas?	TDLinx	%	0.3837	0.4865	0.0	1.0	993
Liquor?	TDLinx	%	0.9527	0.2125	0.0	1.0	993
Real estate price	CoStar	\$/sq.ft.	15.4327	17.4863	2.5	27.4	993
Wages	QCEW	\$/week	416.0393	74.4150	0.0	486.0	993
Retail PPI	BLS	Index	145.1740	15.7292	117.8	167.9	993
Density	ACS	#/sq.mile	2,344.6180	2,117.5720	31.6	14,642.0	993
Household size	ACS	#/household	2.4109	0.3214	1.5	3.4	993
Unemployed	ACS	# people	160.5086	117.2116	5.0	825.0	993
Income	ACS	\$/,000/year	74.8056	30.8758	25.5	248.5	993

*Note:* Data sources are Nielsen-TDLinx, Mid-Ohio Food Bank donation source report (DSR), CoStar CRE prices, Quarterly Census of Employment and Wages (QCEW, Bureau of Labor Statistics or BLS), BLS (Producer Price Index, PPI), and American Community Survey (ACS, Bureau of Census).

salaried, management employees, so their cost is more appropriately defined as fixed rather than variable.

Fourth, our instrumental-variables method requires exogenous variation in input demand at the store level. While we do not have access to macroeconomic data on labour demand at the individual-store level, we approximate local variation in labour demand by using Bureau of Census data, measured at the census-tract level. We summarise all of our estimation data in [Table 1](#). For the purposes at hand, each of the variables shown in [Table 1](#) likely contains sufficient variation to identify the production-function parameters, and the relationship between donations and store sales that is of primary interest.

Food bank donations are not consistent across stores, or even within stores over time in our sample. The fact that some stores donate only sporadically may affect our results, as it is difficult to maintain that food bank donations are a regular part of the merchandising strategy of a retailer if donations only occur a few times per year. In many cases, such infrequent donations are due to supply-chain problems, for instance accidental over-shipment of a particular item, than they are due to an explicit strategy of maintaining high-quality fresh produce without the need to discard degraded-quality items. Therefore, we restrict our sample each year to stores that donate at least once every two weeks ( $N = 25$  donations per year).<sup>10</sup> The median number of donations across all stores and years is  $N = 42$ , so our restriction recognises the left-skewness of the distribution and captures the mean number of donations more accurately. We examine our model results for their robustness to this assumption and find little difference in our conclusions when we restrict donating retailers using either the mean ( $N = 25$ ) or median ( $N = 42$ ) number of donations.

We provide more detail on donations data in [Table 2](#). Although we cannot disclose the identity of each retailer, it is clear that stores in some chains tend to donate more perishable foods, more frequently, than others.<sup>11</sup> In fact, the data in [Table 2](#) show that stores in chains 3 and 5 donate approximately six times as much as stores in the other chains in terms of total pounds per week, and donate roughly 50 per cent more than stores in any of the other chains. However, the fact that these stores also appear to be larger than the others, on average, suggests that donations may simply increase with size. In column 5, we control for this possibility by expressing donations in each store per dollar of store sales.

<sup>10</sup> Feeding America officials assured us that such stores donate only sporadically, out of irregular donation opportunities, and not as a regular policy to dispose of lower-quality, nearly-expired foods. Because food banks absorb the cost of transport, and dispatch trucks to pick up donations, zero-donation observations are due to food banks' rational, cost-minimising response to the expectation that donations will be small. Zero donations, therefore, even from the major retailers in our sample, are due to food-bank logistical considerations and generate the inter-retailer variation in donation strategy that helps identify the key parameters of our model.

<sup>11</sup> Note that donations in [Table 2](#) are defined on a per-store basis, so aggregate donations per chain differ substantially from the data in this table as, for example, there are many more store-year observations for chain 2 ( $N = 532$ ) than for chain 3 ( $N = 63$ ).

**Table 2.** Donations by Store, per Sales Dollar

Chain	Donations	Sales	# Don	Don/Sales
1	29,292.88	\$669.40	46.39	43.76
2	17,580.01	\$575.70	50.82	30.54
3	137,532.17	\$1,130.95	86.65	121.61
4	23,174.29	\$611.46	60.80	37.90
5	116,734.11	\$801.38	79.08	145.67

Note: Donations are in lbs. per store per week, Sales is dollar sales per store (\$,000)/wk, # Don is the number of donations per store per year, Don/Sales is donations per sales dollar. Correlation between columns 2 and 5 is 0.76.

After controlling for size, stores in chains 3 and 5 still substantially out-donate the others. While this summary data cannot be used to draw causal relationships, the statistical association between donation intensity and store sales is clear as the correlation between normalised donations and dollar sales is 0.76. This summary data suggest that there may be a positive statistical relationship between donations and sales performance.

Conclusive statistical support for this finding requires estimating a structural model of markups and donations that circumvents the usual barriers to identification commonly encountered in these models. As described below, we account for the three critical data issues involved in estimating markups from a production perspective noted by [De Loecker and Warzynski \(2012\)](#).

First, we require at least one variable input, or one that is not subject to substantial adjustment costs. The TDLinx data include the number of employees per store, so we assume labour is variable both between stores and, perhaps to a lesser extent, within stores over time.

Second, the TDLinx data define output at the store level as an estimated value of ‘all commodity volume’, which, despite the name, is a revenue-based measure of store output. Because we have no corresponding store-level price index to deflate store-level revenue to any meaningful measure of actual volume, we follow [De Loecker and Warzynski \(2012\)](#) in deflating store-level revenue using as granular a price index as possible.<sup>12</sup> Specifically, we deflate store-level revenue by dividing the total sales revenue for each store by a PPI for retail grocery stores (BLS).

Third, as described above, we account for the endogeneity of labour demand at the store level, and markups using a cross-section variant of the approach developed by Olley and Pakes (1996), [Levinsohn and Petrin \(2003\)](#), and [Akerberg, Caves and Frazer \(2015\)](#). Because the volume measures in TDLinx are only estimated values, generated by a proprietary algorithm developed by

12 Although we readily admit that recovering store output through an aggregate price index is less than perfect, [De Loecker and Warzynski \(2012\)](#) emphasise that when using revenue-deflated measures of output ‘... our approach is still informative about the correlation between markups and firm-level characteristics...’ and that ‘...only the level of markup is potentially affected, but not the estimate of the correlation between markups and firm-level characteristics...’ such as the store-level donations in our data (p. 2438).

Nielsen, we are reluctant to consider our production data as describing a complete panel over the firms in our data, and over time.<sup>13</sup> For this reason, we estimate all of our models as if the data represent repeated cross sections over the same firms and adopt econometric methods appropriate for cross-sectional data. Therefore, we estimate our model in levels, as opposed to first differences as in [De Loecker \(2011a\)](#); [De Loecker \(2011b\)](#), which avoids the long-panel issues involved in creating dynamic series with observations 5 years apart, and the corresponding interpretation problems of the productivity shocks that result. Using repeated cross-sectional data also has the added advantage of preserving degrees of freedom in the estimation process, thereby improving the statistical efficiency of our estimator.

To account for the endogeneity of labour demand, we develop a static analog to [Akerberg, Caves and Frazer \(2015\)](#). Based on [Levinsohn and Petrin \(2003\)](#), they use materials demand as an ‘intermediate input’, which they invert in a control-function procedure. Although we do not have the same level of detail in our store-level data, there is some question as to whether focusing directly on intermediate inputs for retail-focused firms is even appropriate. For a food retailer, ‘materials’ refers to the amount of wholesale products purchased each year, across all categories, and is a function of the size of the store, and the turnover rate for each stock-keeping unit (SKU) that occupies space on the shelf. Accounting for the wholesale value of every SKU is neither possible, nor necessarily desirable. Instead, we seek a measure that aggregates intermediate demand across the entire store. In our data, store size is a useful proxy for materials demand and differs from true materials demand only in variation in turnover rates by store. Therefore, we use store size as our proxy variable for materials demand and account for the resulting measurement error through the CF approach described below.

Essentially, we instrument for store-level turnover using the two-stage, control-function procedure described above. In addition to this procedure, we recognise that labour demand and donations are also likely to be endogenous. Our identification strategy corrects for these additional sources of endogeneity by instrumenting for each endogenous variable in secondary control-function procedures, and we report the quality of our instruments in the Results section.

We identify the endogenous labour variable by instrumenting labour demand with a wage variable. Recall that valid instruments should be correlated with the explanatory variable that is suspected of endogeneity, while mean independent from the dependent variable in the main estimation equation. Our first set of instruments is designed to control for the likely endogeneity of labour employment by each store. Our instrument in this case consists of market-level wage data from the QCEW (BLS). If retail grocery-store managers minimise cost, the number of employees in their store should reflect not only the physical needs within the store, but the prevailing local

13 Others in this literature recognise the value of the TDLinX data for answering firm-level questions, but are similarly reluctant to consider the data as a complete panel for estimation purposes ([Ellickson and Grieco, 2013](#); [Ellickson, Grieco and Khvastunov, 2020](#)).

wage. Indeed, first principles suggest that higher wages should be strongly correlated with lower employment. At the same time, local wages should not be correlated with the output of an individual store, as employment decisions are made at the firm level, and market-level wages are determined beyond the control of any single firm.

Second, we instrument for endogenous donations using CRE prices, and local demand-relevant factors. Our demand shifters consist of a set of socio-economic variables that are likely to capture local-demand variation, at the census-block level surrounding each store. Census data are determined by local market attributes and so represent a plausibly exogenous source of demand variation facing each store. We also derive a proxy measure of materials demand (Akerberg, Caves and Frazer, 2015) from the price of retail space, which is also likely to reflect variation in local demand for food and grocery stores that is independent of the variation in demand facing any particular store. CRE prices, particularly conditional on the other market attributes included in this model, reflect market-level demand shocks for business real estate in general, and have to be independent of the output of any single firm. CRE prices are not functions of the markups due to one specific store, as they are determined by market-level conditions. CRE prices are, therefore, likely to be correlated with the included endogenous variable (donations), but mean independent of output. CRE prices are also exogenous to the retail food industry as they are set by competition among firms from a large number of industries for the same space.

Our data (from CoStar, a CRE data firm) potentially represent very granular geographies—specific to each address in our data set—but we aggregate up to the level of the ZIP code in order to reflect market-level prices that are independent of the output of any particular location. Cost-minimising retail managers should optimise the use of their floor space and manage inventory more carefully by purchasing in a way that more closely mimics a just-in-time replenishment system. If this is the case, we expect stores in more expensive areas to donate less, as the marginal value of additional store sizes is higher. As in the case of our labour variable, therefore, we maintain that each of our instruments are valid, based on first principles, and the maintained assumption that retailer managers seek to minimise the costs of production. In the next section, we report the validity of both sets of instruments, before discussing the estimates obtained from our structural model of production, and markups.

## 5. Results and discussion

We begin this section with a presentation of our main results and conclude with a series of counterfactual simulations that illustrate the policy relevance of our findings. Throughout the paper, we refer to a number of robustness tests that were conducted by estimating multiple specifications of each model to help establish the validity of our results. We begin by presenting the results from a set of ‘reduced-form’ models that seek to examine whether our data are sufficient to estimate the underlying production function we hope to bring to the

data, and whether food bank donations are related to store-level performance, even without imposing the additional structure implied by our two-stage CF method. We then present different specifications of the markup estimation model and interpret them in terms of their implications for store-level markups, both with and without donations.

Our reduced-form evidence suggests that our store-level data can identify important relationships between key production inputs and output. We present the results from our reduced-form specifications in [Table 3](#). In general, across all specifications, we find that the parameters of the production function (output elasticities) are precisely estimated and appear to reflect a relatively well-behaved production technology. As evidence of this assertion, note that we fail to reject the null hypothesis of constant returns to scale in each specification except Model 5. That is, in each of the first four models (Model 1—Model 4), the returns to scale (sum of the output elasticities, evaluated at the means of the data and random parameters) is 0.99, while the returns to scale for Model 5 is 1.09. While there are no benchmarks in the literature against which to compare these estimates, they appear to be logically consistent as it is difficult to imagine large-scale retail chains with substantial unexploited economies of scale at the store level.

The markups implied by our estimates appear to be reasonable. Starting with a basic production-function model (Model 1), we find an implied markup of 2.67, and the markups for Models 2–4 are similar (2.66, 2.71 and 2.72, respectively). When we allow for interactions between donations and the labour input, however, on the assumption that facilitating a more effective price-discrimination strategy allows the store to increase its revenue per available worker (a key metric in retail), we find that implied markups are slightly lower, at 2.53. This finding is due to the fact that the interaction effect between donations and labour in the reduced-form model is negative, meaning that donations actually reduce the marginal productivity of labour. Statistically, Model 5 is preferred as a likelihood ratio (LR) test rejects Model 4 in favour of Model 5 at a 5 per cent level of significance, and 2 degrees of freedom ( $\chi^2 = 11.4$ ). However, we note that these models are in reduced form in nature, so both the elasticity of output with respect to labour and hence the estimate impact of donations on markups are likely to be biased. Accurately accounting for the impact of donations on output requires that we control for the endogeneity of labour, and of donations.<sup>14</sup>

First, however, we provide evidence on the quality of our first-stage, instrumental variables regressions in [Table 4](#). From the first set of results in [Table 4](#),

<sup>14</sup> Note that the size of our implied markups is not directly comparable to the much-smaller estimates in [De Loecker and Warzynski \(2012\)](#), for example, who find markups in the range of 1.17–1.28. Their sample firms are manufacturers, so the role of labour in their production process is very different. In general, the labour share of revenue in manufacturing is much larger (and implied markups smaller) relative to retailers, as cost-of-goods-sold constitutes most of the revenue share for food retailers. Retailers are, by definition, inventory-intensive and labour-extensive relative to manufacturers. Furthermore, these estimates are gross markups over marginal cost, and retailers are well-understood to have relatively high fixed costs ([Bliss 1988](#)).

**Table 3.** Reduced-Form Production Function Estimates

Parameter means	Model 1		Model 2		Model 3		Model 4		Model 5	
	Mean	Std. Err.	Mean	Std. Err.						
Labour	0.2198*	0.0318	0.2191*	0.0338	0.2234*	0.0328	0.2237*	0.0331	0.4367*	0.0739
Capital 1	0.6133*	0.0390	0.6120*	0.0343	0.5819*	0.0346	0.5820*	0.0348	0.5774*	0.0340
Capital 2	0.1521*	0.0354	0.1515*	0.0384	0.1898*	0.0376	0.1898*	0.0381	0.1924*	0.0380
Gas					0.0745*	0.0173	0.0745*	0.0173	0.0739*	0.0169
Liquor					0.1357*	0.0291	0.1355*	0.0293	0.1469*	0.0292
Donations							0.0008	0.0100	0.3429*	0.1008
Don*Labour	Yes		Yes		Yes		Yes		-0.0694*	0.0204
Chain effects	Yes		Yes		Yes		Yes		Yes	
Year effects	Yes		Yes		Yes		Yes		Yes	
Random parameters	No		Yes		Yes		Yes		Yes	
Implied markups (No donations)	2.6704	1.1776	2.6618	1.1738	2.7149	1.1972	2.7176	1.1984	5.3061	2.3399
Implied markups (Donations)	N.A.		N.A.		N.A.		N.A.		2.5341	1.1175
Chi-square			174.692		207.066		207.070		218.468	
LLF			87.346		103.533		103.535		109.234	

Note: All variables in logs. Model 1 is fixed-parameter model, with no covariates. Model 2 is random-parameter model with no covariates. Model 3 is Model 2 with gas and liquor effects. Model 4 adds donations as shifting variable. Model 5 is Model 4 with interaction effects between donations and labour input. No correction for endogeneity in any model. Chi-square is relative to null. All data are from Nielsen TDLinx, retailer Donor Source Reports, and BLS QCEW. A single asterisk (\*) indicates significance at a 5 per cent level. N.A. = not applicable without non-linear labour and donation interaction.

**Table 4.** First-Stage Instrumental Variables Regressions

Instrument	Model: Labour		Model: Donations	
	Mean	Std. Err.	Mean	Std. Err.
Constant	4.0278*	0.1729	4.1517*	0.3608
Wages	-1.0373*	0.2013		
CRE prices			-0.2095*	0.0324
Density			-0.5400*	0.2612
HH size			-0.1121*	0.0502
Unemployment			-0.2785*	0.1143
F-statistic	26.5653		13.5199	
R <sup>2</sup>	0.0261		0.0519	

*Note:* Wages are from BLS, QCEW; CRE prices are from CoStar, defined for specific store locations; density refers to population density; HH size refers to household size; unemployment rate to the unemployment rate of individuals above 16 years of age, each from the American Community Survey, Bureau of Census, measured on a census-census-tract level. A single asterisk (\*) indicates significance at a 5 per cent level.

we find our instrument for the labour input to be not weak in the sense of [Stock and Yogo \(2005\)](#), as the F-statistic from the first-stage instrumental variables regression is 25.6, which is above the threshold of 10.0. In terms of the donation variable, our first-stage instrumental variables regression supports our hypothesis regarding the relationship between CRE prices and donations, as the results in [Table 4](#) show that CRE prices are an important driver of donations. Furthermore, this regression shows that stores in more dense, higher unemployment areas with larger households are likely to donate less. Again, this set of instruments is not weak as the first-stage F-statistic is 13.6. With these instruments, therefore, we are at least reasonably confident that the results from the structural model are as free of bias as possible.

We present the estimates obtained from our control-function approach in [Table 5](#). As in [Table 3](#), we present the results from a number of different models in order to examine the robustness of our findings across different specifications. First, we note that the base labour-elasticity estimates in [Table 5](#) are much lower in Models 1 and 2 than in the reduced-form estimates presented in [Table 3](#) (0.111 and 0.103 relative to an average of 0.241 across all 5 specifications). This finding suggests that our variant of the [Akerberg, Caves and Frazer \(2015\)](#) correction procedure is able to address a considerable amount of the endogeneity bias inherent in the reduced-form models of [Table 3](#).<sup>15</sup>

Second, note that these lower labour-elasticity estimates imply correspondingly lower retail markups—in all but the preferred model. Again using a

<sup>15</sup> We estimated a version of the structural model in [Table 5](#) using a limited-information maximum likelihood (LIML) approach in order to examine the sensitivity of our findings to the fact that our donation instruments are close to the weakness threshold of [Stock and Yogo \(2005\)](#). Our findings, available from the authors, are qualitatively similar, but implausibly high in magnitude. While the small-sample properties of the LIML estimator may be superior to our control-function estimates, we maintain that the LIML model does not adjust for unobserved productivity shocks as completely as the maintained [Akerberg, Caves and Frazer \(ACF\) \(2015\)](#) method.

**Table 5.** Control-Function Markup Estimates

Parameter means	Model 1		Model 2		Model 3	
	Mean	Std. Err.	Mean	Std. Err.	Mean	Std. Err.
Labour	0.1116*	0.0304	0.1033*	0.0201	0.2320*	0.0375
Capital 1	0.6831*	0.0166	0.6504*	0.0083	0.6536*	0.0084
Capital 2	0.1481*	0.0153	0.1459*	0.0099	0.1453*	0.0100
Gas	0.0388*	0.0073	0.0407*	0.0050	0.0411*	0.0051
Liquor	0.0091	0.0158	0.0169*	0.0094	0.0204*	0.0095
Donations	-0.0823*	0.0440	-0.1098*	0.0295	-0.1438*	0.0307
Donations*Labour	0.0181*	0.0089	0.0238*	0.0058	0.0236*	0.0058
CF (Labour)					-0.1298*	0.0328
CF (Donation)					0.0350*	0.0099
Chain effects	Yes		Yes		Yes	
Year effects	Yes		Yes		Yes	
Random parameters	No		Yes		Yes	
Implied markups (No donations)	1.3564	0.5982	1.2552	0.5535	2.8183	1.2428
Implied markups (Donations)	2.0801	0.9173	2.2050	0.9724	3.7628	1.6593
Chi-square	1,893.418		1,943.858		1,952.984	
LLF	946.709		971.929		976.492	

Note: All variables in logs. Model 1 is fixed-parameter model, no CF; Model 2 is a random parameter model with no control function. Model 3 is a random parameter model with CF. Chi-square is relative to a null model. A single asterisk (\*) indicates significance at 5 per cent.

LR test to compare models, given that each is nested in the more-complex model to its right in the table, we find that Model 2 is preferred to Model 1 ( $\chi^2 = 100.0$ ), and Model 3 is preferred to Model 2 ( $\chi^2 = 18.3$ ). Interpreting the results from our Model 5, notice that the equilibrium markups are similar, albeit higher, to the markups estimated from our preferred reduced-form model (3.76 versus 3.14). Because the differences between Model 3 and Model 2 in [Table 5](#) are our controls for the endogeneity of donations and labour input, it is clear that controlling for all sources of endogeneity bias is necessary to obtain accurate estimates of the donation effect. Furthermore, note that our preferred markup effect is, again, relatively large. Finding a markup effect this substantial, and statistically significant, implies that quality-based price discrimination is more than a public-relations strategy by perishable-food retailers to portray themselves as less wasteful than rivals, and indeed may comprise a major component of their perishables pricing strategy. That said, our estimates to this point do not take into account the volume-shifting effects we estimate.

We use these estimates of the structure of retail food production to estimate the impact of food bank donations on the markups implied by the [De Loecker and Warzynski \(2012\)](#) approach, and overall store profitability. Based on the estimation results in [Table 5](#), we conduct a series of counterfactual simulations that aim to show the likely effect of food bank donations on store profitability, taking into account not only the marginal effects on labour productivity identified in [Table 5](#), but the overall store-volume effects encompassed by the entries in that table as well.

We conduct our simulations by running the preferred model in [Table 5](#) (Model 3), and calculating weekly store sales (corrected for the CF procedure, and the PPI deflation protocol) for every observation in the data, taking into account the random nature of the key production parameters. We calculate the implied standard errors using the delta method given the non-linear relationship between donations and store sales, and then vary the level of donations downward, and upward, in increments of 25 per cent from the observed, mean donation levels. Because these effects move in opposite directions, we expect the direct effect on volume to moderate the large markup effects shown in [Table 5](#).

[Table 6](#) reports the results of our numerical model. The entries in [Table 6](#) show a small, positive net effect of donations on store sales. For each 25 per cent increment in donations (roughly 12,500 lbs. per year), the impact on store sales is approximately \$3,500 per week, or \$182,000 per year. Given the relatively small net margins for supermarkets in the USA, this increment in sales represents an economically significant increase for each store.<sup>16</sup> Note further that because we control for individual store attributes, this effect represents an average over what we would expect from a representative store in our sample. Moreover, because perishable food that is thrown out at its expiration date

16 Expressed as a percentage of store sales, a 50 per cent change in donations represents roughly a 1 per cent change in store sales.

**Table 6.** Simulated Store Sales and Donations

Donations	Store Sales		
	Mean	Std. Dev.	t-test
–50 per cent	666.8851	0.0052	–61.4835
–25 per cent	670.4884	0.0033	–42.3750
Base	674.1188	0.0027	
25 per cent	677.7636	0.0041	36.5105
50 per cent	681.4294	0.0063	52.6753

*Note:* Simulations are averaged over each observation in the data; t-ratio values are relative to the base store value. Values are in thousands of dollars per week.

represents an economic loss, a feature described as ‘shrink’ in retailing terminology, this increment to revenue also represents a direct improvement in stores’ bottom lines.<sup>17</sup> Accordingly, we view our findings as a lower-bound estimate of the change in store profit due to store-level food bank donations.

Our findings are important for the study of food retailing on a number of levels. First, food banks form an important part of the food supply chain in general by creating a secondary market for perishable food items. Finding support for the notion of ‘retailer-food bank symbiosis’ therefore casts food bank donations in new light. While we do not doubt that food bank donations are an important part of a retailer’s public relations programme, they also appear to be essential to the marketing and merchandising strategies of donating retailers.

We find evidence that donating perishable food items at the back of the store allows retailers to sell them more profitably at the front of the store. Further on this point, we note that it is somewhat surprising that we observe some stores with zero donations, despite the clear profitability of donating. Because donation amounts are at the discretion of store management, and the local food bank reserves the right to not allocate a truck if donations amount are likely to be small, we believe our findings highlight a key decision error in managing perishable inventories. Failing to donate enough expiring food takes away one opportunity for profitable quality enhancement within the stores.

Second, we show how an increasingly important empirical method that has been limited to date to examining firms at the manufacturing level can be used to study store-level performance at the retail level without the need to construct a large-scale demand model that encompasses thousands of products at a time.

Third, our findings are also relevant to the study of retail food waste, which is important in its own right. Perishable food that is not donated to a food bank is typically either discounted or simply discarded. To the extent that degraded food items would otherwise be discarded by retailers at the end of their saleable lives, food bank donations serve to reduce retail food waste. Studying the effect of food bank donations on retail food waste, in this sense, provides an interesting avenue for future research.

17 In fact, the savings are even greater if we were to add the cost of tipping fees levied by most municipal waste agencies, and the potential tax savings from the donations to food banks.

## 6. Conclusions and implications

Food banks form an important, yet overlooked, part of the retail food-supply system. We have demonstrated that food banks play an essential role in food retailers' perishable-food inventory and pricing strategies by allowing firms to engage in quality-based price discrimination. Donating perishable food that is past its saleable lifetime allows retailers to maintain higher food quality on the shelf, on average, resulting in higher prices and larger markups than would otherwise be the case.

We framed our empirical model of food bank donations using a production-side empirical model of secondary markets and quality-based price discrimination. Due to the fundamental intractability of modelling whole-store markups from a demand-side perspective (Berry, Levinsohn and Pakes, 1995), we use the production-side approach of Hall (1986) following the recent contributions by De Loecker (2007, 2011a, 2011b); De Loecker and Warzynski (2012); and De Loecker and Scott (2016). We show that this method provides a valuable alternative for examining retail margins in multiproduct environments with large numbers. Such an approach is generally applicable for other important questions in empirical industrial organisation settings when the scope of products transacted makes traditional demand-side methods intractable. In this regard, our empirical model is the first in the empirical retailing literature to use a markup approach to estimate retail market performance at the store level.

We find that donations are associated with higher markups among supermarket retailers in our sample. At the same time, removing food from the shelf through donations represents a substantial loss in sales volume relative to a strategy of discounting prices to clear unsold inventory, which makes the effect of donations on sales unclear from our empirical estimates, alone. To address the impact of food donations on retail sales, we constructed a numerical model to show that the net effect of food bank donations is to raise retail sales at donating stores. Following a 25 per cent increment in donations (roughly 650 additional lbs. per year), store-level sales rise by approximately \$182,000 per year. In this regard, food donations create a symbiotic relationship between retailers and food banks in meeting the food consumption needs of households, an outcome that has not been properly acknowledged to date.

Our study has some potential weaknesses that can be improved upon in future research. By extending the Akerberg, Caves and Frazer (2015) framework to an incomplete panel of production-type data, our aim is to open up a new avenue for empirical research on retail market performance. Studying retailing questions, in general, is confounded by the curse of dimensionality, as modern retailers typically sell thousands of products at a time, introducing a potentially rich set of demand relationships between products within and across categories. Further developing methods along these lines to improve the precision of estimated margins at the level of the entire store therefore represents a substantial opportunity to advance knowledge in the empirical retailing literature. For example, the TDLinx data we used for our approach are not the 'usual' form of production data gathered either for census purposes (Census of

Manufacturers) or for financial analysis (Compustat), but are well-suited for our purposes.

In light of the growing importance of dynamic modelling techniques in the retailing literature (e.g. see Arcidiacono *et al.*, 2016), and the fundamental importance of understanding dynamic shopping behaviour more generally, a fruitful avenue for future research would be to consider a dynamic variant of the production-side markup approach we have pursued here. Furthermore, our findings seem to suggest that retailers can improve profitability by donating more, seemingly without bound. However, the practical limit to exploiting the mechanism we describe here is likely the store's own inventory-handling capabilities and the fact that there is a physical limit to a retailer's ability to raise quality simply by donating end-of-life product. That is, the as-purchased quality of the food represents a natural ceiling to the strategy implied by our findings.

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