# Farmers, Workers, Neither, or Both: Who Is Exploited? *

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**Abstract**

The firms of the highly concentrated U.S. meatpacking industry are often suspected of exploiting livestock farmers and meatpacking workers, and maybe exercising market power in the product market. We test for monopsony in the two markets concerned and for product market power, and we assess how much each market contributes to meatpacking firms' gross profits. We reject the exercise of market power in the livestock market, but find that some plants exploit their share of local employment to set wages with an important markdown. Firms also exercise some power in the product market.

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# 1 Introduction

Dominated by a small number of firms (currently four), the U.S. meatpacking industry has been suspected of exercising market power in the product market and monopsony power in the market for its livestock inputs, as well as accused of imposing poor working conditions on its workforce.[1] The latter suggests the presence of monopsony power in the labor market.

We use an unbalanced panel of more than 500 plants of varying sizes, spanning the years from 1997 to 2020, to estimate the production function for meatpacking and assess potential markdowns in livestock and meatpacking labor. In doing this, we control for both neutral productivity and labor-augmenting productivity (LAP). We then use our estimates to decompose the observed firms' profitability into its components. On average, gross profitability is about 20 percentage points, of which our model attributes 11 percentage points to technology (the difference between marginal and average cost), and the remainder to a combination of product and labor market power. We reject the presence of monopsony power in the livestock market but find evidence of monopsony power in the labor market and some market power in the product market.[2]

The exercise is based on the semiparametric estimation of the elasticities. Using the restrictions implied by production theory, the elasticities of variable inputs can be expressed as a function of the short-run scale parameter, the markdowns, and the observed shares of the inputs in variable cost. In our case, three variable elasticities are expressed in terms of three elements to be estimated. The first is the elasticity of scale, which is a parameter. The second and third are the markdowns of two markets, which are modeled as functions of observable variables. As long as the three elasticities can be identified, the three elements can also be identified.

Naturally, unobserved productivity must be controlled for. Hicksian productivity does not pose any particular difficulty. We apply a dynamic panel method after assuming that it follows an AR(1). LAP can be controlled by the ratio of FOCs (i.e., expressed in terms of observables and estimable parameters).

The paper constructs a regression model to estimate the relevant parameters (including the values of the parameters of the markdowns), plugging the semiparametric elasticities into the production function of each estab-

[1]The effects of the COVID-19 pandemic raised concerns about working conditions; see Congress of the United States (2021),

[2]A streamlined version of the model, used in an earlier version of the paper with aggregate data prior to accessing the plant-level data, was notably able to detect the main traits of competition, though with much less accuracy.

lishment in our sample. Using enough valid sample moments, we identify the parameters using a nonlinear GMM.

The estimated parameters and markdown values implicitly define the marginal cost, allowing the markup to be computed after estimation (up to an uncorrelated error). This allows for the decomposition of firm profitability into all its sources and components: technology, product market power, and monopsony power in the market for each input.

This paper joins the recent interest in monopsony power in input markets simultaneously with market power in the product market, from a microeconomic point of view. See, for example, Kroft, Luo, Mogstad, and Seltzer (2025), a case analysis close to ours. [3] We adopt the point of view of identification from the production side, using a production function, an approach applied often in product markets after De Loecker and Warzynski (2012) and in input markets after Dobbelaere and Mairesse (2013, 2018). See also the application to U.S. manufacturing by Yeh, Macaluso, and Hershbein (2022). To make reliable inferences, we control for both neutral productivity and LAP, following recent works such as Doraszelski and Jaumandreu (2018) and Demirer (2025). We use a semiparametric specification of the production function, as justified in Jaumandreu (2026).

The remainder of the paper is organized as follows. Section 2 introduces the industry settings to model and relates them to the literature. Section 3 shows how the evaluation of the exercise of monopsony power in the livestock market can be reduced to the evaluation of a wedge. Section 4 develops the specification needed to assess the presence of monopsony power in the labor market. Section 5 establishes the production model that we use. The estimation of the production function and the assessment of market power are presented in Section 6. Section 7 compares our estimator to other estimators of market power in the product and labor markets. Section 8 concludes. Appendix A assesses substitution between livestock and other inputs; Appendix B describes the construction of the sample and the variables.

# 2 A primer on meatpacking

The meatpacking industry encompasses the slaughter, processing, packaging, and distribution of meat from animals such as cattle, pigs, sheep, and lambs (excluding poultry). These activities are carried out in plants of widely varying sizes, ranging from very large to very small. According to the U.S.

[3]Our contribution is a more general analysis, robust to the form of competition in the product market, with a general production function and non flexible capital. Crucially, we control for biased technical change and decompose the profits of firms.

Department of Agriculture (USDA), in 2023, 267 beef packing plants slaughtered 1,000 or more head of cattle. Of these, 11 plants slaughtered more than one million head. Similarly, there were 206 pork slaughter plants processing 1,000 or more head, of which 14 slaughtered more than 4 million head each. There were also 103 sheep and lamb plants slaughtering 1,000 or more head, with 13 of them processing more than 25,000 head each (USDA NASS 2024).[4] These numbers yield a total of 576 plants of significant size, which is very close to the total number of plants in our empirical analysis.

The industry is highly concentrated at the firm level, with companies operating several plants. According to USDA, in 2021, four major producers - Tyson, Cargill, JBS and National Beef - represented 81% of all slaughtered steers and heifers, 65% of hogs and 42% of sheep and lambs (USDA AMS 2022).

Concentration in the industry increased sharply between 1960 and 1990, as plant sizes grew.[5] Facilities moved from the Midwest and Northern Great Plains to the Southern Great Plains, nearer to the main feedlots. Since then, concentration has grown more slowly. For example, the four-firm concentration ratio (CR4) in beef processing rose from 41% in 1982 to 79% in 2006 and has remained relatively stable since. For a historical overview, see MacDonald and McBride (2009), and for a more recent account, see MacDonald (2024).

The conduct of packers has traditionally been a source of concern in two input markets, livestock and labor, and in the market for the output.

**Livestock Market**

The high level of buyer concentration in the livestock market, complaints from livestock producers, and the prevalence of alternative market arrangements (AMAs) raise concerns about the market's competitiveness. However, the sellers' part of the market must also be understood as relatively organized. The 1999 Livestock Mandatory Reporting Act introduced a system of price transparency based on daily reports published by USDA. The concentration of sellers is also significant, since it is estimated that 132 feedlots produce half of the feed cattle in the U.S. In fact, a proof of non-defenselessness is that, in 2019, cattle producers coordinated with beef buyers to file class action

[4] The biggest plants collectively account for 46% of all cattle slaughtered, 60% of hogs and 39% of sheep.

[5] Technology improvements, in particular through automation, have probably had an ambivalent effect. Plants could become very large, but production became also possible at the same average cost at smaller sized plants. A movement towards constant returns to scale resulting in increasing inequality, destroying the sources of traditional economies of scale.

antitrust lawsuits against the four largest packers, which resulted in some settlements and the denial of wrongdoing (Bolotova, 2023).

Currently, approximately 80% of livestock procurement is done through AMAs. These are long-term contracts under which a packer agrees to purchase a specified quantity of livestock over the course of a year. Prices can be tied to the cash market or to a forward variant based on the Chicago Mercantile Exchange.

Many authors have raised concerns about the input market power impact of these formula contracts. [6] We develop a "neutral" model of pricing integrating the AMAs. We start from the existence of two supply functions (formula contracts and cash) that differentiate the supply market and relate the prices. Although the model can explain market power, it can also explain the opposite, depending on unknown elasticities and behavior. What is important is that the model shows that pricing of livestock by packers can be summarized in a unique first order condition on the price of livestock. The wedge in this first order condition reveals the amount of exerted market power, and this is what we want to estimate.

**Labor Market**

The industry has a long history of controversial labor practices. Increasingly located in rural areas, the sector employs a low-skilled workforce with a large proportion of immigrant workers, from which an unknown fraction is not in a fully regular legal situation. Training for meatpacking work can be acquired in a short period of time, and the conditions of work are bad and dangerous (with a high incidence of accidents). For a recent description, see Grimes, 2024. Controversy over industry labor practices intensified during the onset of the COVID-19 pandemic, when at least 59,000 meatpacking workers were infected and 269 died (Congress of the United States, 2021). Workers are often non-unionized.

Production plants are spread across many counties. Plants are, as mentioned above, highly unequal in size. However, even the smallest plants account for an important part of the manufacturing employment of the county (at least one-third, see Table 2 on the description of our sample).[7] Some-

[6] Studies such as Xia and Sexton (2004), Xia, Crespi, and Dhuyvetter (2018), Garrido, Kim, Miller, and Weinberg (2024), and Hummel (2023), include both some theoretical modeling and empirical analysis of the effects of AMAs. While the theoretical work explores the potential for packers to increase the markdown on livestock, the empirical analysis focuses on the widening of the spread (defined as the difference between the price received by the packer for the meat they sell and the price paid for the livestock). However, no clear link has been established between the observed spread expansion and the use of AMAs.

[7] There is a sociological literature that stresses the likelihood of company strategies to

times they are the only meatpacking plant, and sometimes they share the location with (similar-sized) plants of competitors. In this case, all relevant employment for the county is meatpacking. What this means is that workers have, in general, few employment options. This is not contradictory with big plants trying to attract and retain workers by offering some benefits in addition to health insurance and retirement plans, such as wellness programs, education assistance, English as a Second Language, etc. (AMI 2009).

Consequently, we expect effects of local monopsony power on the wages paid by firms (see, e.g., Manning, 2011). We attribute an increasing supply curve for each plant to the presence of a local distribution of reservation wages (probably linked to the different status of the workers) and assume that the firms compete in quantities of employment, given competitors' employment. This provides a schedule of wage markdowns that we test. Of course, our model is not detailed enough to assess the rich workings of these labor markets (which would be great to explore), but it is enough to clearly state the presence of exploitation of the labor force .

**Competition**

The literature on meatpacking competition is extensive. Azzam (1998) reviews the literature from the 1960s through the 1990s, while Wohlgenant (2013) covers research through the 2010s. The literature focuses almost exclusively on cattle pricing, with one recurring question being whether oligopsony affects pricing. [8] To the authors' knowledge, there are no studies of oligopsony power in meatpacking labor markets. As summarized by Wohlgenant (2013), the consensus in the existing literature is that, despite varying empirical approaches, there is no evidence of significant market power exercised either in the market for packed meat or in the input market for livestock. In contrast, he stresses the evidence of reduced processing and distribution costs stemming from reorganization, technical innovation, and increased plant size.

In a broader time perspective, meatpacking is an industry with more than a century of questionable competitive practices. Huang (2024) studied price manipulation by firms acting as a monopsonist cartel at the beginning of the twentieth century. At the other extreme, very recently, persistent concentration, new forms of contracting and setting prices, complaints from

build immigration pools of low-skilled workers (modern variants of "Company Towns") in some rural areas. See Champlin and Hake (2006).

[8] An earlier study by Schroeter (1988) finds no evidence of serious price distortions in the beef packing industry; Azzam and Pagoulatos (1990) address oligopoly and oligopsony in meatpacking simultaneously, concluding with moderate evidence that market power was greater in the input market; Morrison (2001) finds evidence of cost economies but not of market power in beef packing.

farmers and ranchers, as well as concerns about labor practices, have again drawn attention to the sector's competitiveness. Garrido, Kim, Miller, and Weinberg (2024), Hummel (2023), and Moschini and Smith (2025), address recent pricing practices; Bolotova (2022) addresses collusion in the industry; and MacDonald (2024) discusses recent structural developments. None of these papers finds significant departures from competition.[9]

# 3 The livestock market

The big companies have many plants, but there are many more plants than those belonging to the largest companies. The price of a head of cattle was about \$2,000 in 2021, and the data show that the variation between regions is small, probably only related to different transportation costs. Our first assumption about the market is that packers rely on plants to set the quantities purchased. [10] This naturally provides the opportunity for some geographic price discrimination in a good that is homogeneous. To simplify notation, we will not explicitly distinguish regions although in the empirical exercise we do. We also drop for the moment the time subindices. We index plants simply by $j$.

There are two markets to sell and buy cattle, formula contracts $F$, and cash $C$. Let the total cattle supplies for each market be $R_F = R_F(P_F, P_C)$ and $R_C = R_C(P_C, P_F)$, where $P_F$ and $P_C$ are the corresponding prices. These supplies represent the preferences of ranchers and farmers, and supplies are likely to be unequal at the same price (the $F$ market, at minimum, reduces risk). As long as the system is invertible, $P_F = P_F(R_F, R_C)$ and $P_C = P_C(R_C, R_F)$, and in equilibrium we can also write $\sum_j R_{Fj} = R_F$ and $\sum_j R_{Cj} = R_C$ (demand of the packers equals supply).

Packer $j$ short-run profits are

$$\begin{aligned}\pi_j &= P(Q)Q_j(K_j, R_{Fj} + R_{Cj}, L_j, M_j) \\ &\quad -WL_j - P_F(R_F, R_C)R_{Fj} - P_C(R_C, R_F)R_{Cj} - P_M M_j,\end{aligned}$$

where $Q_j$ is the quantity of output produced by $j$, $Q = \sum_j Q_j$, and $P = P(Q)$

[9]Moschini and Smith's (2025) calibration of the detailed county-level study of livestock buyer power by the beef packers finds a markdown of 2.6%.

[10]Garrido, Kim, Miller, and Weinberg (2024) and Moschini and Smith (2025) assume packers' competition in prices with an inelastic supply. If the product is homogeneous and the buyers equal, this produces a Nash equilibrium with input price equal to marginal productivity of the input, because if this is not the case each competitor has incentives to offer a price above the prevailing price, a version of the Bertrand "paradox" (see, e.g., Azar and Marinescu, 2024).

is the inverse of the total demand for packed meat. Note that production $Q_j$ uses capital, cattle, labor, and materials: $Q_j = Q_j(K_j, R_{Fj} + R_{Cj}, L_j, M_j)$.

The decision with respect to the $F$ market can be characterized by means of FOC

$$\frac{\partial \pi_j}{\partial R_{Fj}} = MR_j \frac{\partial Q_j}{\partial R_{Fj}} - P_F - R_{Fj} \frac{\partial P_F}{\partial R_{Fj}} - R_{C_j} \frac{\partial P_C}{\partial R_{Fj}} = 0,$$

where $MR_j$ stands for marginal revenue, and we may think of the quantity and the price in the cash market as expected. We write $MR_j$ to avoid making any assumption on the form of competition in the output market.[11] As we want to admit different behaviors in the market for cattle as well, we will write $R_{F_j} \frac{\partial P_F}{\partial R_{Fj}} = P_F \frac{R_F}{P_F} \frac{\partial P_F}{\partial R_F} \frac{R_{Fj}}{R_F} \frac{\partial R_F}{\partial R_{Fj}} = P_F \varepsilon_F^F \theta_j^F$, where variable $\theta_j^F$ can take the values 1 (collusion); $S_j^F$, Nash; and 0, competition. Do a similar rewriting of $R_{C_j} \frac{\partial P_C}{\partial R_{Fj}}$.

A simpler way to write the FOC is thus

$$MR_j \frac{\partial Q_j}{\partial R} - P_F(1 + \varepsilon_F^F \theta_j^F) - P_C \varepsilon_F^C \lambda_j \theta_j^F = 0,$$

and the equivalent for the cash market is

$$MR_j \frac{\partial Q}{\partial R} - P_F \varepsilon_C^F \lambda_j^{-1} \theta_j^C - P_C(1 + \varepsilon_C^C \theta_j^C) = 0,$$

where $\lambda_j = \frac{R_{Cj}}{R_{Fj}}$ or the ratio of cattle sold in the cash market with respect to the quantity sold through contracts. Elasticities $\varepsilon_F^F, \varepsilon_F^C, \varepsilon_C^C$ and $\varepsilon_C^F$ are the elasticities of the inverse supplies in each of the $F$ and $C$ markets with respect to the own and cross quantities.

With the prices in the formula contracts and cash market set contractually equal, say $P_F = P_C = P_R$, then

$$\begin{aligned} MR_j \frac{\partial Q_j}{\partial R} &= P_R(1 + (\varepsilon_F^F + \varepsilon_F^C \lambda_j) \theta_j^F), \\ MR_j \frac{\partial Q_j}{\partial R} &= P_R(1 + (\varepsilon_C^F \lambda_j^{-1} + \varepsilon_C^C) \theta_j^C). \end{aligned}$$

At equilibrium, since the left-hand side is the same, we can write $(\varepsilon_F^F + \varepsilon_F^C \lambda_j) \theta_j^F = (\varepsilon_C^F \lambda_j^{-1} + \varepsilon_C^C) \theta_j^C$. Notice that, if $\theta_j^F = \theta_j^C = 1$, then $\lambda_j = \lambda$.

[11] However, we may want to keep in mind that, when there is Nash competition in quantities, $MR_j = P(1 - S_j \varepsilon)$, where $S_j$ is the share of firm $j$ in output, and $\varepsilon = -\frac{Q}{P} \frac{\partial P}{\partial Q}$ is the (absolute value of the) elasticity of the inverse demand for the output.

What the model shows in general is that, since the firms are maximizing profits and $MR_j = MC_j$, pricing through the AMAs yields FOCs with a wedge $\rho_j$ on the price of the unit of livestock $P_R$[12]

$$MC_j \frac{\partial Q}{\partial R} = P_R(1+\rho_j).$$

This wedge is equal to $\rho_j = \rho = \varepsilon_F^F + \varepsilon_F^C \lambda = \varepsilon_C^F \lambda^{-1} + \varepsilon_C^C$ if there is collusion among packers in both markets, $\rho_j = S_j^F(\varepsilon_F^F + \varepsilon_F^C) = S_j^C(\varepsilon_C^F + \varepsilon_C^C)$ if the behavior of the packers is Nash, and $\rho_j = 0$ if they compete. The possible coordination of sellers can be seen as reducing the elasticity of the inverse demands to zero, and the wedge would be reduced to zero in all cases. We exclude any situation of negotiation of two coordinated sets of buyers and sellers because there is no evidence of such a situation.

Summarizing, we expect a uniform markdown if there is collusion among the buyers, heterogeneous markdowns varying with the buying shares if there is quantity competition, and zero markdown in the cases of either greater competition of the buyers or sellers' coordination.

# 4 The labor market

County workers have a distribution of reservation wages for working in a particular meatpacking plant. Relatively high proportions of workers have very low reservation wages because there are very few alternative jobs they can access, sometimes because of their non-fully regular situation. We thus assume that a particular plant has a relative labor supply function in the county

$$S_j = G(W_j, size_j),$$

where $S_j = \frac{L_j}{\overline{L}}$, with $\overline{L}$ being the county labor force. Size refers to a measure of the absolute size of the plant or the county (as mentioned before, they are highly correlated), which allows the distributions to differ according to this characteristic.

We assume that plants decide employment.[13] The distribution of reservation wages confers some monopsony power to the plant that can be used

[12] In the case of Cournot behavior, this formula readily provides the ratio price of meat/price paid for the cattle (or "spread")

$$\frac{P}{P_R} = \frac{(1 + \frac{1}{N}(\varepsilon_F^F + \varepsilon_F^C))}{(1 - \frac{\varepsilon}{N})\frac{\partial Q}{\partial R}}.$$

[13] With undifferentiated unskilled workers, there is not much sense in assuming wage

in deciding optimal employment. Let $W_j = G^{-1}(S_j, size_j)$ be the inverse of the supply curve. The first order condition for cost minimization is

$$MC_j \frac{\partial F_j}{\partial L_j} = \frac{\partial (W_j(L_j)L_j)}{\partial L_j} = W_j + L_j \frac{\partial G^{-1}(S_j, size)}{\partial S_j} \frac{1}{\overline{L}},$$

which can be written as

$$MC_j \frac{\partial F_j}{\partial L_j} = W_j(1 + \tau(S_j, size_j)),$$

where $\tau(S_j, size_j)$ is the proportional markdown or degree of labor market power of the plant.

The degree of market power varies in the first place with the share of workers in the county, an effect of the distribution of reservation wages and quantity competition, but also with the absolute size of the plant (county). This second effect can be important because of the usual differences attributed to large plants with regard to wage setting (see, e.g., Manning, 2011; recall the benefits provided by large plants, which we mentioned before) or because of the difference in the distribution of county reservation wages according to their absolute size (more alternative jobs).

We do not consider the frequent foundation for the upward sloping supply curve derived from the workers' choices among alternative jobs because this does not seem to reflect well the reality of the quite undifferentiated unskilled meatpacking labor force. For the different monopsony models, see Azar and Marinescu (2024). However, notice that, if we wanted to adopt the differentiation model, we would simply get a $\tau_j$ which is again a function of the share of the plant in the county and a common parameter across plants that could be considered county-specific.

In practice, we will specify $\tau_{jt} = \tau(S_j, size_j)$ as a constant plus linear effects of the log of the arguments and an effect of their interaction. It should be clear that, with no more detail on the labor markets, the purpose cannot be to detect a particular model but to robustly assess the existence and amount of labor market power.

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competition; plants have incentives to attract workers by raising the wage until marginal productivity is reached and the model would produce perfect competition (again a form of the Bertrand "paradox," discussed in the case of livestock).

# 5 Model

## 5.1 Production function

Consider the establishment-level production function

$$Q_{jt}^* = F(K_{jt}, R_{jt}, L_{jt}^*, M_{jt}) \exp(\omega_{Hjt}), \tag{1}$$

with $L_{jt}^* = \exp(\omega_{Ljt})L_{jt}$, where $Q_{jt}^*$ is the quantity of meat, $K_{jt}$, $R_{jt}$, $L_{jt}$, and $M_{jt}$, are capital, livestock, labor, and materials, respectively, and $\omega_{Ljt}$ and $\omega_{Hjt}$ are persistent variables representing LAP and Hicks-neutral productivity.

We take capital, labor, and materials as substitutable for livestock for three reasons. First, because the produced output, even measured in units of meat, has some degree of product differentiation that makes substitutability the natural technological relationship. The packed beef sold to different retail supermarket or restaurant chains, for example, is very different. Second, there is industry-specific accumulated evidence that has concluded unequivocally that there is substitution. And third, we have reached the same conclusion with all our specifications (for more details, see Appendix A). In what follows, $P_{Rjt}$, $W_{jt}$, and $P_{Mjt}$ denote the observed prices for livestock, labor, and materials.

There is a population of establishments endowed with production functions (1). Production functions are weakly separable in capital, which is given and has a constant output elasticity $\beta_K$. In the short term, firms can freely vary input quantities $R_{jt}, L_{jt}$, and $M_{jt}$. The variable inputs exhibit a constant elasticity of scale (sum of elasticities) of arbitrary value $\nu$.

**Assumption 1**
The output of each establishment can be written in the log-quantities of the inputs that the establishment is using as

$$q = \beta_0 + \beta_K k_{jt} + \beta_{Rjt} r_{jt} + \beta_{Ljt} l_{jt}^* + \beta_{Mjt} m_{jt} + \omega_{Hjt} + \varepsilon, \tag{2}$$

where $\beta_0$ is a constant, and $\beta_{R_{jt}}, \beta_{Ljt}$, and $\beta_{Mjt}$ are establishment and time-specific elasticities $\beta_X(K_{jt}, R_{jt}, L_{jt}^*, M_{jt}) = \frac{\partial \ln F(K_{jt}, R_{jt}, L_{jt}^*, M_{jt})}{\partial \ln X_{jt}}$ for $X_{jt} = R_{jt}, L_{jt}, M_{jt}$, and $\varepsilon_{jt}$ is an error of zero mean and uncorrelated with any information available for the firm at $t$.

**Assumption 2**
Firms minimize short-term costs by optimally choosing the quantities of variable inputs $R_{jt}, L_{jt}$, and $M_{jt}$. Markets for livestock and labor may

possibly be monopsonistic, so we allow for the potential presence of input market power represented by the proportional differences $\rho_{jt}$ and $\tau_{jt}$ between marginal product and input price (markdowns).

Denoting the marginal cost by $MC_{jt}$, the FOCs are thus

$$\begin{aligned} MC_{jt}\frac{\partial Q^*_{jt}}{\partial R_{jt}} &= (1+\rho_{jt})P_{Rjt}, \\ MC_{jt}\frac{\partial Q^*_{jt}}{\partial L^*_{jt}}\exp(\omega_{Ljt}) &= (1+\tau_{jt})W_{jt}, \\ MC_{jt}\frac{\partial Q^*_{jt}}{\partial M_{jt}} &= P_{Mjt}. \end{aligned}$$

**Discussion**

Assumption 1 says that the production function can be written in a log-linear form with plant- and time-specific elasticities for the inputs $R_{jt}, L_{jt}$, and $M_{jt}$. This is a perfectly plausible production function that can be called "extended Cobb-Douglas." The assumption that the production function has this form is as legitimate as, for example, assuming it has the CES or homogeneous translog forms. Each case implies considering that the errors of observation to which the output is subject are uncorrelated with the available information. [14] We will use this specification to obtain a semiparametric transformation that allows us to identify easily the possible markdowns $\rho_{jt}$ and $\tau_{jt}$. The details on when this specification can be considered exact for an unknown heterogeneous production function and when it is likely to coincide with a CES or homogeneous translog can be checked in Jaumandreu (2026).

Assumption 2 ensures at the outset that our specification is compatible with any behavior in the product market. The implicit marginal cost is not trivial because the potential market power in the input markets (which would imply equilibrium at marginal input prices) affects it. However, cost minimization is sufficient to implicitly determine the marginal cost. That makes it possible to estimate the market power from profitability, once the parameters of the production function and input market power have been estimated (see below).

Assumption 2 also ensures that we can identify market power in the input markets using our semiparametric transformation. We discuss this in detail

[14] Of course, the empirical exercise could reject the validity of the assumption, but there are no signs that this happens in our data.

after we show in Proposition 1 that the expressions of the FOCs can be rewritten in terms of the elasticities for the variable inputs, the markdowns $\rho_{jt}$ and $\tau_{jt}$, and the observable shares in variable costs.

**Proposition 1**

Under assumption 2, production elasticities have the following (nonlinear) expressions

$$\begin{aligned} \beta_{Rjt} = & \quad \nu^*_{jt}(1+\rho_{jt})S_{Rjt}, \\ \beta_{Ljt} = & \quad \nu^*_{jt}(1+\tau_{jt})S_{Ljt}, \\ \beta_{Mjt} = & \quad \nu^*_{jt}S_{Mjt}, \end{aligned} \tag{3}$$

where $\nu^*_{jt} = \nu/(1 + S_{Rjt}\rho_{jt} + S_{Ljt}\tau_{jt})$ is a corrected short-run elasticity of scale, and $S_{Rjt}, S_{Ljt}$, and $S_{Mjt}$ are the input cost shares in the variable cost.

Also, under assumptions 1 and 2, with $\rho_{jt}$ and $\tau_{jt}$ specified in terms of observables and parameters, knowing the productivity unobservables $\omega_{Ljt}$ and $\omega_{Hjt}$, the parameters and values $\beta_K, \nu$, $\rho_{jt}$, and $\tau_{jt}$ (elasticity of capital, short-run scale, and markdowns) could be estimated from the production function using nonlinear regression,[15]

$$\begin{aligned} q_{jt} = & \beta_0 + \beta_K k_{jt} + \nu^*_{jt}(S_{Rjt}r_{jt} + S_{Ljt}l^*_{jt} + S_{Mjt}m_{jt}) \\ & + \nu^*_{jt}\rho_{jt}S_{Rjt}r_{jt} + \nu^*_{jt}\tau_{jt}S_{Ljt}l^*_{jt} + \omega_{Hjt} + \varepsilon_{jt}. \end{aligned} \tag{4}$$

The establishment-specific elasticities $\beta_{Rjt}, \beta_{Ljt}$ and $\beta_{Mjt}$ are implicitly determined.

**Proof**

Multiplying each FOC by $X_{jt}/Q^*_{jt}$ and re-arranging, they can be written as $\frac{X_{jt}}{Q^*_{jt}}\frac{\partial Q^*_{jt}}{\partial X_{jt}} = (1+a_{Xjt})\frac{AVC_{jt}}{MC_{jt}}S_{Xjt}$, with $a_{Xjt} = \rho_{jt}, \tau_{jt}$, and 0, where $\frac{X_{jt}}{Q^*_{jt}}\frac{\partial Q^*_{jt}}{\partial X_{jt}} = \beta_{Xjt}$, and $S_{Xjt}$ is the share of input $X_{jt}$ in variable cost. Adding these elasticities to obtain the short-run scale, we have $\nu = \beta_{Rjt}+\beta_{Ljt}+\beta_{Mjt} = \frac{AVC_{jt}}{MC_{jt}}(1+S_{Rjt}\rho + S_{Ljt}\tau)$, and we can write $\frac{AVC_{jt}}{MC_{jt}} = \nu/(1+S_{Rjt}\rho + S_{Lj}\tau) = \nu^*_{jt}$.[16] This gives the expressions for the elasticities (3).

[15] In the absence of monopsony power, our use of the FOCs would amount to writing the production function as

$$q = \beta_0 + \beta_K k_{jt} + \nu(S_{Rjt}r_{jt} + S_{Ljt}l^*_{jt} + S_{Mjt}m_{jt}) + \omega_{Hjt} + \varepsilon_{jt}.$$

[16] Notice that input market power changes the simple relationship between $MC_{jt}$ and $AVC_{jt}$ in which $\nu = \frac{AVC_{jt}}{MC_{jt}}$ (Chambers, 1988).

Substituting these expressions for the elasticities into (2), we obtain regression (4) to estimate $\beta_K$, $\nu$, $\rho_{jt}$, and $\tau_{jt}$. From these parameters and values and the observed cost shares, the variable elasticities can be backed out according to (3).

**Discussion**

We have constructed a regression model in terms of observables, four unobservables (two markdowns and the productivities), and the parameters to be estimated to recover the elasticities. We now discuss how this model can identify input market power.

If we were able to estimate the elasticities of the variable inputs, equation (3) makes clear, as said before, that the markdowns would be identified. We could use the ratios with respect to the input without market power and get the markdowns without any restriction. We would estimate the input market power, as is common in the case of the product market power, entirely from the information in the production function.

However, we cannot estimate the elasticities without controlling for $\omega_{Ljt}$ (term of $l^*_{jt}$) and $\omega_{Hjt}$. The control for $\omega_{Hjt}$ can be done by dynamic panel methods, but the control for $\omega_{Ljt}$ requires the use of the ratio of FOCs, and this reintroduces the unobservables of the input market power.

Full identification of varying markdowns without any particular restriction can be achieved, even in this circumstance, [17] but what we do here is somewhat more limited. We control for $\omega_{Ljt}$ using the ratio of the FOCs and then consider $\rho_{jt}$ and $\tau_{jt}$ as unobservables that can be modeled in terms of observables, which is what we do in the empirical exercise.

## 5.2 Profitability decomposition (and a bound to market power)

### Proposition 2

Observable gross profitability, defined as $\ln \frac{R}{VC}$ (that is, readable as a percentage and approximately Bain's (1951) measure), can be decomposed (up to an uncorrelated error) into parts due to technology and the firm's

[17] Full identification could be reached by solving a system of three equations for the three unobservables $\omega_{Ljt}, \rho_{jt}$, and $\tau_{jt}$, and replacing the unobservables in (4). Dobbelaere, Jaumandreu, and Mairesse (2026) is an ongoing paper that uses this route with two variable inputs: labor and materials.

market power across the product and input markets:

$$\ln \frac{R_{jt}}{VC_{jt}} = -\ln \nu + \ln \mu_{jt} + \ln(1 + S_{Rjt}\rho_{jt} + S_{Ljt}\tau_{jt}) + \varepsilon_{jt}$$
$$\simeq -\ln \nu + \ln \mu_{jt} + S_{Rjt}\rho_{jt} + S_{Ljt}\tau_{jt} + \varepsilon_{jt}, \qquad (5)$$

where $\mu_{jt} = \frac{P_{jt}}{MC_{jt}}$, and the second approximate equality divides the contributions of each input market power.[18] Under $\nu < 1$, the averages of this equation set an upper bound to the sum of the effects of market power on profitability (markup and markdown) for any group of firms.

**Proof**
Note that

$$\frac{R_{jt}}{VC_{jt}} = \frac{P_{jt}Q_{jt}}{AVC_{jt}Q^*_{jt}} = \frac{P_{jt}Q_{jt}}{\nu^*_{jt}MC_{jt}Q^*_{jt}} = \frac{\mu_{jt}}{\nu^*_{jt}}\exp(\varepsilon_{jt}),$$

where the second equality uses our definition of $\nu^*$ from above and in the third equality $\varepsilon_{jt}$ comes from the ratio (in levels) of equations (1) and (2). Inserting the value of $\nu^*$, expression (5) follows.

**Discussion**
Note that all terms in the decomposition are likely to be positive and the error $\varepsilon_{jt}$ tends to cancel out, on average. The parameter $\nu$ represents the short-run elasticity of scale, which economic theory suggests should be less than one. The markup is generally expected to be non-negative, as pricing below marginal cost would only occur as a short-run dynamic optimizing solution under price adjustment costs. Monopsony power implies non-negative markdowns. Therefore, the value $\ln \frac{R_{jt}}{VC_{jt}}$ (plus the log of the elasticity of scale) sets an upper bound to the sum of the profitability effects of market power (markup and markdowns).

With parameter estimates, we can decompose observed profitability for any group of firms large enough that the error terms $\varepsilon_{jt}$ tend to cancel out. The bound serves as a theoretical requirement for the validity of market power estimates. Note that this supports the approach that Bain (1951) used to measure market power ($(R_{jt} - VC_{jt})/R_{jt}$), interpretable as a reduced form of market power in the output and input markets. As we will show, it also introduces a valuable discipline into the estimation process.

[18] To obtain an exact expression in the decomposition of the input market power terms, use $\theta(x + y) = \theta x + \theta y$ where $\theta = (1 + \frac{ln(1+x+y)-(x+y)}{x+y})$.

## 5.3 The control for unobserved productivity

To apply equation (4) to the data, we need to determine how to control for unobserved productivity $\omega_{Ljt}$ and $\omega_{Hjt}$. Doing this properly is likely to have a significant impact on the estimation of elasticities and, consequently, on all inferences about market power.

Hicksian productivity $\omega_{Hjt}$ enters the equation additively and, assuming it follows a linear Markov process, can be controlled for by applying pseudo-differences to the nonlinear model. That involves subtracting the lagged equation multiplied by the autoregressive parameter. In this method, the autoregressive parameter is estimated, and the resulting composite error includes innovations of the Markov process, which capture all transitory productivity shocks. This type of estimation generalizes the approach commonly used in a production function, referred to as the dynamic panel method. [19]

In estimations dealing with LAP, unobserved productivity $\omega_{Ljt}$ has typically been replaced by expressions in terms of observables derived from the ratio of the FOC for labor to that of material inputs. This method was applied by Doraszelski and Jaumandreu (2018) and later was generalized by Demirer (2025). Given the form of the production function we use, the most appropriate approach appears to be the log-linear approximation derived in Doraszelski and Jaumandreu (2018) for any function that is separable in capital. For example, given our specification, we can use

$$r_{jt} - l_{jt} = cons - \sigma(p_{Rjt} - w_{jt}) + \sigma(\tau_{jt} - \rho_{jt}) + (1-\sigma)\omega_{Ljt},$$

where $\sigma$ is the elasticity of substitution implicit in the production function.[20] If this elasticity is not constant, we take its value as a local approximation. From this expression, we can get

$$\omega_{Ljt} = c_0 - \frac{\sigma}{1-\sigma}(\tau_{jt} - \rho_{jt}) + r_{jt} - l_{jt} - \frac{\sigma}{1-\sigma}\ln\frac{S_{Ljt}}{S_{Rjt}}.$$

The control of $\omega_{Ljt}$ is made mainly from the observable variations in the ratio $r_{jt} - l_{jt}$ and the relative shares.

[19]The dynamic panel method is based on the papers by Arellano and Bond (1991) and Blundell and Bond (2000). Another method is the approach of Olley and Pakes (1996) and Levinsohn and Petrin (2003), which would replace $\omega_{Hjt}$ with the inverted demand for an input. This seems more problematic in that it needs to yield a solution to the unobservability of marginal cost in the FOCs used to derive the input demand and introduces the presence of the markdown or markdowns.

[20]In practice, we utilize a combination of the intermediate inputs. See subsection 5.2

### 5.4 Empirical specification

We rewrite the production function (4) to estimate the log-run parameter to scale directly $\lambda = \beta_K + \beta_{Rjt} + \beta_{Ljt} + \beta_{Mjt}$. The model is

$$
\begin{aligned}
q_{jt} = \beta_0 + \lambda k_{jt} + \nu^*_{jt} SUM_{jt} + \nu^*_{jt}\rho_{jt} S_{Rjt}(r_{jt} - k_{jt}) \\
+ \nu^*_{jt}\tau_{jt} S_{Ljt}(l^*_{jt} - k_{jt}) + \omega_{Hjt} + \varepsilon_{jt},
\end{aligned} \tag{6}
$$

where

$$
\begin{aligned}
SUM_{jt} &= S_{Rjt}(r_{jt} - k_{jt}) + S_{Ljt}(l^*_{jt} - k_{jt}) + S_{Mjt}(m_{jt} - k_{jt}), \\
l^*_{jt} &\equiv \omega_{jt} + l_{jt} = c_0 - \frac{\sigma}{1-\sigma}(\tau_{jt} - \rho_{jt}) + r_{jt} - \frac{\sigma}{(1-\sigma)} \ln \frac{S_{L_{jt}}}{S_{Rjt}} \\
\nu^*_{jt} &= \nu/(1 + S_{Rjt}\rho + S_{Ljt}\tau). \\
\omega_{Hjt} &= \rho_{AR}\omega_{Hjt-1} + \xi_{jt}
\end{aligned}
$$

The parameters and values to be estimated (in addition to the constants $\beta_0$ and $c_0$) are $\rho_{AR}, \lambda, \nu, \sigma, \rho_{jt}$ and $\tau_{jt}$. Once estimated, these parameters and values can be used to calculate $\mu_{jt}$, which depends on the implicit $MC_{jt}$, and to perform the profitability decomposition.

### 5.5 Moments

The model in equation (6), even without the unobserved productivity terms $\omega_{Ljt}$ and $\omega_{Hjt}$, is nonlinear in both parameters and variables. Therefore, it must be estimated using a procedure such as a nonlinear GMM, which we implement later. We need enough valid moments to identify the six values, and it is not difficult to determine the moments.

After controlling for the unobservables of productivity, only transitory unobserved productivity shocks $\xi_{jt}$ remain, which can be correlated with the variable inputs. We must choose the moments carefully to avoid variables that may be correlated with these shocks. Capital, under the usual assumption that it results from investment made in previous years, can be considered uncorrelated with the shocks. For livestock, labor, and materials, since we assume these variables are chosen every period, we can use their lagged values, which were determined when the shocks were not predictable. We also consider the observed lagged values of wages and livestock prices, which are presumably exogenous with respect to future unpredictable transitory productivity shocks. If the (lagged) quantities and prices of the variable inputs are not correlated with the shocks, then (lagged) shares in variable cost can be used as instruments, as we do.

In some cases, the nonlinearity of the model makes it convenient to use combinations of variables as instruments. Therefore, we use moments based on the composite variable (lagged) $SUM_{jt-1}$ and on a calculation for (lagged) $l^*_{jt-1}$ based on a guess for the value of the parameter sigma.

We complement these instruments with three additional external variables: the cattle cycle (see Rosen, Murphy, and Shinkman, 1994), (lagged) employment in the plant as a proportion of total (lagged) employment in the county where the plant is located,[21] and an indicator of state laws implying a "right to work." In right-to-work states, employees are not required to join a union, which presumably weakens collective bargaining.

# 6 Assessing market power in meatpacking

## 6.1 Descriptive statistics and LAP

Here we briefly discuss the context of our exercise with aggregate annual industry data, which combines USDA information with the NBER-CES database for the industry NAICS 311611. Table 1 reports descriptive statistics for the period 1997-2018, which is the last year covered by the NBER-CES data. Our exercise using plant-level data extends through 2020.

Industry output, measured in pounds of meat, increased by about 24% during the 22-year period. The input of livestock, measured in pounds of liveweight, closely followed the evolution of the output. Capital, reported by NBER-CES in real terms, outgrew the evolution of output and labor (measured in number of workers), while labor remained relatively stable. The evolution of the capital, livestock, and labor indices, detailed in Figure 1, suggests some substitution of capital and livestock for labor. This aligns with reported technological progress and is likely one of the sources of LAP.

Table 1 also reports the industry's hourly wage for production workers. Although it lags wage growth in the rest of manufacturing, it doubles over the study period. This double implies faster growth than the price of livestock and other materials. The index of the price of livestock appears below. Despite this, the shares of all three variable inputs in total variable cost have remained notably stable, suggesting that LAP had a role.[22]

[21] In practice, we are going to use the proportion of employment in county meatpacking employment. See Section 6.3.

[22] The level of shares reported in Table 1 should be viewed with caution. The share of materials is residual, depending on the detail on the livestock provided by the aggregated USDA data. It is much higher than the share in the Census sample that we use for estimation and suggests some mismeasurement. However, what we want to stress is the more reliable stability of the shares.

This is to be expected because of the important investment in capital and evidence that speaks of fast chains combined with human intervention using tools (such as knives managed by hand, the cause of many injuries; see Grimes, 2024). If processes have been improved over time, even if some new "box-tasks" can involve more labor, labor efficiency should have improved.

The moderate evolution of the ratio of livestock to labor (a 17% increase), compared to the increase in wages 52% above the price of livestock, suggests that the substitution elasticity must be below one. However, even with an elasticity of substitution significantly smaller than unity, this change in relative prices should have led to a significant increase in labor's share of variable costs. The fact that this did not occur strongly suggests that LAP was simultaneously driving down this labor share.

The story cannot be very different in the case of investment, at least in the long-run, given that the user cost of capital remained relatively stable over the period. The evolution of capital relative to employment supports the view that the elasticity of substitution is below one and that LAP plays a non-negligible role.

## 6.2 The sample of plants

Using the Longitudinal Business Data base (LBD) as a framework (see Appendix B), we include all available information from the Censuses and the inter-Census Annual Survey of Manufactures, from 1997 to 2020, covering a span of 24 years. We drop plants with abnormal values and those with fewer than five workers, and then select all establishments with complete information for the variables used in the analysis. The final sample is an unbalanced panel consisting of 550 time sequences and 3,500 time observations. The time sequences correspond to a slightly smaller number of establishments (due to a few discontinuities).

Table 2 summarizes the characteristics of the sample, with plants grouped into bins based on their average size. Columns (4) and (5) detail the number of plants and observations corresponding to each bin.

There are many plants, but their sizes vary greatly. Column (2) shows that most employment is explained by a little more than one-tenth of the total number of plants, each with a labor force of 1,000 workers or more. (There are plants with up to 5,000 workers.) We include plants of all sizes in the econometric analysis (as long as they have at least five workers), which is very challenging for the analysis of the effects of scale. However, the largest plants, as shown in column (6), have a greater presence in the sample over time.

An important dimension of the analysis is the local weight of the plant.

To assess this, we construct the variable that computes, for each plant and point in time, the ratio of plant employment to total county employment in manufacturing. Column (7) reports the average of this variable for each type of plant. Interestingly, there is no difference between smaller plants: even the smallest plants account for a significant 30% of local manufacturing employment. However, the largest plants are different. They are not only large, but also, on average, the primary source of manufacturing employment in their areas.

Concentration at the firm level, which is known to be important in slaughtering and sales, also affects employment, but does not significantly affect the panorama of plants. No firm operates more than 30 plants at any moment, and no firm's plants are all very large. As a result, all size bins are populated by several firms. This fragmentation of production suggests that the plant level is the appropriate level for any production analysis.

## 6.3 Specification and estimation

We apply model (6), with the details described below. According to the model, the dependent variable is the log of deflated sales, $q_{jt}$. The explanatory variables are the logs of capital, livestock, labor, and materials, $k_{jt}, r_{jt}, l_{jt}$, and $m_{jt}$, with the nominal variables deflated, as well as the shares in the variable cost of livestock, labor, and materials, $S_{Rjt}$, $S_{Ljt}$, and $S_{Mjt}$. Appendix B provides an exact definition of these variables. We estimate the six parameters and values $\rho_{AR}, \lambda, \nu, \sigma, \rho_{jt}$, $\tau_{jt}$, and two constants. From the beginning, it is clear that the values $\rho_{jt}$ and $\tau_{jt}$ will be the most challenging.

In a series of tests with different instruments and slightly different specifications, it becomes apparent that the value $\tau_{jt}$ is heterogeneous within the sample, while the value $\rho_{jt}$ is always statistically non-different from zero. With $\tau_{jt}$, the trials suggest adopting the modeling

$$\tau_{jt} = \tau_0 + \tau_1 shce_{jt} + \tau_2 l_{jt} + \tau_3(shce_{jt} \times l_{jt}),$$

where $shce_{jt}$ =log of the share of plant employment in meatpacking employment in the county, and where we include plant size as the log of the number of workers, $l_{jt}$. There may be a question about employing the narrower share in total meatpacking employment or the share in manufacturing employment. Replacing county meatpacking employment affects the estimation very little, so we keep the first variable because it is more robust to measurement errors (some counties do not report employment due to confidentiality). Using the artificial variable $RTW_{jt}$, we also attempt to assess whether this relationship varies with the presence of "right to work" laws in the state, but the results are inconclusive.

We finally specify the ratio of first order conditions (used to replace labor-augmenting productivity) in terms of the FOC for labor relative to the combination of both FOCs for other variable inputs: livestock and materials. This implies that, in (6), we finally use $l^*_{jt} \equiv \omega_{jt} + l_{jt} = cons - \frac{\sigma}{(1-\sigma)}(\tau_{jt} - \rho_{jt}) + r_{jt} + m_{jt} - \frac{\sigma}{(1-\sigma)} \ln \frac{S_{Ljt}}{(1-S_{Ljt})}$. Additionally, we estimate imposing the positivity of sigma.

We have expanded the equation by including the modeling for $\tau_{jt}$, so we must finally estimate eight parameters and three constants. We use moments based on the following variables: a vector of ones, a time trend, $k_{jt}$, and $k_{jt}$ squared; $w_{jt-1}$, its square and cube, and $p_{Rt-1}$ and its square; $S_{Rt-1}$, $S_{Lt-1}$, $S_{Mt-1}$ , and their squares; $SUM_{jt-1}$ and its square; the approximation to $l^*_{jt-1}$ computed as $r_{jt-1} + m_{jt-1} - (0.6/0.4)\ln(S_{Ljt-1}/(1 - S_{Ljt-1}))$; and the variables $cycle_t$, $shce_{jt}$, and $1-RTW_{jt}$. In total, we use 21 moments, resulting in 10 overidentifying restrictions.

We use nonlinear optimization of a quadratic GMM form with consistent weight $\left(N^{-1}\sum_j Z_j' Z_j\right)^{-1}$, where $Z_j$ is the matrix of instruments for the time sequence $j$. We compute analytical asymptotic standard errors and apply the delta method to approximate the standard errors of the elasticities, evaluated at the means of the observed variables.

## 6.4 Production function estimates

The results of the production function estimation are reported in Table 3. The control for unobserved productivity works well. The autoregressive process modeling Hicks-neutral productivity gives a parameter of about 0.8, which aligns with many estimates of the production function using panel data. The specification of labor-augmenting productivity yields surprisingly good results. The elasticity of substitution is about 0.5, a reasonable value estimated with high precision. The estimation of the production function allows for recovering both productivities for each plant and time period (as differences from the mean). This interesting piece of analysis is beyond the scope of this paper.

The long-run elasticity of scale is not statistically different from one. The components of this long-run elasticity are shown in the last rows of Table 3. The elasticity of capital is somewhat imprecisely estimated, but the point estimation is reasonable. The elasticities of the variable inputs are well estimated and precise. The virtual unit value of the long-run elasticity indicates that the incorporation of the smaller plants in the sample is done with full success, allowing us to perfectly explain the production of any plant at any point in time based on its inputs. This is notable given the degree of asymmetry (see above) and, from the economic point of view, suggests that meatpacking is fundamentally characterized by constant returns to scale.

The short-run elasticity of scale is estimated to be about 0.9. This implies that the marginal cost is approximately 11 percentage points higher than the observed average variable cost. This seems reasonable and implies that the difference between the short-term marginal cost and the average variable cost will explain roughly this number of percentage points of profitability.

We were unable to make the value $\rho_{jt}$, which models the market power in the livestock market, statistically significant. We attempted to let $\rho_{jt}$ vary with the level or concentration or the size of the plant, but the results indicated that it was not a problem of heterogeneity. In fact, whenever we found a greater or more significant coefficient, it was associated with a negative markup in profitability accounting. This led us to conclude that insisting on the presence of $\rho_{jt}$ was not the right modeling approach. This highlights an important and useful property of the decomposition of profitability: although it is not an imposed restriction, it introduces a sharp discipline in modeling. The compatibility of a positive markup in the product market and a high markdown in the livestock market with a relatively modest profitability, could only be consistent with a short-run elasticity of scale above one (indicating short-run increasing returns to scale). However, there is no evidence of this situation in the estimates for $\nu$.

The schedule for the labor markdown exhibits substantial heterogeneity, and the plant's share in county employment, $shce_{jt}$, emerges as an important determinant of this heterogeneity. The interaction between share and plant size is negative, which implies that markdowns are slightly more moderate in the largest plants. However, we cannot ensure that the entire schedule remains nonnegative without imposing a value on the imprecisely estimated $\tau_0$. All signs point to an identification problem related to the level of the markdown, which is quite understandable for two reasons. First, the model does not include a normalization of efficient labor. Second, the level of markdown may be difficult to discern by itself.

A reasonable minimum value for the constant implies that no plant is paying a wage above marginal productivity (no plant is exploited by its workers). In fact, if we impose this restriction, the estimates barely change. Therefore, we adopt this assumption to reach specific numbers in the profitability decomposition exercise, which may imply that we are overly conservative on labor market power (and hence overstate the importance of product market power).

### 6.5 Decomposition of profitability

The results are reported in Table 4. The numbers are computed under two restrictions. First, we set $\rho_{jt}$ to zero due to its lack of significance. Second, we impose a value for the constant $\tau_0$ that ensures that there is no negative $\tau_{jt}$ for any plant (no plant pays more than marginal productivity).

The value of gross profitability is calculated from the data for each plant. The value for technology is simply the negative of the log of the short-run estimated scale parameter. The value of the markup is estimated residually for each plant and includes the decomposition error, which we expect to average zero. We first report the average decomposition for the whole sample. Then, we order the sample according to the value of the market power in the labor market for each plant averaged over all observations for the particular plant/sequence. We then consider the average for plants above the third quartile (the upper 25% in labor market power). With a total of 550 sequences, this corresponds to an average of 137 plants.

The average decomposition shows that the gross profitability is approximately 20%, with half of this value due to a marginal cost that exceeds the average variable cost by 11%. The remaining 9% is evenly divided between the profitability of the market power in the product market and the market power in the labor market. Next, we examine this average from the perspective of plants with a labor market power higher than the third quartile (the top 25%). These plants have somewhat higher gross profitability. They are not particularly large, as their average number of workers is close to the overall mean. They tend to extract profitability from the labor market, which means that their wages tend to be low relative to the marginal productivity of labor.

Using data detailed by periods (not shown) becomes clear that profitability has tended to rise slightly over the years. The decomposition does not reveal a particular source for this increase, with both the markup and labor market power rising modestly.

## 7 Relation to other measurements

A reader who has closely followed the derivations in Section 2, might ask the following question: Would we draw the same conclusions if we applied the popular measurements of De Loecker and Warzynski (2012), henceforth DLW, and Yeh, Macaluso, and Hershbein (2022), henceforth YMH, for product and input market power, respectively, using the elasticities estimated in Table 3? The short answer is that, if applied, these measures would yield the same results we have obtained, so our findings fully agree with the DLW and YMH measures in their application to this particular market with these elasticities. However, this is not proof of the validity of these two measures, but rather an insight into their limitation: these measures can only produce the same result as ours if the production function is estimated as we have done. Otherwise, they may generate unreasonable measurements that, generally, might even be incompatible with each other.

Start with the DLW measurement of market power, which consists of the estimate of the elasticity for a variable input divided by its revenue share $\widehat{\beta}_X/S_X^R$.[23] If you divide any of the elasticities estimated for the variable inputs by the input's revenue share (and by one plus the markdown, if there is monopsony power), you obtain an estimate of the markup that may differ from our estimate for average market power in column (4) of Table 3 only for rounding reasons. YMH proposes measuring the markdown by dividing the ratio of estimated elasticities of an input with monopsony power to one without it, by the ratio of shares in cost $\widehat{\beta}_X/\widehat{\beta}_Z/(S_X/S_Z)$. [24] If we applied this measure to our average values for labor and materials, we would obtain a result very close to our average estimate for $\tau_{jt}$.

What is happening? Our estimation imposes the theoretical relationships on which DLW and YMH are based. In fact, we estimate the elasticities from these theoretical restrictions as embodied in the FOCs of the problem. What differs from the usual application of DLW and YMH is that their measures rely on estimating an unrestricted elasticity, which may be inconsistently estimated. Estimates based on a free specification of the elasticities often embody unrealistic degrees of rigidity that overlook the potential bias generated by technical change and are unlikely to provide a realistic description of market power. This issue becomes even more serious when such estimates are used to assess the change in markups and markdowns.

# 8 Concluding remarks

We have assessed competition in the product and input markets of the U.S. meatpacking industry, which is often suspected of exploiting livestock farmers and the meatpacking labor force, as well as exercising product market

[23]For simplicity, we set aside the correction of the observed output with the estimated error for the equation. This is likely to result in only minor differences here. See Doraszelski and Jaumandreu (2021) for a discussion of the broader issues involved in estimating this error.

[24]Since the denominator is a ratio, it does not matter if shares are in variable cost or revenue.

power. Using an unbalanced panel of more than 500 plants of varying sizes from 1997 to 2020, we have successfully estimated the production function while controlling for both neutral productivity and LAP. We find no evidence of market power exercise in the livestock market; however, some plants exploit their local employment share to set wages with a significant markdown. Plants above the third quartile of labor market power earn, on average, 10 percentage points of profitability from this practice. Other firms exhibit a combination of moderate power in the labor market and some power in the product market. Overall, gross profitability averages around 20 percentage points, with the model attributing 11 percentage points to technology and the remainder to a combination of product and labor market power. We also have detected a modest recent upward trend in market power.

From the methodological point of view, this paper has simultaneously measured the power of firms in the product and input markets, in a form that is robust to the presence of unobserved labor-augmenting productivity (or other biased variants of technological change). The approach does not rely on detailed assumptions about product demand, competition in the product market, or the specific form of competition in input markets. It relies on a semiparametric specification of a firm's production function, at each moment in time, fully exploiting the structure of the FOCs for cost minimization.

In practice, the method involves estimating the long- and short-run elasticities of scale, along with the degree of input market power in each market for the input. Input market power may be modeled according to observed determinants, as we do in this paper. A method for estimating varying market power without observables is explained but left for further research.

The estimated elasticities are robust to input market power and LAP because they are estimated together with their gaps with respect to their cost shares, and allowed to vary with any technologically biased increase in productivity. For example, the labor share, and hence labor elasticity, decreases, as Hicks's (1932) pointed out, because the elasticity of substitution is less than unity. Estimation is carried out using nonlinear GMM, employing moments based on lagged quantities, prices, and input shares, which can be supplemented by some exogenous shifters.

The marginal cost is implicitly estimated up to an uncorrelated error. Then, the estimated market power across all markets, along with the short-run production elasticity, enables the decomposition of observed gross profitability (Bain, 1951) into its underlying sources. This introduces a valuable element for analysis as well as a precise tool to discipline estimation and results. Compared to other methods of measuring market power, our approach provides unbiased estimates that are both theoretically and practically consistent.

## Appendix A: Substitutability

As mentioned in the text, we take capital, labor, and materials as inputs that are substitutable for livestock for three reasons. First, because the produced output, packed meat, even if measured in units of meat, has some degree of product differentiation that makes substitutability the natural technological relationship. Second, because there is industry-specific evidence for substitution. And third, because we have reached the same conclusion with all our specifications. In this appendix, we first flesh out these statements and then briefly explain the not so well-understood reasons why the absence of substitutability can be a problem for identification and the solutions at hand.

Meatpacking has produced a more complex and diverse product over time, relying on technology changes adopted in various ways by producers. As explained in MacDonald and Ollinger (2005), meatpackers initially shipped entire carcasses for further processing to all kinds of retailers. Over time, the practice was progressively replaced by processed products that were cut, prepared and packed -the product known as "boxed beef." They estimate that it accounted for only 10% of shipments in the 1970s, but that share had risen to 50% by 2000. Even with an important degree of commensurability, it is natural that the product mix/technological diversity determines input substitutability that is reflected in the variety of input ratios in the cross-section. The high times series correlation between the aggregate measures of output and livestock only reflects that the heterogeneity in the cross-section is not experiencing dramatic changes. The correlation alone cannot even say anything about, for example, what the trends have been in the substitution between livestock and labor over time.

Wohlgenant (2013) makes the case for substitution. An entire generation of early studies used "fixed proportions" in livestock and even other inputs. Although this produces simpler cost functions, it can misapprehend the effects of changes in prices (see, e.g., Vohlgenant, 2012) and is a practice that changed in the 1980s. Empirical evidence for substitution has been accumulated. Wohlgenant (1989) estimated a consistent system of product demands and used it (via the Hicks formula) to measure the elasticities of substitution. The substitution elasticities found are 0.72 for beef and 0.35 for pork, fully significant (but estimates could not reject the null of fixed proportions in poultry, which is not included in meatpacking). MacDonald and Ollinger (2005), after estimating a translog subject to the share equations, evaluate Morishima elasticities of substitution. Some significant elasticities are: materials and meat, 0.244; capital and meat, 0.792; labor and materials, 0.609;

and materials and labor, 0.358. Wohlgenant (2013) cites other works.

Finally, our own estimation obtains an elasticity of substitution of 0.5, which sounds quite reasonable. Of course, this is only a rough mean approximation to a value that possibly is heterogeneous. However, together with the reasonable elasticities and estimated productivities of the production function, this provides some confidence that the elasticity of substitution is not zero.

In the production function approach, the monopsony power over one input is identified because the firm substitutes other inputs for it. If the input is non-substitutable, that is, if it must be used in fixed proportions with the combination of other inputs, identification based on the gap between the input elasticity and cost share disappears (the elasticity is always one).[25]

The problem is, in fact, similar to what happens if the relevant production function has only one input (and therefore substitution is not possible). Suppose that the production function is $Q = F(L)$, and hence $\beta_L = (1+\tau)(\frac{WL}{Q})/MC$. It turns out that $(\frac{WL}{Q})/MC = \frac{\beta_L}{1+\tau}$ and there is no semiparametric form of the elasticity that can be used to identify. Of course, one can use $\beta_L = (1+\tau)\frac{P}{MC}S^R = (1+\tau)\mu S^R$, but then identification probably needs to rely on too strong assumptions about $\mu$.

In a multi-input market problem, with a non-substitutable input, we can still assess market power for the substitutable inputs (subject to the condition that one market does not exhibit monopsony power). However, without additional information, we would neither be able to assess input market power for the non-substitutable input nor to separate, in our profitability decomposition, the relative contributions of product market power and power in the market for the non-substitutable input.

Livestock could be considered a non-substitutable input that enters the production of meat in fixed proportions. Researchers have contested this claim, and we have argued that livestock can, in fact, be taken as a substitutable input. However, suppose for a moment that this is not the case and that the production function should instead be specified as

$$Q = \min\{\beta_R R, H(K, L^*, M)\},$$

where $\beta_R$ is a fixed coefficient and $H(\cdot)$ is the amount of the variable composite input made from the contribution of all other variable inputs (and fixed capital).[26] $H(\cdot)$ constitutes a subfunction that is homogeneous of degree $\nu_H$

[25]Rubens (2023) realized this in his tobacco exercise and switched to identification by means of a supply function estimated separately from the production function.

[26]Usually, researchers include $exp(\omega_H)$ affecting the composite input H. Here we ignore this for simplicity.

in the variable inputs, whose cost is minimized, and for which all the relationships described above hold.[27] Since $MC = \frac{P_R}{\beta_R}(1+\rho) + \frac{AVC_H}{\nu_H}(1+S_L^H\tau)$, it is not difficult to see that

$$\ln\frac{R}{VC} \simeq S_H(\frac{1}{\nu_H} - 1) + \ln\mu + S_R\rho + S_L\tau.$$

Since we cannot estimate $\rho$, we cannot deduce $\mu$, even if all the other variables are known. We would be able to assess the roles of profitability of both technology and the labor market but could not separate the contributions of market power in the product market from monopsony power in the livestock market.

This discussion makes clear what can be, on the one hand, the effects of no identification and, on the other, what can be the solution. It means finding ways to identify $\rho$ through the cost function or separately from the production function. However, all this is outside the scope of this paper .

**Appendix B: Data sources and management**

Our plant sample is derived from the Census of Manufactures (CMF), the Annual Survey of Manufactures (ASM), and the Longitudinal Business Database (LBD), which are restricted data provided by the U.S. Census. The key for the construction of the panel is the use of the LBD database, which allows us to identify the entry and exit dates of the establishments, articulating the data from CMF and ASM. The work of the Census Bureau on the LBD database is summarized in Jarmin and Miranda (2002) and Chow, Fort, Goetz, Goldschlag, Lawrence, Perlman, Stinson, and White (2021). We select plants whose activity is classified under NAICS 311611.

Using LBD as a framework, we include all available information from the Censuses (CMFs of 1997, 2002, 2007, 2012 and 2017) and the intermediate Annual Survey of Manufactures (ASMs of 1998-2001, 2003-2006, 2008-2011, 2013-2016, and 2018-2020). This yields a sample of 24 years. We drop abnormal values and plants with fewer than five workers. Then, we select all establishments that have complete information for the variables we use. As some establishments lack intermediate years' information, we split their history into two or more time sequences with continuous information (our econometric exercise requires the use of lags). Our final sample is an unbalanced panel with 550 time sequences and 3,500 time observations. The time sequences belong to a slightly smaller number of establishments or plants.

[27] Variable cost function is $VC = \frac{P_R}{\beta_R}Q + c(K, W, P_M)Q^{\frac{1}{\nu_H}}$ where $c(.)$ depends on the specification of $H$.

The CMF and ASM have the same variables. We complementarily used the additional data assembled in the NBER-CES database, mainly prices, documented by Becker, Gray, and Marvakov (2021). We also use information from the USDA and BLS, as we detail in the following.

We use prices as follows. For deflating sales, we use the PSHIP provided by NBER-CES. The wage is calculated from plant to plant as the wage bill divided by the number of workers. We construct nine regional prices for livestock (based on the 10 regions defined by the USDA, using the detailed data on values and head of cattle and hogs acquired provided by the USDA,[28] and deduce the price of other materials by disentangling the price of livestock from the price of materials.

The variables used in the exercise are the following. Deflated plant sales is the value of plant shipments deflated by the NBER-CES deflator. Capital is constructed using the perpetual inventory method, with the total expenses in capital reported by the plant, lagged one period, and a depreciation rate of 0.15. Livestock is computed from the reported plant value, as a component of materials consisting of parts and pieces, deflated by the constructed deflator. Other expenses for materials are deflated using the appropriate deflator. Labor is measured by the total number of employees.

Using the expenses for livestock, labor, other materials, and energy, we construct a total of variable costs. With this total, we compute the shares of livestock, labor, and materials in variable costs.

Using the Quarterly Census of Employment and Wages from the U.S. Bureau of Labor Statistics (2025), we count manufacturing employment at the county level for each year. We experiment with two possible measures of the impact of the plant's employment: the share of plant employment in total county manufacturing and the share in county meatpacking employment. We also collect information on the existence of "right to work" laws in each state and enter it as a binary variable.

We construct a cattle cycle variable that equals 1 for the years when the cow inventory trended upward and zero otherwise. Data on the inventory was obtained from USDA NASS (2024). Details on the cycle can be found in Rosen, Murphy, and Schinkman (1994).

[28]Due to their relatively low volume of cattle and hogs and their geographic proximity, we merged the New England states with NY and NJ, resulting in nine regions; we construct Tornqvist price indexes for each region

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Table 1: Descriptive statistics for the meatpacking industry

| | 1997 | 2018 |
|---|---|---|
| Output (Index)[a] | 1 | 1.236 |
| Capital (Index)[b] | 1 | 1.560 |
| Livestock (Index)[a] | 1 | 1.221 |
| Labor (Index)[c] | 1 | 1.043 |
| | | |
| Wage per hour ($)[d] | 9.518 | 19.710 |
| Price of livestock (Index) | 1 | 1.364 |
| | | |
| Input shares in cost[e]: | | |
| Livestock | 0.701 | 0.727 |
| Labor | 0.074 | 0.086 |
| Materials | 0.225 | 0.186 |

[a] Pounds of meat, USDA
[b] Real capital, NBER-CES
[c] Total employees, NBER-CES
[d] For production workers, NBER-CES
[e] NBER-CES, using detail from USDA

Table 2: The Meatpacking plants sample 1998-2020

| Average plant size intervals (workers)[a] | Total workers in 2020 | Average size in 2020 | No. of plants | No.of observations | More than 10 obs. (% plants) | Average proportion of county manufacturing employment[b] |
|---|---|---|---|---|---|---|
| (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| 5-99 | 1,400 | 50 | 300 | 700 | 4 | 0.28 |
| 100-499 | 16,500 | 300 | 150 | 1,100 | 31 | 0.30 |
| 500-999 | 18,500 | 750 | 40 | 500 | 55 | 0.32 |
| >1000 | 118,000 | 2,200 | 60 | 1,200 | 93 | 0.66 |
| All | 154,000 | | 550 | 3,500 | | |

[a] Plants are assigned to each interval by averaging their observations over the available years.
[b] County manufacturing employment over the years as given by the Quarterly Census on Employment and Wages, BLS.

Source: FSRDC Project Number 2585 (CBDRB-FY25-0125). Clearance request #11975.

Table 3: The production function of meatpacking plants

| Parameters and elasticities | Symbol | Estimated value | Standard error[a] |
|---|---|---|---|
| (1) | (2) | (3) | (4) |
| Autoregressive | $\rho_{AR}$ | 0.795 | 0.046 |
| Long-run scale | $\lambda$ | 1.014 | 0.063 |
| Short-run scale | $\nu$ | 0.894 | 0.113 |
| Elasticity of substitution | $\sigma$ | 0.499 | 0.294 |
| Markdown in livestock | $\rho$ | 0.097 | 0.251 |
| Markdown in labor | $\tau_0$ | -0.014 | 0.202 |
| | $\tau_1$ | 0.448 | 0.029 |
| | $\tau_2$ | -0.005 | 0.039 |
| | $\tau_3$ | -0.023 | 0.013 |
| Elasticity of capital | $\beta_K$ | 0.119 | 0.154 |
| Elasticity of livestock | $\beta_R$ | 0.707 | 0.094 |
| Elasticity of labor | $\beta_L$ | 0.139 | 0.023 |
| Elasticity of materials | $\beta_M$ | 0.049 | 0.012 |

No. of observations: 3,500

[a] Analytical standard errors. Standard errors of the elasticities computed with the delta method at the sample mean of the observed variables.

Source: FSRDC Project Number 2585 (CBDRB-FY25-0125). Clearance request #11975.

Table 4: Decomposition of profitability 1997-2020

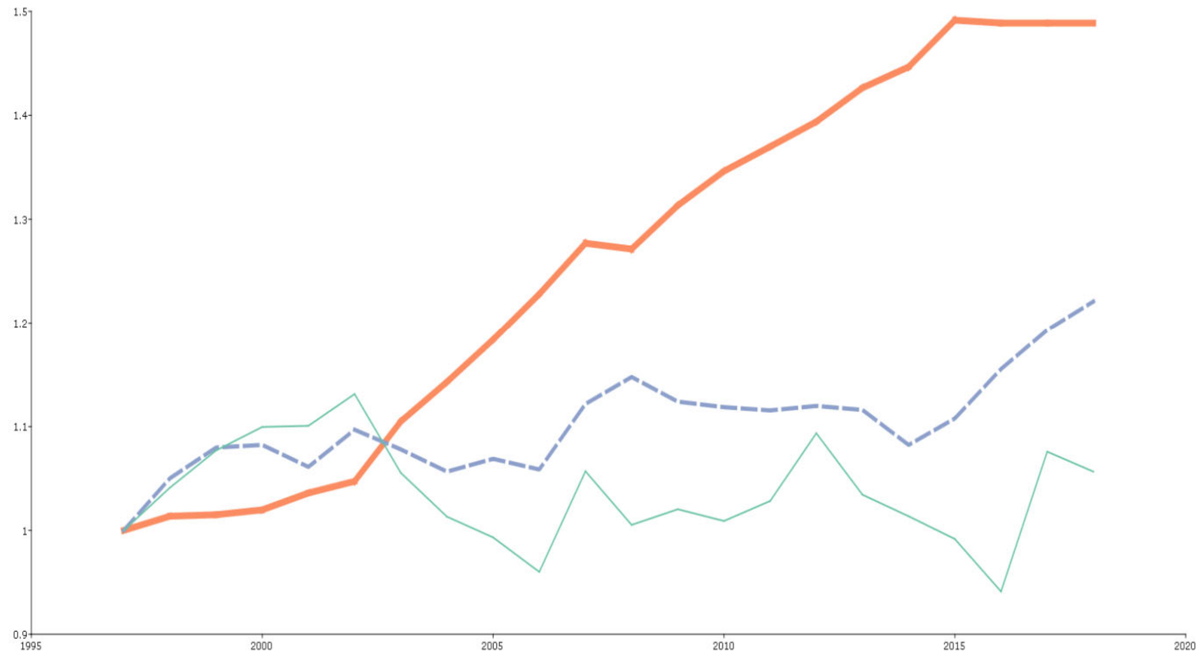
| Sample | Average size (workers) | Gross profit ($\ln \frac{R}{VC}$) | Technology ($-\ln \nu$) | Markup ($\ln \mu$) | Labor market power ($\ln(1 + S_L \tau)$) |
|---|---|---|---|---|---|
| (1) | (2) | (3) | (4) | (5) | (6) |
| All plants | 347 | 0.199 | 0.112 | 0.045 | 0.042 |
| >75% ordered by LMP | 331 | 0.238 | 0.112 | 0.016 | 0.110 |

No. of observations: 3,500

Source: FSRDC Project Number 2585 (CBDRB-FY25-0125). Clearance request #11975.

Figure 1: Evolution of three meatpacking inputs: capital, livestock and labor, 1997-2018

Indices, 1997=1




Years

Thick solid line: Capital

Dashed line: Livestock

Thin solid line: Labor