Input and Output Market Power with Non-neutral Productivity: Livestock and Labor in U.S. Meatpacking*

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Abstract

Identification of firm input and output market power requires unbiased estimation of production elasticities. We propose a method that is robust to biased technological change and apply it with panel data on plants in the highly concentrated U.S. meatpacking industry, which is often suspected of exploiting livestock farmers and immigrant workers. Inference can be checked by assessing how much each market contributes to gross profits. We reject the exercise of market power in the livestock market but find that some firms exploit their share of local employment to set wages with an important markdown, and exercise some product market power.

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1 Introduction

This paper proposes a method to estimate market power in several input markets of a firm, in addition to its product market power, while controlling for labor-augmenting productivity (henceforth LAP). Then, it applies the method to U.S. meatpacking firms. The meatpacking industry is often suspected of monopsony power in the livestock and labor markets, and monopoly power in the product market. We show that LAP has also been an issue in the industry.

Market power can be present in a firm's product and input markets, allowing for supranormal profits to the detriment of social welfare. Economists seek to measure the degree of this market power in a simple and unequivocal way, and the production approach does so by using production data with no need to specify and estimate the demand for firm's products or the supply of their inputs, and avoiding assumptions about the specific game that firms play. Our paper proceeds along these lines. The approach, at least as old as Bain's (1951) work on the product market, has been recently revived in an intense debate about the evolution of markups and how to measure them in practice.

Interest in the exercise of market power has recently tended to focus more on firms' input markets (monopsony power), with the goal of assessing their ability to set input prices with positive markdowns or proportional differences between an input's marginal product and the price paid for the input. Some economists have even asserted that this kind of market power is prevalent, especially in the U.S.

With output and input market power, the first-order conditions (FOCs) that determine the optimal quantities of the inputs, which is exactly where empirical measurements start, become different than they are for competition. Under unspecified market power the FOCs must use marginal cost instead of price to value physical marginal productivity and, under monopsony power, must show a wedge with respect to the price of the input. This implies that output market power cannot be properly measured without accounting for input market power, if it exists, and, conversely, input market power cannot be measured without considering output market power, so a joint approach is essential. Our work contributes to the simultaneous estimation of input and output market power.

Biased technological change becomes important here because it modifies the marginal productivity of the input or inputs that are affected. Recently, a general recognition of the importance of LAP has raised serious concerns about how productivity and markups are usually measured. Under a production elasticity of substitution less than one, LAP determines the fall of the labor share in costs (variable and total) and revenue. Ignoring LAP, the researcher can interpret the fall as an increase in revenue with respect to variable costs due to a rise in markups (an increase in prices with respect to costs). Or, since monopsony power in the labor market also pushes down the share of labor costs in variable cost (and the use of labor relative to other variable factors), the researcher could mistake LAP for monopsony power. To make consistent inferences, the production approach to market power measurement in output and input markets must necessarily address LAP.

1.1 Production elasticities

Measuring market power requires dealing with marginal cost, which is non-observable. However, under cost minimization, marginal cost can be recovered from observed data using production elasticities. For example, De Loecker and Warzynski (2012) proposed the popular current approach to estimating the price-marginal cost ratio by dividing the elasticity of a variable input by its share in revenue. As another example, this paper uses average variable cost divided by the short-run elasticity of scale (sum of elasticities of variable inputs) to calculate marginal cost. Estimating elasticities is usually done estimating a production function. The problem is that the presence of input and output market power and LAP crucially impacts the conditions for consistent estimation of elasticities.

The FOCs are used to solve for unobserved Hicks-neutral productivity by production function estimators of the type Olley and Pakes (1996) and Levinsohn and Petrin (2003) usually applied with Ackerberg, Caves, and Frazer (2015) implementation. With product market power, the FOCs include unobserved marginal cost, creating a difficult problem to solve because marginal cost should be used to estimate the elasticities that are needed to get marginal cost.

With monopsony power, the firm restricts the use of a variable input, and the input elasticity shows a disproportionate gap with respect to the input share in observed variable cost. Estimated elasticities should reflect this gap, which suggests explicitly accounting for the gap when elasticities are estimated, in the spirit of Dobbelaere and Mairesse (2013, 2018). This makes estimation challenging. In addition, the control for unobserved Hicksian productivity faces the presence of an additional unobservable in the FOCs.

With LAP, the production elasticity of labor in terms of efficiency and of the raw quantity of labor is the same, but omission of the efficiency term multiplying labor introduces a correlated omitted variable in the regression (as it does in any input demand deduced from the FOCs). In addition, greater productivity brings down the elasticity of labor when the elasticity of substitution is less than one. To estimate the production function consistently, the researcher faces two challenges: specifying the varying elasticities and accounting for the evolving unobservable efficiency that modifies the quantity of labor relevant to estimating the production function.

1.2 Methodology

We propose a method that simultaneously addresses these difficulties. It consists of estimating the elasticities of the production function, including the relevant input market power specification (in the simplest case a parameter), while allowing these elasticities to change with labor-augmenting productivity. It is a straightforward method that accounts for the relationships that input and output market power, in combination with labor-augmenting productivity, induce among the FOC expressions for the elasticities of the variable factors.

In practice, it amounts estimating the short-run elasticity of scale corresponding to the elasticities of the variable inputs at the same time as the proportional monopsony markdowns in the relevant markets. Using these markdowns, in combination with production observables, we can compute marginal cost and hence market power in the product market. Then, we decompose firm profitability in all its sources/components: technology (marginal cost-average variable cost difference), product market power, and monopsony power in the market for each input.

Hall (1988), to account for imperfect competition, wrote Solow's (1957) share approximation to elasticities in terms of the markup times the revenue shares. Klette (1999) used this specification to measure productivity and markups, and De Loecker and Warzynski (2012) proposed using Hall's identity to solve for the markup. (Note, however, their proposal sidesteps how elasticity is estimated.) We deviate from this convention by instead using the short-run elasticity of scale times the cost shares to model the elasticities. Estimating the elasticity of scale directly is natural and has several advantages over first estimating the varying markup. Once the elasticity is estimated, we can estimate the markup.

1.3 The U.S. meatpacking industry

We apply the method to the U.S. meatpacking industry, which has been at the center of controversy and the object of intensive research. Dominated by a small number of firms (currently four), the meatpacking industry has been suspected of exercising market power in the product market and monopsony power in the market for its livestock input, and 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 unequal size, encompassing from 1997 to 2020, to estimate the production function for meatpacking, controlling for both neutral productivity and LAP and assessing the possible markdowns in livestock and labor. Then, we decompose the profitability of the firms into its components. On average, gross profitability is about 20 percentage points, of which our model attributes 11 percentage points to technology and the rest to a combination of product and labor market power. We reject the presence of monopsony power in the livestock market, but we find a combination of monopsony power in the labor market and market power in the product market.

A streamlined version of the model, applied in a previous version of the paper with aggregate data before we accessed the plant-level data, was notably able to detect the main traits of competition, although, of course, with much less accuracy.

1.4 Literature review

We adopt the production approach to measure market power. The production approach received a strong impulse from the proposal for measuring markups contained in De Loecker and Warzynski (2012). An incomplete list of significant applications is: De Loecker, Goldberg, Khandelval, and Pavcnik (2016); Brandt, Van Biesebroeck, Wang, and Zhang (2017, 2019); De Loecker and Scott (2016), De Loecker, Eeckhout, and Unger, (2021); and Autor, Dorn, Katz, Patterson, and Van Reenen (2021). The recent debate has addressed problems of data measurements (Traina, 2018; Basu, 2019; Syverson, 2019), methodology (Doraszelski and Jaumandreu, 2019, 2021; Raval, 2023; Demirer, 2020; Bond, Hashemi, Kaplan, and Zoch, 2021; Hashemi, Kirov, and Traina, 2022), and outcomes (Jaumandreu, 2022, 2024).

A production approach to the simultaneous measurement of monopsony power and product market power starts with Dobbelaere and Mairesse (2013, 2018), although the exercise was previously tried with tightly specified models. The basic method compares the FOC of an input with market power to the FOC of another without. Our paper can be considered in this tradition. A series of papers adapt to the De Loecker and Warzynski (2012) framework: Morlacco (2019), Brooks, Kaboski, Li, and Qian (2021) and, notably, Yeh, Macaluso, and Hershbein (2022), who claim that the average markdown in

[1]The effects of the Covid-19 pandemic raised concerns about working conditions. See Congress of the United States (2021).

wages in the U.S. manufacturing is 53% (and that markups average 21%). Rubens (2023) considers non-sustitutability of the relevant input and considers necessary to adopt a model for supply (more on this later).

This literature coexists with more tightly specified micromodels such as Lamadon, Mogstad and Setzler (2022) and Berger, Herkenhoff, and Mongey (2022). Deb, Eekhout, Patel, and Warren (2024) even specify and estimate a general equilibrium model to explain wage inequality. Azar, Berry, and Marinescu (2022) take a different approach and estimate labor supply to firms with suitable microdata.

A paper that particularly stresses the need for simultaneous estimation and finds it relevant in the U.S. construction industry is Kroft, Luo, Mogstad, and Setzler (2022). In this paper, we estimate product market power and input market power and provide an analytical framework to analyze the profitability of market power.

We develop a framework compatible with the specification and estimation of LAP. Many recent papers have addressed the importance of this type of technological progress: Doraszelski and Jaumandreu (2018, 2019), Zhang (2019), Raval (2019, 2023), Demirer (2020), Jaumandreu and Mullens (2024), and Kusaka, Okazaki, Onishi, and Wakamori (2024). Yeh, Macaluso, and Hershbein (2022) point out that this is an unresolved matter, observing "..., our econometric methodology does not explicitly allow for factor-biased technological change. While there are estimation methods that do account for labor-augmenting technological change, they do not allow for a generalized production function ... and/or labor market power... We leave investigation of these themes for future research..." (p. 2132)

Also, as mentioned before, demand for any variable input subject to market power contains, in the presence of monopsony power or LAP, a new unobservable that violates the "scalar unobservable assumption" of the Olley and Pakes (1996)/Levisohn and Petrin (2003) method to control for productivity. This affects any Ackerberg, Caves, and Frazer (2015) type of estimation. Rubens (2023) recognizes this regarding monopsony power.

Another consequence of LAP is varying elasticities. With the elasticity of substitution less than unity the share of labor in variable costs is a negative function of labor-augmenting productivity (Hicks, 1932). For the elasticity to fall, it is sufficient that the short-run elasticity to scale is not increasing in labor augmenting productivity. In practice, labor shares are documented to be falling almost everywhere. For the U.S. manufacturing plants, see Kehrig and Vincent (2021) or Jaumandreu and Mullens (2024). The elasticities in this paper are varying and include the modeling of the unobservables.

Meatpacking is an industry with more than a century of questionable competitive practices. Huang (2024) studies the price manipulation practiced by firms acting as a monopsonist cartel at the beginning of the 20th century. However, reviews of the literature around the 2000's, such as Azzam (1998) and Wohlgenant (2013), did not find any strong evidence of the exercise of market power in the product or the livestock markets. More recently, persistent concentration and new forms of contracting and setting prices, as well as complaints from farmers and ranchers, and concerns about labor practices, have again drawn attention to the competitiveness of the sector. Garrido, Kim, Miller, and Weinberg (2024) provide an account of recent research on pricing practices, Bolotova (2022) an assessment of suspicions of collusion, and MacDonald (2024) an account of recent developments.

1.5 Contributions

The paper makes six incremental contributions to the literature. First, it crafts a novel approach for the joint assessment of market power in the product and (possibly several) input markets in the context of the production framework for market power measurement, that is, measurement without specifying the demand for the firm's product or the supply for the inputs and placing no restriction on the nature of competition in these markets.

Second, the method constitutes an alternative to the classical approach by Hall (1988), Klette (1999), and De Loecker and Warzynski (2012) to the measurement of market power. It hinges on the measurement of the short-run elasticity of scale in production as the way to obtain the relationship between (unobserved) marginal cost and (observed) average variable cost.

Third, the method is developed for an environment in which input-augmenting productivity (in our case LAP) is present, and perhaps prevalent. To our knowledge, this is the first time a procedure has been developed that is consistent with biased technological change.

Fourth, the paper shows the separate identification of LAP and monopsony power, establishing how the corresponding unobservables map onto observed relative behaviors that make identification possible.

Fifth, it derives an observed profitability bound for the sum of market power contributions to profits in addition to the contribution of technology. This bound disciplines estimation, is met by the estimates, and can be used as a natural test for checking the outcome of any alternative market power measurement.

Sixth, the paper explores competition in the U.S. meatpacking industry, paying formal attention for the first time to the labor market and establishing that it is monopsonistic.

1.6 Organization of the paper

The rest of the paper is organized as follows. Section 2 presents the model and Section 3 discusses identification. Section 4 presents background on meatpacking and descriptive statistics. The empirical application and the assessment of market power are carried out in Section 5. Section 6 addresses the difference between our estimator and other estimators of market power in the product and labor markets. Section 7 concludes. Appendix A is dedicated to identification, Appendix B develops a model for the contracts that have tended to replace the spot market for livestock, and Appendix C describes the construction of the sample and variables.

2 Model

2.1 Production function

Consider a first order approximation in logs of the unknown production function of each firm $Q = F(K, R, \exp(\omega_L)L, M)\exp(\omega_H)\exp(\varepsilon^*) = Q^*\exp(\varepsilon^*)$, where Q is the quantity of meat, and K, R, L and M, represent capital, livestock, labor, and materials, respectively, ω_L and ω_H are persistent unobservables representing labor-saving and Hicks-neutral productivity, respectively, and ε^* is a serially uncorrelated error. The approximation can be written as

$$q = \beta_0 + \beta_K k + \beta_R r + \beta_L(\omega_L + l) + \beta_M m + \omega_H + \varepsilon, \tag{1}$$

where we use small case letters for the logs, β_X are the elasticities of the inputs, ε acknowledges the expansion of the error ε^* with the residual of the approximation. We will often write the model in terms of "efficient labor," $l^* = \omega_L + l$.

We stress that this approach to the production function allows the elasticities to be firm- and time-specific. Later, we impose equality across firms and time of (only) the long-run and short-run scale parameters (and implicitly of the fixed input capital).[2]

2.2 First order conditions

We remain agnostic on the nature of competition in the product market, where we consider without loss of generality that the firm has an unspecified

[2] We also take the constant as a common parameter by including all deviations from the common constant in the residual.

amount of market power (the firm maximizes profits by equating marginal revenue and marginal cost), and we assume that the firm minimizes costs in the short-run (cost of the variable factors R, L and M). The markets for livestock and labor are possibly monopsonistic, so we want to allow for the potential presence of input market power. We do this by specifying the presence of a percentage gap between the marginal productivity and the price of the corresponding input, popularly known as the "markdown."[3] We write ρ and τ for the markdowns in the livestock and labor markets, respectively. FOCs for cost minimization are then

$$\begin{aligned} MC\frac{\partial Q^*}{\partial R} &= (1+\rho)P_R, \\ MC\frac{\partial Q^*}{\partial L^*}\exp(\omega_L) &= (1+\tau)W, \\ MC\frac{\partial Q^*}{\partial M} &= P_M, \end{aligned}$$

where MC represents marginal cost and P_R, W and P_M are the prices of livestock, labor, and materials respectively.[4] For the moment we may think of ρ and τ as parameters, but in practice we will need consider their heterogeneity across plants.

It is easy to see that, multiplying each equation by X/Q^* and re-arranging, they can be re-written as $\frac{X}{Q^*}\frac{\partial Q^*}{\partial X} = (1+a_X)\frac{AVC}{MC}S_X$, $a_X = \rho, \tau$ and 0, where $\frac{X}{Q^*}\frac{\partial Q^*}{\partial X} = \beta_X$, and S_X is the share of the input in variable cost.[5] Define $\nu = \beta_R + \beta_L + \beta_M$, the sum of the elasticities of the variable inputs, as the short-run elasticity of scale. It happens that $\nu = \frac{AVC}{MC}(1 + S_R\rho + S_L\tau)$, and we can write $\frac{AVC}{MC} = \nu/(1 + S_R\rho + S_L\tau) = \nu^*$. Using this relationship and notation, cost minimization implies the following (nonlinear) expressions for

[3] Markdowns are often interpreted as the inverse of the elasticity of supply of the factor. However, this only corresponds to a market with a supply of finite elasticity and Bertrand input demand behavior by the oligopsonists. We do not need to abide by any particular specification of monopsonistic behavior. The model is general enough to accommodate other possible imperfect market models and even different signs of the parameter, as discussed in Dobbelaere and Mairesse (2018). For example, collective bargaining with powerful unions may result in rent sharing, implying a negative gap between productivity and wages.

[4] The FOCs could be extended to account for adjustment costs. See the discussion in Dorazelski and Jaumandreu (2019).

[5] Note that the elasticity of labor and "efficient labor" are the same.

the production elasticities:

$$\begin{aligned}\beta_R = & \quad \nu^*(1+\rho)S_R, \\ \beta_L = & \quad \nu^*(1+\tau)S_L, \\ \beta_M = & \quad \nu^* S_M. \end{aligned} \tag{2}$$

We express the production elasticities in terms of the (modified) elasticity of scale ν^* and shares in variable cost S_R, S_L and S_M. This is an alternative to what Hall (1988) and Klette (1999) do. As in those papers, we could use $\beta_X = \mu(1 + a_X)S_X^R \exp(\varepsilon)$, where $\mu = \frac{P}{MC}$ is the markup and S_X^R is the (observed) share of input cost in revenue, but this would introduce two problems: the need to deal with the presumably highly varying unobservable markup μ, and the presence in the expressions of the unobservable error ε in estimation. Instead, we deal with the short-run elasticity of scale parameter ν, which we assume can be safely taken as constant, and our expressions do not involve error.[6]

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

$$q = \beta_0 + \beta_K k + \nu(S_R r + S_L l^* + S_M m) + \omega_H + \varepsilon,$$

focusing on the estimation of the elasticities of capital and scale. Monopsony power makes the model considerably more nonlinear,

$$q = \beta_0 + \beta_K k + \nu^*(S_R r + S_L l^* + S_M m) + \nu^* \rho S_R r + \nu^* \tau S_L l^* + \omega_H + \varepsilon, \tag{3}$$

since ν is replaced by $\nu^* = \nu/(1+S_R\rho+S_L\tau)$ and we have two more terms and must estimate the enlarged set of parameters β_K, ν, ρ and τ. However, this is all we have to estimate to compute the markups and identify the sources of the firm's profitability.

2.3 Markups and a bound for market power

Let R and VC denote revenue and variable cost. Note that

$$\frac{R}{VC} = \frac{PQ}{AVCQ^*} = \frac{PQ}{\nu^* MCQ^*} = \frac{\mu}{\nu^*} \exp(\varepsilon^*),$$

where the second equality uses our definition of ν^* from above.

[6]The short-run elasticity of scale is, for a generic production function, a function of the inputs and the unobservable LAP $\nu = \nu(k, r, \omega_L + l, m)$. Under appropriate restrictions on the dependence of ω_L, it can be modelled as a varying function of observables across sample and time.

This has at least two important consequences. First, from this expression we can get the (log) markup in terms of ν^*, revenue, and variable cost as

$$\ln \mu = \ln \nu^* + \ln \frac{R}{VC} - \varepsilon^*.$$

It includes the production function error ε^*, but the effect of this error will tend to cancel, on average, across enough observations (consistency).

Second, observable gross profitability, defined as $\ln \frac{R}{VC}$ (that is readable as a percentage) can be decomposed into parts due to technology and the firm's market power across the product and the input markets:

$$\ln \frac{R}{VC} = -\ln \nu + \ln \mu + \ln(1 + S_R\rho + S_L\tau) + \varepsilon^* \simeq -\ln \nu + \ln \mu + S_R\rho + S_L\tau + \varepsilon^*, \tag{4}$$

where in the second approximate equality we split the contributions of each input market power.

Note that all terms in the decomposition are likely to be positive. Parameter ν is a short-run elasticity of scale that we expect to be less than one, according to economic theory. The markup is expected in general to be non-negative because price below marginal cost can only be a short-run dynamic optimizing solution under cost of adjustment of prices. Monopsonistic power implies non-negative markdowns. So, the value $\ln \frac{R}{VC}$ (plus the log of the elasticity of scale) sets an upper bound to the sum of market power profitability effects (markup and markdowns). Note that this upholds the approach that Bain (1951) used to measure market power ($(R - VC)/R$).

2.4 The control for unobserved productivity

Of course, to apply equation (3) to the data we need to decide how to treat unobserved productivity ω_L and ω_H. The decisions about how to treat unobserved productivity, in particular LAP, are likely to strongly impact the estimation of the elasticities and hence all inferences about market power.

Hicksian productivity ω_H enters the equation additively and, assuming that it follows a linear Markov process, can in principle be controlled for by taking pseudo-differences of the nonlinear model. The autoregressive parameter is estimated, and the equation includes the innovations of the Markov process in the composite error, which picks up all transitory productivity shocks. This sort of estimation is a generalization of what has been commonly applied in the estimation of production functions under the name "dynamic panel."[7]

[7]Another method, in the style of Olley and Pakes (1996) and Levinsohn and Petrin

In the estimations to date, LAP ω_L has typically been replaced by expressions in terms of observables based on the ratio of the FOC for labor and a materials input. Given the unspecified form of the production function, the most adequate is to use the log linear approximation derived in Doraszelski and Jaumandreu (2018) for any function separable in capital. For example, we can use

$$r - l = cons' - \sigma(p_R - w) + \sigma(\tau - \rho) + (1-\sigma)\omega_L,$$

where σ is the elasticity of substitution implicit in the production function. From this expression we can get

$$\omega_L = cons - \frac{\sigma}{(1-\sigma)}(\tau - \rho) + r - l - \frac{\sigma}{(1-\sigma)} \ln \frac{S_L}{S_R}.$$

We keep the terms in ρ and τ separate from the constant to have them as reference, in case either of the two parameters is modeled as varying.

2.5 Empirical specification

We rewrite the production function (3) to directly estimate the log-run parameter to scale $\lambda = \beta_K + \beta_R + \beta_L + \beta_M$. We take both parameters of scale λ and ν as constants.[8]

In terms of sample notation, indexing firms by j and time by t, model is

$$q_{jt} = \beta_0 + \lambda k_{jt} + \nu^*_{jt} SUM_{jt} + \nu^*_{jt}\rho S_{Rjt}(r_{jt} - k_{jt}) + \nu^*_{jt}\tau S_{Ljt}(l^*_{jt} - k_{jt}) + \omega_{Hjt} + \varepsilon_{jt}, \tag{5}$$

where

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

The parameters to estimate (in addition to the constants) are $\rho_{AR}, \lambda, \nu, \sigma, \rho$ and τ. In turn, we can use the estimates to calculate μ_{jt} and compute the profitability decomposition.

(2003), would replace ω_H 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 FOC(s) used to derive the input demand and, even more challenging, to the presence of the input market power unobservable(s).

[8] Alternatively β_K could be modeled as a function of K and λ become a varying long-run elasticity of scale.

2.6 How the model works

The model is very general in that, given a sample of firms, it only requires equality of the long-run and short-run elasticities of scale. Individual elasticities of the variable inputs can change over time and across firms, in a useful generalization of the Cobb-Douglas specification.

The estimation of the production function identifies the scale elasticities and the gaps between marginal productivity and input prices in two markets. Identification of monopsony power is possible because the individual output elasticities are modified by the presence of market power in the input market. This requires, however, the presence of at least one input market that is competitive. Intuitively, we need at least one market in which the elasticity equals the observed share times the scale parameter to disentangle the scale from the gaps in estimation.

The estimation of the short-run elasticity of scale allows us to estimate the (log of the) price-marginal cost ratio or markup for every firm and moment of time up to a zero-mean error. Average product market power estimates are hence consistent, and the presence of market power in the product market is assessed at the same time that monopsony power is assessed in any number (but not all) input markets. No assumptions about the behavior of the firm in the product or input markets are needed, and only cost minimization is assumed.

3 Identification

The model in equation (5), even with the productivity unobservables ω_L and ω_H removed, is nonlinear in parameters and variables. It must be estimated by a procedure like nonlinear GMM, which we do later. We need enough valid moments to identify the six parameters, and it is not difficult to determine them. In this section, we first briefly discuss these moments. Then, we switch to two more subtle identification questions: how the absence of substitution of a relevant input can hinder identification, and how we can identify monopsony power separately from labor-augmenting productivity.

3.1 Moments

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

In some cases, the nonlinearity of the model makes it convenient to use combinations of variables as instruments. We will use moments based on the (lagged) composite variable SUM and we will use as instrument a calculation for (lagged) l^* based on a guess for the value of parameter sigma. We will complement these instruments with the inclusion of three more external variables: the cattle cycle, the (lagged) employment in the plant as a proportion of the total (lagged) employment of the county in which the plant is located, and an indicator of state laws implying a "right to work." In right to work states, employees are not required to join a union, what presumably weakens collective bargaining. We continue the discussion of instruments in more practical terms when we list the instruments for estimation.

3.2 A non-substitutable input

In the production function approach, monopsony power over one input is identified because the firm substitutes other inputs for it. If the input is non-substitutable, that is, if the input must to be used in fixed proportions with the combination of the other inputs, identification based on the gap between the input elasticity and share in cost evaporates. Rubens (2023) realizes this and warns: "...this class of models, which imposes only a model of production and input demand, fails to separately identify markups and markdowns as soon as a subset of inputs is non-substitutable" (p. 2383).

The problem is in fact similar to what happens if the relevant production function has only one input (and hence substitution is not possible). Suppose that the production function is $Q = F(L)$, and hence $\beta_L = \frac{(1+\tau)}{MC}\frac{WL}{Q}$. It happens that $\frac{R}{WL} = \frac{1}{\beta_L}\mu(1+\tau)$ and, without more information, output market power cannot be separated from market power in the input market as a source of total profitability.

In a multi-input market problem, however, we can still assess market power for the substitutable inputs (subject to the condition of one market without monopsony power). But, without more information, we will not be able to assess input market power for the non-substitutable input or to separate, in our profitability decomposition, the relative roles of product market power and power in the market of the non-substitutable input.

It has been suggested that livestock is a non-substitutable input that enters the production of meat in fixed proportions. Researchers have contested this claim, and we argue later that livestock is a substitutable input. However, suppose for a moment that this is not the case and that the production function should be specified as

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

where β_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). $H(\cdot)$ constitutes a subfunction homogeneous of degree ν_H in the variable inputs, whose cost is minimized, and where all the relationships shown above hold. Since $MC = \frac{P_R}{\beta_R}(1+\rho) + \frac{AVC_H}{\nu_H}(1+S_L^H\tau)$, it is easy 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 ρ we cannot deduce μ even if we know all the rest of variables. We are able to assess the role of both profitability of technology and the labor market, but we are not able to separate the contributions of market power in the product market and monopsony power in the livestock market.

3.3 Monopsony power and labor-augmenting productivity

An important question seems to linger. Can we identify monopsony power separately from LAP? The question arises because LAP introduces an unobservable in the FOC for labor in a very similar way that monopsony power does (see the second expression conducing to equation (2)). Even if we substitute an expression for the unobservable ω_L, separating it from the effects of the markdown τ, how can we be sure that these two effects can be neatly distinguished?

To consider the answer to this question, in Appendix A we look in detail at the effect of an exogenous increase in LAP and an exogenous increase in monopsony power on our cost-minimizing firm. Without loss of generality, we assume that ω_L and τ increase from an initial zero value to a positive value. Ceteris paribus, both effects give incentives to the cost-minimizing firm to reduce employment. To facilitate the comparison of results, we consider that the increase in LAP and monopsony power is such that in each case the firm adopts the same new ratio of materials to labor.

The outcomes are as follows. An exogenous increase of LAP induces the cost-minimizing firm to reduce both labor and materials, but labor proportionally more so. As a result, the share of labor in variable cost S_L is reduced. In addition, productivity improvement implies that MC decreases. On the contrary, an exogenous increase in monopsony power induces the firm to contract labor while it expands materials. If the firm adopts a ratio of materials to labor that matches the case of the ω_L increase, the share of labor in variable cost S_L diminishes, but somewhat more than with the ω_L increase. However, now MC increases. The different behavior of MC implies that the firm has incentives to move further in different directions: expanding output in the case of a productivity increase and contracting output in the case of an increment in monopsony power, through an expansion or contraction of both inputs in the same newly adopted proportion.

4 The meatpacking industry

We apply the model to the U.S. meatpacking industry. In what follows, we highlight some background on this industry (concentration, competition or lackthereof, labor concerns) and report a few descriptive statistics.

4.1 The U.S. meatpacking industry

The meatpacking industry consists of the slaughtering, processing, packaging, and distribution of meat from animals such as cattle, pigs, sheep and lambs (but not poultry). The activities are carried out in plants of very different sizes, some very large and many very small. For example, according to the U.S. Department of Agriculture (USDA), in 2023, 267 beef packing plants slaughtered 1,000 and more head, of which 11 slaughtered more than one million head of cattle each, accounting for 46% of all cattle slaughtered. Similarly, there were 206 plants dedicated to pork slaughtering of 1,000 and more head, of which 14 plants slaughtered more than 4 million head each, accounting for 60% of hogs. And there were 103 sheep and lamb plants slaughtering 1,000 and more head, of which 13 plants slaughtered more than 25,000 head each, accounting for 39% of sheep slaughtered (USDA NASS 2024). This results in 576 plants of significant size, which is very close to the total number of plants in our empirical exercise.

The activity is very concentrated at the firm level, with a few companies operating several plants. According to USDA, in 2019 four big producers (Tyson, Cargill, JBS, and National Beef) slaughtered 85% of all cattle, 67% of hogs, and 53% of sheep and lambs (USDA AMS 2020).

Concentration in the industry increased sharply from 1960 to 1990, as plant size grew, and plants moved from the Midwest and Northern Great Plains to the Southern Great Plains. Afterwards, concentration grew more slowly. The four-firm concentration ratio (CR4) in beef processing increased from 41% in 1982 to 79% in 2006 and has since remained more or less stable. Similarly, the CR4 for pork processing increased from 36% to 63% in the same period. For a historical description, see MacDonald and McBride (2009) and, for a recent account, MacDonald (2024).

Packer conduct has been traditionally an object of concern in two input markets: labor and livestock.

On the one hand, the industry has a long history of controversial labor practices. Increasingly located in rural areas, the sector employs a workforce composed of low-skill workers, including above-average proportions of immigrants, refugees, and people of color who have fewer employment options. Working conditions are famously known to be very poor. Controversy about the industry's labor practices raged 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).

On the other hand, the level of buyer concentration, complaints from livestock producers, and the consolidation of alternatives to the spot market (alternative market arrangements or AMAs), have generated concerns about the competitiveness of the market.

Hence, the literature on competition is vast. Azzam (1998) reviews the literature from 1960s through the 1990s and Wohlgenant (2013) through the 2010s. The literature focuses almost exclusively on cattle and beef pricing, and the additional question is invariably if there is oligopsony in cattle markets.[9] To the authors' knowledge, there are no studies of oligopsony power in meatpacking labor markets. As summarized by Wohlgenant (2013), the takeaway from the existing literature is that, despite the different empirical approaches, there is no evidence of the exercise of significant market power either in the market for "packed meat" or in the input market for livestock. On the contrary, Wohlgenant (2013) stresses the evidence for lower processing and distribution costs due to cost savings from reorganization, technical innovation, and increased plant size.

The quality of the product (meat) may in fact have been increasing over time, which can be seen as a part of technological progress. At the start,

[9] 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.

meatpackers shipped carcasses for further processing by wholesalers and retailers. Processed products, cut, prepared, and packed, known as "boxed beef," accounted for only 10% of the shipments. By 2000, they reached 50% (MacDonald and Ollinger, 2005).

Evidence suggests that livestock presents some substitutability, and we correspondingly assume that it doesn't enter the production function in a fixed proportion. The idea is that, in principle, it is possible to combine different amounts of used capital and labor, as well as materials, with different liveweight livestock amounts to get the same quantity of (standardized) output. Wohlgenant (2013) makes the case for this, and there is plenty of evidence on elasticities of substitution for different ouputs and inputs (see, for example, MacDonald and Ollinger, 2001). Our current exercise supports substitutability very well.

The AMAs are long-term contracts under which a packer agrees to buy a specified amount of livestock through a given year. The price can be based on price in the cash market or a forward variant based on the Chicago Mercantile Exchange. Something like 80% of the procurement of livestock is currently done by means of AMAs.

Many authors have raised concerns about the effects of these formula contracts on the erosion of the cash market, with possible competitive effects. Xia and Sexton (200); Xia, Crespi, and Dhuyvetter (2018); Garrido, Kim, Miller, and Weinberg (2024); and Hummel (2023) contain some theoretical modeling and empirical analysis of the effects of the AMAs. The theoretical modeling looks for the possibilities for packers to enlarge the markdown on livestock. Empirical analysis has focused on an enlargement of the spread (the difference between the price received by the packer for the meat they sell and the price they pay for the livestock). However, no clear link has been established so far between the enlargement of the spread documented for 2015-2020 and the AMAs.

In Appendix B we briefly develop a "neutral" model for the AMAs in the spirit of Xia, Crespi, and Dhuyvetter (2018) and Garrido, Kim, Miller, and Weinberg (2024). While the model can explain increases in the spread, it can also explain the opposite, depending on unknown elasticities. What is important is that the model shows that the pricing of livestock by the packers with input market power throughout two markets (formula contracts and cash) is completely compatible with our modelling. We hence take our evaluation as a first negative structural assessment of the effects of the AMAs. Obviously, more research is needed. (Garrido, Kim, Miller, and Weinberg, 2024, is research in progress.)

4.2 Descriptive statistics

Here we briefly discuss the context of our exercise with industry data, which combines some 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 final year of NBER-CES data. Our exercise with plant-level data extends to 2020.

The industry output, measured in pounds of meat, grew about 24% during the 22 years. The livestock input, measured in pounds of liveweight, followed output very closely. Capital, as reported by NBER-CES in real terms, outgrew the evolution of output and of labor (measured in workers). Labor tended to stay quite stable. The evolution of the indices for capital, livestock, and labor, detailed in Figure 1, suggests some substitution of capital and livestock for labor. This matches the reports on technological progress well and is likely to be one of the sources of LAP.

The fifth line of Table 1 reports the industry hourly wage for production workers. Despite trailing the evolution of wages in the rest of manufacturing, it doubles during the study period. This implies faster growth than the price of livestock and other materials (we include the index of the price of livestock on the sixth line). Still, the shares of all three variable inputs in total variable cost have been notably stable. When one compares the evolution of relative prices and relative quantities, it becomes clear that the elasticity of substitution must be below one. However, even under an elasticity of substitution smaller than unity, the evolution of the relative prices should have implied a large increase in the labor share in variable costs. The fact that this has not happened strongly suggests that labor-augmenting productivity is pushing this labor share down (or moderating its increase).

If one believes that investment should follow similar rules, at least in the long-run, and since the user cost of capital tended to stay relatively stable during the period, the evolution of capital relative to employment gives support to the same ideas of an elasticity of substitution smaller than one and a non-negligible LAP.

5 Assessing market power in meatpacking

5.1 The sample of plants

Using the Longitudinal Business Data Base (LBD) as a framework (see Appendix C), we include all available information from the Censuses and the inter-Census Annual Survey of Manufactures, 1997-2018. These constitute a sample of 24 years. We drop abnormal plant values and those with fewer than five workers. Then, we select all establishments that have complete information for the variables we will use. 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.

Table 2 summarizes the characteristics of the sample, split in size bins in which we classify the plants according to 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 are very unequal. Column (2) shows that most of the employment is explained by a little more than one tenth of the total number of plants, each one with a labor force of a thousand workers or more. (There are plants with up to 5,000 workers.) We want to encompass plants of all sizes in the econometric analysis (as long as they have at least five workers) because we think this helps the analysis of the effects of scale. However, the whole analysis is rather dominated by the observations for the largest plants, as one can see in column (6) through the greater sample presence over time of those plants.

An important dimension of the analysis is the local weight of the plant. To check this, we construct a variable that computes, for each plant and moment of time, the ratio employment of the plant/total county employment in manufacturing. Column (7) averages this variable for each type of plant. Interestingly, there is not much difference for the smaller sizes: even the smallest plants control almost a significant 30% of the local manufacturing employment. However, the biggest plants are different. They are not only big, but they are also, on average, the most important source of manufacturing employment in their areas.

Concentration at the firm level, which we know is important in slaughtering and sales, also affects employment, but this does not greatly impact the panorama of plants. No firm has more than 30 plants at any moment, and no firm's plants are all super big. So, all size bins are populated by several firms. Because of this fragmentation of production, plant level seems the right level for any production analysis.

5.2 Specification and estimation

We apply model (5) with a few enlargements that we explain below. According to the model, the dependent variable is (log) deflated sales, q. The explanatory variables are the (log) of capital, livestock, labor and materials, k, r, l and m, with the nominal variables deflated, and the shares in variable cost of livestock, labor and materials, S_R, S_L and S_M. See Appendix C for the exact definition of the variables. We need to estimate the six parameters $\rho_{AR}, \lambda, \nu, \sigma, \rho$, τ and two constants. Parameters ρ and τ show from the beginning that they are going to concentrate the difficulties.

In a host of trials with different instruments, and even slightly different specifications, it becomes very clear that parameter τ is heterogeneous in the sample and parameter ρ is never statistically significant. With τ, the trials suggest adopting the modeling

$$\tau = \tau_0 + \tau_1 shce + \tau_2 l + \tau_3(shce \times l),$$

where $shce$ =log of the share of employment of the plant in meatpacking employment in the county, and where we include size of the plant as the log of the number of workers, l. We expect this to show in the final estimation that the markdown increases with the impact of the plant in meatpacking employment and the size of the plant. The replacement of county meatpacking employment by county manufacturing employment affects the estimation very little, so we leave the first variable. We try also to assess if this relationship changes with the presence in the state of "right to work" laws by means of the artificial variable RTW_{jt}, but we do not get any clearcut answer.

After different trials, we finally specify the ratio of first order conditions (used to replace labor-augmenting productivity) in terms of the FOC for labor versus the combination of both FOCs for other variable inputs: livestock and materials. This implies that, in (5), we finally use $l^*_{jt} \equiv \omega_{jt} + l_{jt} = cons - \frac{\sigma}{(1-\sigma)}(\tau - \rho) + r_{jt} + m_{jt} - \frac{\sigma}{(1-\sigma)} \ln \frac{S_{Ljt}}{(1-S_{Ljt})}$. On the other hand, we estimate imposing the positivity of sigma.

We have enlarged the equation with the modeling for τ and hence we must 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} is 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 $1 - RTW_{jt}$. We use a total of 21 moments, and hence we have 10 overidentifying restrictions.

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

5.3 Production function

The results of estimating the production function are reported in Table 3. The control for unobserved productivity works well. The autoregressive process to model Hicks-neutral productivity gives a parameter of about 0.8, which matches many production function estimates with panel data. The specification of labor-augmenting productivity gives surprisingly good results. The elasticity of substitution is about 0.5, a reasonable value estimated with great precision. The estimation of the production function allows for the backup of both productivities for each plant and moment of time (in differences with respect to the mean). This is an interesting piece of analysis that we cannot pursue here.

The long-run elasticity of scale is not statistically different from one. The components of this long-run elasticity can be checked in the last rows of Table 3. The elasticity of capital is somewhat imprecisely estimated, but the point estimation is reasonable, and the elasticities of the variable inputs are good and precisely estimated. The virtual unit value of the long-run elasticity means that the incorporation of the smaller plants of the sample is done with full success, and we can perfectly explain the production of any plant at any point in time with the amount of its inputs. This is quite notable given the degree of asymmetry (see above), and it tells us that meatpacking is basically an activity characterized by constant returns to scale.

The short-run elasticity of scale is estimated to be about 0.9. This means that marginal cost is approximately 10 percentage points above the observed average variable cost. This seems a reasonable number and implies that the difference between the short-run marginal cost and average variable cost is going to explain about this number of percentage points of profitability.

Despite several trials, we were not able to make parameter ρ, which models market power in the livestock market, statistically significant. That this is not a problem of heterogeneity is shown by the absence of significant variation of ρ with the size or concentration of the plants. On the contrary, every time we tended to get a greater and/or more significant coefficient was associated with a negative markup in the accounting for profitability. This convinced us that insisting on the presence of ρ was not a correct direction for modeling, and it underlines one important and useful property of the decomposition of profitability: although it is not an imposed restriction, it introduces a sharp discipline in the modeling. The compatibility of a high markup in the product market and a high markdown in the livestock market with a relatively modest profitability could only be upheld by a short-run elasticity of scale above one (short-run increasing returns to scale). However, there is no trace of such a situation in the estimates for ν.

The schedule for the markdown shows it has substantial heterogeneity driving it, and that the share of the plant in county employment, *shce*, is an important determinant of this heterogeneity. The interaction between share and the size of the plant is positive (the log of *shce* is negative), and the term in the share is clearly increasing. So, both share and size of the plant have a role. However, we are not able to make the whole schedule nonnegative if we do not impose some value on the imprecisely estimated τ_0. All indications are that we have an identification problem on the level of the markdown, which is quite understandable for two reasons. One is that the model stands without a normalization of efficient labor. The other is that the level of the markdown can 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 can imply that we are too conservative on labor market power (and hence attribute too much importance to product market power).

5.4 Decomposition of profitability

The results are reported in Table 4. The numbers are computed under two restrictions. First, we impose zero ρ due to its lack of significance. Second, we impose the value of the constant τ_0, which implies no negative τ for any plant. The value of gross profitability is as computed from the data for each plant. The value for technology is simply the negative of the log of the short-run estimated parameter. The value of the markup is estimated residually for each plant and includes the error of the decomposition, which we expect to average zero as soon as we consider enough plants. We first report the average decomposition for the whole sample. Then we proceed to 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 the plants above the third quartile (the upper 25% in labor market power). As we have a total of 550 sequences, we take an average of 137 plants.

The average decomposition says that short-run or gross profitability is virtually 20%, and half of this value is due to a marginal cost that is above average variable cost by 11%. The remaining 9% is split evenly between profitability from market power in the product market and market power in the labor market. Next, we examine this average from the point of view of the plants with more labor market power than the third quartile (the upper 25%). They have a somewhat greater gross profitability. They are not particularly big, since their average number of workers is close to the mean. They tend to extract profitability from the labor market, for example, by paying lower wages.

Data detailed by periods (not shown) reveal that profitability has tended to rise a little over the years. The decomposition doesn't reveal a particular origin of this increase, and both the markup and the market power in the labor market have increased slightly.

The first version of this paper, when we still had no access to plant data, developed a streamlined version of the model that we applied with aggregate data (49 years of the aggregate NBER-CES database). The estimation notably detected, with much less accuracy of course, the main traits that we confirm now.

6 Relationship to other measurements

A reader who has followed the derivations in section 2 in detail, will likely 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, with the elasticities estimated in Table 3? The short answer is that, if applied, they would give the same results we have obtained, so we are perfectly in agreement with the DLW and YMH measures in their application to this particular market. However, this is not proof of the validity of these two measures, rather an insight into their incompleteness: these measures can only give the same answer as ours if the production function is estimated as we have done. Otherwise, they may produce unreasonable measurements that are, in general, even incompatible between them.

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 $\widehat{\beta}_X / S_X^R$.[10] If you divide any of the elasticities estimated for the variable inputs by the share in revenue of the input (and by one plus the markdown if there is monopsony power), you get an estimate of the markup that differs only for rounding reasons from our estimate for average market power in column (4) of Table 3. YMH propose measuring the markdown by dividing the ratio of estimated elasticities of an input with monopsony power to an

[10]For simplicity, we put aside the correction of the observed output with the estimated error for the equation. This is likely to result in only minor differences.

input without, by the ratio of shares in cost, say, $\widehat{\beta}_X/\widehat{\beta}_Z/(S_X/S_Z)$.[11] If we apply this measure to our average numbers for labor and materials we would get a number very close to our average estimate for τ.

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 DLW and YMH as usually applied is that their measures rely on the estimation of an unspecified elasticity that may be inconsistently estimated. Estimates based on a free specification of the elasticities, often with unrealistic amounts of rigidity that ignore the possible bias in technical change, are likely to fail to give a realistic description of market power. And this is likely to be even more serious when they are used to estimate the change in markups and markdowns.

To give a simple (aggregate) example, estimates of market power recently offered by papers for all U.S. manufacturing, and even the economy, seem to be way beyond what the data say. Suppose a standard short-run elasticity of scale $\nu = 0.95$, and share of labor in variable cost $S_L = 0.25$. Take the average manufacturing markdown of 1.53 estimated by YMH, and either the 1.21 YMH markup or the 1.61 markup of De Loecker, Eeckhout, and Unger (2021). The implied gross profitabilities are 36% and 65%, respectively. Both numbers are too large to be defended as compatible with the existing firm-level data on profitability. The accompanying trends over time are based on neglecting part of the evolution of elasticities over time (and biases of aggregation).

7 Concluding remarks

This paper provides a method to simultaneously measure product and input market power (possibly in several markets) that is robust to the presence of labor-augmenting unobserved productivity (or other biased variants of technological change). No assumptions about product demand, competition in the product market, or competition among oligopsonists in input markets are used. The method specifies an approximation to the production function of each firm, in each moment of time, by fully exploiting the structure of the FOCs for cost minimization.

In practice, it amounts to estimating the long and short-run elasticities of scale as well as the degree of input market power in each market of interest. The baseline version of the model requires the scale elasticities and degree of

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

input market power to be constant across firms and over time, but the model can be generalized. Scale elasticities may vary with the inputs, and power in the input markets modelled according to observed determinants.

The estimated elasticities are robust to input market power and labor-augmenting productivity because they are estimated with their gaps with respect to the shares in cost and, in addition, allowed to vary with any technologically biased increase in productivity. For example, the labor shares can fall according to Hicks's (1932) prediction when the elasticity of substitution is less than unity. Estimation is simple using nonlinear GMM and moments based on lagged quantities, prices and hence shares of the inputs and, perhaps, some exogenous shifters.

Estimating market power in all markets, together with the short-run production elasticity, allows us to decompose observed gross profitability in its sources, which introduces a sharp tool to discipline estimation and results, as well as a useful element of analysis.

We apply the model to assess 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 power. With an unbalanced panel of more than 500 plants of unequal size, the estimation of the production function controlling for both neutral and labor-augmenting productivity works well. We reject the exercise of market power in the livestock market, but we find that some firms exploit their share in local employment to set wages with an important markdown. The firms above the third quartile of market power get on average 10 percentage points of profitability from this practice. Other firms combine more moderate labor market power with some product market power. On average, gross profitability is about 20 percentage points of which the model attributes 11 percentage points to technology and the rest to a combination of product and labor market power. A recent modest upward trend in market power is detected.

A streamlined version of the model, applied with aggregate data (49 years of the aggregate NBER-CES database) before we had access to the plant-level data, was remarkably able to detect, though with much less accuracy, the main traits involved. This says that useful econometric analysis with competition policy purposes does not necessarily need to be a long process with difficult-to-access data.

Compared with other ways of measuring market power, our method has the advantage of providing measures that are both unbiased and theoretically and practically consistent among themselves, decomposing the observed gross profitability of the firm into its technological and market power sources.

Appendix A: The effects of an exogenous increase of labor-augmenting productivity and labor market power

Let us examine in turn, with the help of Figure A1, what happens to the equilibrium of a short-run cost-minimizing firm that experiences: 1) an increase in its labor-augmenting productivity, and 2) an increase in its monopsony power in the labor market. (You may think of this as a rotation of the supply curve around the equilibrium wage: the relevant elasticity moves from infinity to a finite value.) Without loss of generality, we assume that ω_L and τ increase from an initial zero value to a positive value. Ceteris paribus, both effects give incentives to a cost-minimizing firm to reduce employment. To facilitate the comparison of results, we consider that the increase in labor-augmenting productivity and monopsony power is such that the firm adopts the same new ratio of materials to labor in each case.

Consider the production function of the model, dropping R and e^* to simplify the reasoning: $Q = F(K, \exp(\omega_L)L, M)\exp(\omega_H)$. Under standard regularity conditions we can invert it for effective labor

$$\exp(\omega_L)L = G(K, M, Q/\exp(\omega_H)),$$

and, for given K and ω_H, the slope of an isoquant in the plane (M, L) is

$$\frac{\partial L}{\partial M} = \frac{1}{\exp(\omega_L)}\frac{\partial G}{\partial M}.$$

The starting equilibrium A is the minimization of short-run cost $WL + P_M M$ for producing an output $\overline{Q}$, given input prices and subject to the technical feasibility condition given by the production function. As is well known, the condition for cost minimization to produce $\overline{Q}$ is the choice of the quantities of M and L such that the ratio of their marginal productivities equals the ratio of input prices[12]

$$\frac{\partial Q/\partial M}{\partial Q/\partial L} = \frac{P_M}{W}$$

This implies that any of the prices divided by the marginal productivity of the input gives a unique value. Using the inverse function rule, it is easy to see

[12] Multiplying both sides of the equality, the condition can also be written as

$$\frac{\beta_M}{\beta_L} = \frac{1 - S_L}{S_L},$$

where S_L is the share of labor cost in variable cost.

that this ratio coincides with the definition of marginal cost (e.g. $W/\partial Q/\partial L = \partial(WL)/\partial Q = \partial VC/\partial Q = MC$).

An increase in ω_L is easily represented by a displacement of the isoquant corresponding to $\overline{Q}$ towards the $M-$axis. An increase in τ will be accommodated without any change in the isoquant. Let us compare the new minimization point under the two situations.

When labor-augmenting productivity increases, the new relevant isoquant shows a smaller slope in absolute value for each value of M. The firm realizes that it can now produce quantity $\overline{Q}$ with much less labor, but since prices have not changed and the slope of the isoquant is consistently lower in absolute value, the new equilibrium B also implies a reduction in materials. Both inputs are reduced and hence their marginal productivities increase. Note that greater marginal productivities with the same input prices imply a fall in MC.

The effects of this movement on the ratio M/L and the share S_L depend on the properties of the production function, as represented by the curvature of the isoquant. If the elasticity of substitution σ is less than one, the ratio M/L rises and the share S_L falls.

With a positive τ, the relevant relative prices become $P_M/W'(1+\tau)$, and point A is no longer an equilibrium. Assume that the change in τ is such that the firm minimizes costs at point C, where the ratio $\frac{M}{L}$ is the same as in B. To achieve the new relationship between marginal productivities the firm must expand materials and decrease the use of labor along the isoquant. Point C is on the same ray as B and, if observed input prices were the same as in B, the observed labor share would have fallen by the same amount as in B. However, the new finite-slope supply curve implies that the observed wage falls and hence the fall in the share will be larger. With the same price, marginal productivity of materials is now lower, and it follows that MC increases.

Appendix B: Modeling the effects of AMAs

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

Let us assume a given number N of packers that exploit their monopsony power, setting quantities behaving Nash towards each other. Packer j short-run profits are

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

where Q_j is the quantity of output produced, $Q = \sum\limits_j Q_j$, and $P(Q)$ is the inverse of total demand for output. Note that the production Q_j uses capital, labor, cattle and materials: $Q_j = Q_j(K_j, L_j, R_{Fj} + R_{Cj}, M_j)$.

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

$$\frac{\partial \pi_j}{\partial R_{Fj}} = [P + Q_j \frac{\partial P}{\partial Q}] \frac{\partial Q_j}{\partial R_{Fj}} - P_F - R_{Fj} \frac{\partial P_F}{\partial R_F} - R_{C_j} \frac{\partial P_C}{\partial R_F} = 0,$$

where we may think of the quantity and the price in the cash market as expected. A simpler way to write the previous expression is

$$P(1 - S_j \varepsilon) \frac{\partial Q}{\partial R} - P_F(1 + S_j^F \varepsilon_F^F) - P_C S_j^C \varepsilon_F^C = 0,$$

and the equivalent for the cash market is

$$P(1 - S_j \varepsilon) \frac{\partial Q}{\partial R} - P_F S_j^F \varepsilon_C^F - P_C(1 + S_j^C \varepsilon_C^C) = 0.$$

Shares S_j, S_j^F and S_j^C are the shares of firm j in the output, formula contracts cattle, and cash cattle markets respectively, and $\varepsilon = \frac{Q}{P}\frac{\partial P}{\partial Q}$ is the elasticity of the inverse demand for the output while $\varepsilon_F^F, \varepsilon_C^F, \varepsilon_C^C$ and ε_F^C 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, $P_F = P_C = P_R$ say, then

$$S_j^F(\varepsilon_F^F - \varepsilon_C^F) = S_j^C(\varepsilon_C^C - \varepsilon_F^C)$$

and it is clear that the different elasticities imply a different endogenous choice of quantity for each market. With equal firms, $S_j = S_j^F = S_j^C = \frac{1}{N}$, and we can also write.

$$\varepsilon_F^F + \varepsilon_F^C = \varepsilon_C^C + \varepsilon_C^F.$$

The FOC for formula contracts, for example, is then

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

This provides a formula for the ratio price of meat/price paid for the cattle, which has been called the "spread"

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

The formula shows how the spread can change with the level of concentration (which affects both the prices set and paid) and also with the relative inverse elasticities in both markets.

What the model shows is that, since the firms are maximizing profits and $MR = P(1 - \frac{\varepsilon}{N}) = MC$, pricing through the AMAs is perfectly compatible with our model FOC

$$MC\frac{\partial Q}{\partial R} = (1 + \frac{1}{N}(\varepsilon_F^F + \varepsilon_F^C))P_R = (1 + \rho)P_R,$$

where a varying ρ can be used as a check for arbitrary variations of the elasticities in the formula and cash markets.

Appendix C: Data sources and management

Our sample of plants is derived from the Census of Manufactures (CMF), the Annual Survey of Manufactures (ASM), and the Longitudinal Business Database (LBD), which are U.S. Census-provided restricted data. 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 all the establishments, articulating the data from CMF and ASM. The Census Bureau work on the LBD database is summarized in Jarmin and Miranda (2002) and Chow, Fort, Goetz, Goldschlag, Lawrence, Perlman, Stinson, and White (2021). We select the 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 are lacking intermediate years' information, we split their history in 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.

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

We use the prices as follows. For deflating sales, we use the deflator of shipments (PSHIP) provided by NBER-CES. Wage is calculated 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 heads of cattle and hogs acquired, provided by the USDA.[13] We 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 are the value of plant shipments deflated by the NBER-CES deflator. Capital is constructed using the perpetual inventory method, with total expenses 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

[13] Due to their relative 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.

materials, consisting of parts and pieces, deflated by the constructed deflator. Other material expenses are deflated using the previously defined 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 cost.

Using the Quarterly Census of Employment and Wages by 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 trends upward and zero otherwise. Data on the inventory was obtained from USDA NASS (2022, 2024). Details on the cycle can be found in Rosen, Murphy, and Schinkman (1994).

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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 deviation
(1)	(2)	(3)	(4)
Autoregressive	ρ_{AR}	0.795	0.046
Long-run scale	λ	1.014	0.063
Short-run scale	ν	0.894	0.113
Elasticity of substitution	σ	0.499	0.294
Markdown in livestock	ρ	0.097	0.251
Markdown in labor	τ_0	-0.014	0.202
	τ_1	0.448	0.029
	τ_2	-0.005	0.039
	τ_3	-0.023	0.013
Elasticity of capital	β_K	0.119	0.154
Elasticity of livestock	β_R	0.707	0.094
Elasticity of labor	β_L	0.139	0.023
Elasticity of materials	β_M	0.049	0.012

No. of observations: 3,500

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

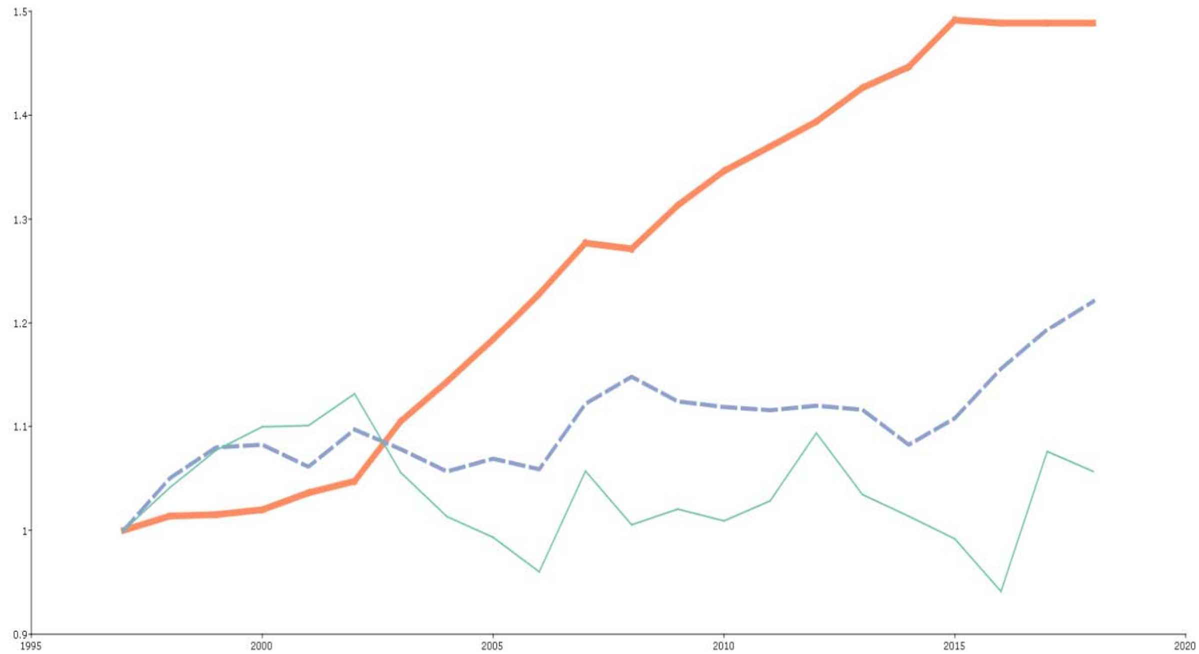
Table 4: Decomposition of profitability 1997-2020

Sample	Average size (workers)	Gross profit ($\ln \frac{R}{VC}$)	Technology ($-\ln \nu$)	Markup (μ)	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

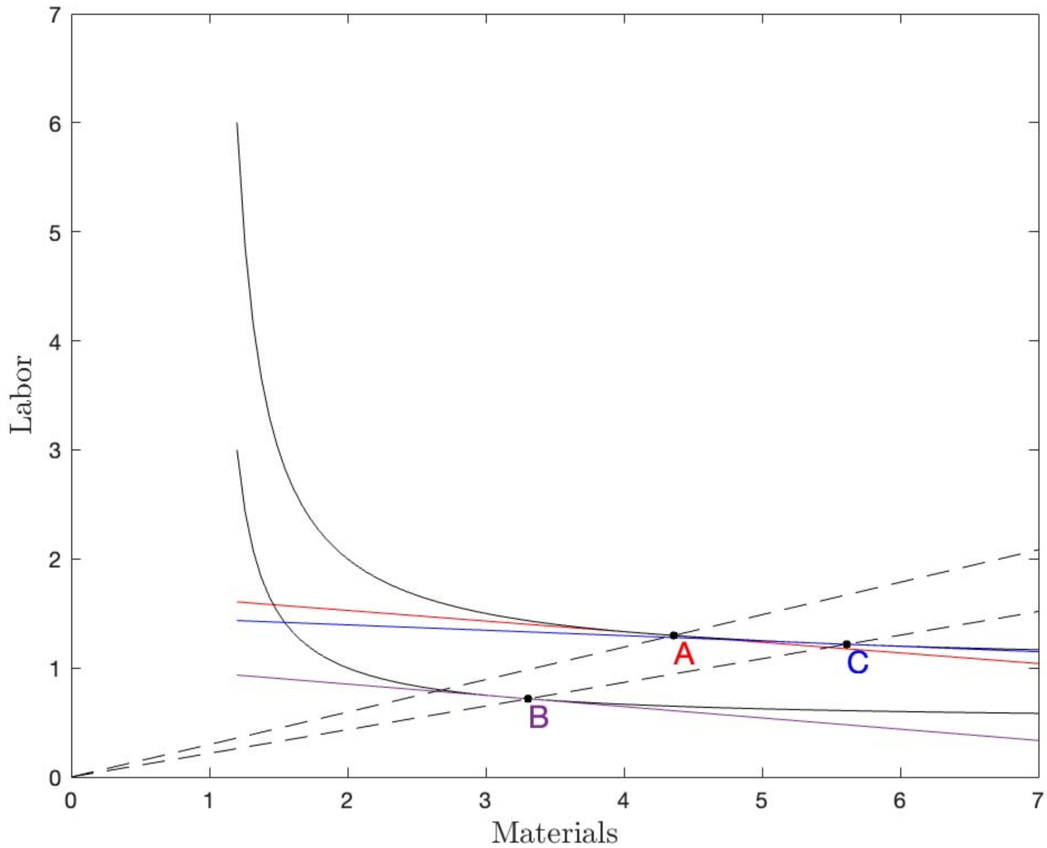


Thick solid line: Capital

Dashed line: Livestock

Thin solid line: Labor

Figure A1: The effects of an exogenous increase of labor-augmenting productivity and labor market power



Labor-augmenting productivity (A to B): The isoquant moves closer to the Materials axis and the firm chooses an equilibrium on the new isoquant given prices.

Input market power (A to C): On the unique original isoquant, the firm chooses an equilibrium in which the slope equates the new (absolute) price ratio $P_M / W'(1+\tau)$ flattened by the increase in monopsony power.