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 meatpacking 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 exercising monopsony power in the livestock and labor markets, and monopoly power in the product market (Azzam, 1998; Wohlgenant, 2013; Grimes, 2024). Industry data suggests the presence of LAP. While the nominal wage increased by more than 50% over the price of materials during our sample period, the labor share in costs remained stable, with an almost constant number of workers.[1]

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 simply and unequivocally, and the production approach does so by using production data. There is no need to specify and estimate the demand for the firm's products or the supply of its inputs, and assumptions about the specific game that firms play can be avoided. Our paper proceeds along these lines.

On the side of production, the approach is at least as old as Bain's (1951) work on the product market. It has been revived after De Loecker and Warzynski (2012), with an intense debate about the evolution of markups and how to measure them in practice.[2]

Interest in the exercise of market power has recently focused more on firms' input markets (monopsony power), to assess 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 even think that this kind of market power is prevalent, especially in the U.S.

A production approach to the simultaneous measurement of monopsony power and product market power originated with Dobbelaere and Mairesse (2013, 2018), although similar exercises had previously been attempted using tightly specified models. The basic method compares the first-order condition

[1] LAP presumably pushed down the share.

[2] An incomplete list of notable applications includes 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). Recent debates have focused on issues related to data measurements (Traina, 2018; Basu, 2019; Syverson, 2019), methodology (Doraszelski and Jaumandreu, 2019, 2021; Raval, 2023; Demirer, 2025; Bond, Hashemi, Kaplan, and Zoch, 2021; Hashemi, Kirov, and Traina, 2022; Kusaka, Okazaki, Onishi, and Wakamori, 2024; Kirov, Mengano and Traina, 2025), and outcomes (Jaumandreu, 2022, 2025).

(FOC) of an input with market power with the FOC of another without it.[3] Our paper follows this tradition.

With output and input market power, the FOCs that determine the optimal quantities of inputs, which is exactly where empirical measurements begin, differ from those under competition. To value physical marginal productivity under unspecified market power, the FOCs must use marginal cost instead of price and, under monopsony power, must reflect a wedge relative to the input price. Hence for an input X we typically have

$$MC\frac{\partial Q}{\partial X} = (1+\gamma)W_X, \tag{1}$$

where MC is marginal cost, $\frac{\partial Q}{\partial X}$ is marginal productivity of input X, γ is a measure of input market power, and W_X the price of X. This implies that output market power cannot be properly measured without accounting for input market power, if it exists. Conversely, input market power must be measured considering output market power, making a joint approach essential. Our work contributes to the simultaneous estimation of input and output market power.

Biased technological change becomes important here because it alters the marginal productivity of the affected input (instead of X we have $\exp(\omega_X)X$, where ω_X represents productivity). A recent general recognition of the importance of LAP has raised serious concerns about how productivity and markups are usually measured.[4]

Under a production elasticity of substitution less than one, LAP determines the fall of the labor share in costs (variable and total) and revenue.[5]

[3] Some papers have adapted the De Loecker and Warzynski (2012) framework: Morlacco (2019), Brooks, Kaboski, Li, and Qian (2021) and, notably, Yeh, Macaluso, and Hershbein (2022), who estimate that the average markdown in wages in the U.S.manufacturing is 53% (while markups average 21%). Rubens (2023) considers the non-substitutability of the relevant input and argues that it is necessary to adopt a model for supply (more on this later). This literature coexists with more tightly specified micro-models, 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, estimating labor supply for firms with suitable microdata.

[4] Papers that have addressed this topic include Doraszelski and Jaumandreu (2018, 2019), Zhang (2019), Raval (2019, 2023), Demirer (2025), Jaumandreu and Mullens (2024), Kusaka, Okazaki, Onishi, and Wakamori (2024), and Zhao, Malikov and Kumbhakar (2025).

[5] Labor shares have been documented to be falling in many places and times. For evidence from the U.S. manufacturing plants, see Kehrig and Vincent (2021) or Jaumandreu and Mullens (2024).

Ignoring LAP, the researcher can interpret the fall as an increase in revenue with respect to variable costs (i.e., an increase in prices with respect to costs). Alternatively, since monopsony power in the labor market also pushes down the share of labor costs in variable costs (and the use of labor relative to other variable factors), the researcher could mistakenly attribute the effects of LAP to monopsony power. To make consistent inferences, the production-based approach to measuring market power in both output and input markets must necessarily account for LAP.

Dorazelski and Jaumandreu (2018) derived a form to control LAP by means of a ratio of FOCs, and Demirer (2025) generalizes this method. However, some researchers argue that, in the presence of monopsony power, separate identification is not possible without a detailed behavioral model of the labor market (as in the past was thought to be the case for the product market).[6] This paper shows that identification is possible with a production approach.

1.1 Production elasticities

Measuring market power requires identifying marginal cost, which is generally not directly observable. However, under cost minimization, marginal cost can be recovered from observed data using production elasticities. For example, De Loecker and Warzynski (2012) proposed a widely used approach to estimate the price-marginal cost ratio by dividing the elasticity of a variable input by its share in revenue. Similarly, this paper calculates marginal cost by dividing average variable cost by the short-run elasticity of scale (i.e., the sum of elasticities of variable inputs).

Elasticities are hence needed, and estimating elasticities is typically done by estimating a production function. However, the problem is that the presence of input and output market power, as well as LAP, crucially impacts the conditions for consistent estimation of elasticities. A brief summary of the main challenges follows.

The firms' FOCs are used to control for unobserved Hicks-neutral productivity ($Q = F(.) \exp(\omega_H)$) in production function estimators such as those proposed by Olley and Pakes (1996) and Levinsohn and Petrin (2003) and typically implemented using the Ackerberg, Caves and Frazer (2015) procedure. However, with product market power, the FOCs should use unobserved marginal cost, rather than price, to value physical marginal productivity, as shown in (1). That introduces a challenging problem, as we need to estimate marginal cost to determine the elasticities, which are in turn expected to be

[6] See Rubens, Wu, and Xu (2025 a,b).

used to estimate marginal cost.

With monopsony power, the firm restricts the use of the affected variable input, causing the input elasticity to exhibit a disproportionate gap relative to the input share in variable cost. Estimated elasticities should reflect this gap, which suggests the need to explicitly account for it when estimating production elasticities. That makes estimation difficult. Additionally, the control for unobserved Hicksian productivity, discussed in the previous paragraph, is complicated by the presence of an additional unobservable in the FOCs.

With LAP, the production elasticity of labor is the same whether measured in terms of efficient labor or the raw quantity of labor. However, omitting the efficiency term that augments the input in the production function introduces a correlated omitted variable in the regression, as occurs in any input demand deduced from the FOCs. Additionally, greater productivity reduces the production elasticity of the input when the elasticity of substitution is less than one (a value with broad consensus among economists). Therefore, to estimate the production function consistently, the researcher faces two challenges: the need to specify elasticities that vary across productive units, and to account for evolving unobservable efficiency that modifies the quantity of labor relevant to estimating the production function.

1.2 Methodology and identification

We propose a method that addresses these difficulties simultaneously. The key is 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. Given this, to estimate elasticities, it is enough to estimate the elasticity of scale and the markdowns.

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 can be either assumed and recovered as parameters or modeled as a function of observable variables. As long as the three elasticities can be identified, the three elements are also identified.

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

This paper shows how a regression model can be constructed to estimate the relevant parameters (including the markdowns or the parameters of the variables explaining the markdowns). It exploits the sample variation of the cost shares in addition to the level of the inputs. We plug the semiparametric elasticities into the unknown production function of each establishment in our sample. Using enough valid sample moments, we identify the parameters by nonlinear GMM.

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

Hall (1988), to account for imperfect competition, wrote Solow's (1957) shares approximation to elasticities in terms of the markup multiplied by the revenue shares. Klette (1999) used this specification to measure productivity and markups. De Loecker and Warzynski (2012) proposed using Hall's identity to solve for the markup (note: sidestepping how elasticity is estimated). Nearly all work to date on markup estimation has been based on Hall's approach. We deviate from this convention by instead modeling elasticities using the short-run elasticity of scale multiplied by the cost shares. Estimating the elasticity of scale directly is natural and has advantages over estimating a presumably highly variable 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 the subject of controversy and intensive research. Dominated by a small number of firms (currently four), the industry has been suspected of exercising market power in the product market and monopsony power in the market for its livestock input, as well as being accused of imposing poor working conditions on its workforce.[7] 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. We control for both neutral productivity and LAP, and assess potential markdowns in livestock and meatpacking labor. We then decompose firm's profitability into its components. On average, gross prof-

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

itability is about 20 percentage points, of which our model attributes 11 percentage points to technology, with the remainder due 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.

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.[8]

1.4 Relation to other literature

A paper close to ours, modeling a very specific market, is Kroft, Luo, Mogstad, and Setzler (2025), who examine product market power and labor market power in the U.S. construction industry.

The article specifies both the markup and the markdown as constant under tightly behavioral assumptions: monopolistic competition in the product market with a demand characterized by a common price elasticity, and a common labor supply and quantities (Cournot competition) to determine the wage. The article also employs the Leontief form of the production function to replace unobserved output with materials. The model is estimated by pieces, and capital is assumed to be perfectly flexible. The results seem reasonable, with a markup of 0.16 and a markdown of 0.25.

An important difference with our specification is that we can obtain similar results without conduct assumptions. The main difference is that our estimation is robust to the presence of LAP, whereas theirs is not. Unfortunately, in construction, LAP can be a significant determinant of productivity differences.

Another difference with Croft, Luo, Mogstad, and Setzler (2025) is that we are able to present a sensible decomposition of our results in the form of profitability of each source: technology, product market power, livestock market power, and labor market power, while they only present overlapped total markups and markdowns in the product and labor markets. Knowing the decomposition may be very relevant for economic policy.

Rubens, Wu, and Xu (2025 b) estimate markups and markdowns in the nonferrous metals industry in China, by means of a CES production function, accounting for LAP. Monopsony power is previously estimated using firm-level residual supply elasticities derived from a model of labor supply under Bertrand competition of firms. The model implies that markdowns are a positive function of the employment shares.

[8] We summarize the aggregate model in Appendix D.

In practice, when confronted with the fact that labor markdowns exhibit important heterogeneity, we adopt a similar approach. We model our (conduct free markdown) as an unknown function of the size and market share of the firms. Notice that our modeling allows for this type of fully integrated one-step flexibility, as testing reveals that monopsony power does not conform well to a constant across firms.

Rubens, Wu, and Xu (2025 b) obtain an average markup of 0.08 and an average markdown that is roughly constant at around 0.27. They use the results to discuss the relative efficiency of state-owned and private firms. The differences that we find in the degree of exploitation of workers across establishments are greater.

Meatpacking is an industry with more than a century of questionable competitive practices. Huang (2024) studies price manipulation by firms acting as a monopsonist cartel at the beginning of the twentieth century. However, literature reviews from the 2000s, such as Azzam (1998) and Wohlgenant (2013), did not find strong evidence of market power being exercised in either the product or livestock markets. More recently, persistent concentration, new forms of contracting and setting prices, complaints from farmers and ranchers, and concerns about labor practices have again drawn attention to the sector's competitiveness. Garrido, Kim, Miller, and Weinberg (2024) provide an account of recent research on pricing practices; Bolotova (2022) addresses collusion in the industry; and MacDonald (2024) discusses recent structural industry 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 within 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 approaches to measuring market power developed by Hall (1988), Klette (1999), and De Loecker and Warzynski (2012). It relies on estimating the short-run elasticity of scale to uncover the relationship between (unobserved) marginal cost and (observed) average variable cost.

Third, the method is designed for an environment where input-augmenting productivity (in our case LAP) is present and perhaps prevalent. To our knowledge, this is the first production approach procedure developed that is consistent with biased technological change.

Fourth, the paper demonstrates the separate identification of LAP and monopsony power, establishing how the corresponding unobservables map onto different observed behaviors (more and less output) that enable identification.

Fifth, it derives an observable profitability bound for the combined contributions of market power to profits, in addition to the contribution of technology. This bound, is met by the estimates and serves as a natural test for validating alternative market power measurements.

Sixth, the paper examines competition in the U.S. meatpacking industry, giving formal attention for the first time to the meatpacking 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 presented in Section 5. Section 6 compares our estimator to 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 are increasingly replacing the spot market for livestock; Appendix C describes the construction of the sample and variables; and Appendix D briefly describes the aggregate model.

2 Model

2.1 Production function

Consider the establishment-level production function

$$Q^* = F(K, R, L^*, M) \exp(\omega_H), \tag{1}$$

with $L^* = \exp(\omega_L)L$, where Q^* is the quantity of meat, K, R, L, and M, represent capital, livestock, labor, and materials, respectively, and ω_L and ω_H are persistent variables representing LAP and Hicks-neutral productivity. P_R, W, and P_M denote the observed prices of livestock, labor, and materials.

Assumption 1

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 β_K. In the short-run, firms can freely vary the inputs R, L, and M. The variable inputs exhibit constant elasticity of scale (the sum of elasticities), denoted by ν, and an elasticity of substitution σ.

Assumption 2
Firms minimize short-run costs by optimally choosing the quantities of the variable inputs R, L, and M. The 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 ρ and τ between the marginal product and the input price (markdowns).

Denoting marginal cost by MC, the FOCs hence are

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

Assumption 3
The production function of each establishment can be approximated, at the input quantities that the establishment is using, by the expression in logs

$$q^* \simeq \beta + \beta_K k + \beta_R r + \beta_L l^* + \beta_M m + \omega_H, \tag{2}$$

where β is an establishment-specific constant, and β_R, β_L, and β_M are establishment-specific elasticities computed as $\beta_X(K, R, L^*, M) = \frac{\partial \ln F(K,R,L^*,M)}{\partial \ln X}$ for $X = R, L, M$.

Discussion
In assumption 1 we do not adopt a particular functional form because we want to be as general as possible, including varying elasticities (implied, for example, by LAP) and an unspecified elasticity of substitution. We could alternatively suppose, as simple examples, a CES in variable inputs (fixed σ) nested in a CD including capital, or a translog (variable σ) nested as well in a CD . The specification would become completely parametric.[9] Later we

[9] A CES function has been used to model LAP by Doraszelski and Jaumandreu (2018), Raval (2019), and Zhang (2019). Assumption 1 is consistent with the homothetically separable production function used by Demirer (2025), as well as with the translog, homogeneous in variable factors but allowing for a variable σ, used by Doraszelski and Jaumandreu (2019) and Jaumandreu and Mullens (2024).

will comment as to why we think that our general specification is a good approximation.

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 marginal cost. That makes it possible to estimate 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. We discuss this in detail after we show in Proposition 1 that the expressions can be rewritten in terms of the elasticities for the variable inputs, the markdowns ρ and τ, and observable shares in variable costs.

Assumption 3 states that an approximation of the production function in terms of the elasticities of the inputs is good enough. The concern is whether, due to our assumption of general production functions at the establishment level, the approximation can result in an error correlated with the inputs.

Certainly not all production functions can be written exactly in the elasticities form (2). However, the quadratic identity lemma introduced by Diewert (1976), and used by Caves, Christensen and Diewert (1982) to discuss the construction of productivity measures, shows that a broad class of quadratic log-approximations to production functions can be expressed in terms of an average of the elasticity of the firm and the elasticity used as base for comparison.[10] Ours is a case of (small T) unbalanced panel data, in which elasticities are likely to be firm-idiosyncratic but quite stable over time. We show later that the shares of the inputs are effectively very stable over time due to changes in the opposite direction in the ratio intermediate inputs to labor and the price of labor to other prices. That way, we can argue that the error of approximation is unrelated to the inputs.

Proposition 1

Under assumptions 1 and 2, production elasticities have the following (nonlinear) expressions

$$\begin{aligned}\beta_R &= \nu^*(1+\rho)S_R,\\ \beta_L &= \nu^*(1+\tau)S_L,\\ \beta_M &= \nu^* S_M,\end{aligned}\tag{3}$$

[10] That is, $q - q_0 = \sum_i (1/2)(\beta_i + \beta_{i,0})(x_i - x_{i,0})$. With the $\beta_i' s$ replaced by each corresponding share, this way of estimating has sometimes been called the factor shares approach (De Loecker and Syverson, 2021).

where $\nu^* = \nu/(1+S_R\rho+S_L\tau)$ is a corrected short-run elasticity of scale, and S_R, S_L, and S_M are the shares of input cost in variable cost.

Also, under assumptions 1,2, and 3, knowing the productivity unobservables ω_L and ω_H, the parameters β_K, ν, ρ, and τ (capital, short-run scale, and markdowns) can be estimated from the production function using nonlinear regression,

$$q = \beta_0 + \beta_K k + \nu^*(S_R r + S_L l^* + S_M m) + \ \nu^* \rho S_R r + \nu^* \tau S_L l^* + \omega_H + \varepsilon, \quad (4)$$

where β_0 is a constant.[11] The establishment-specific elasticities β_R, β_L and β_M turn out to be implicitly determined.

Proof

Multiplying each FOC by X/Q^* and re-arranging, they can be written as $\frac{X}{Q^*}\frac{\partial Q^*}{\partial X} = (1+a_X)\frac{AVC}{MC}S_X$, with $a_X = \rho, \tau$, and 0, where $\frac{X}{Q^*}\frac{\partial Q^*}{\partial X} = \beta_X$, and S_X is the share of input X in variable cost. Adding these elasticities to obtain the short-run scale, we have $\nu = \beta_R + \beta_L + \beta_M = \frac{AVC}{MC}(1 + S_R\rho + S_L\tau)$, and we can write $\frac{AVC}{MC} = \nu/(1 + S_R\rho + S_L\tau) = \nu^*$.[12] This gives the expressions for the elasticities (3).

Substituting these expressions for the elasticities into (2) and defining $\varepsilon = \beta + \textit{approximation error} - \beta_0$, with β_0 appropriately measured, we get regression (4) to estimate β_K, ν, ρ, and τ. From these parameters and the observed cost shares, the variable elasticities can be backed out according to (3). We assume that ε has a mean of zero and is uncorrelated with any information available for the firm at t.

Discussion

We have constructed a regression model in terms of observables, four unobservables (the two parameters of input market power and the productivities), and the parameters to be estimated to recover the elasticities. Let us 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 that the markdowns would be identified.[13] We could use the

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

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

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

[13] We insist on this because some papers argue that it is not possible; see for example Rubens, Wu, and Xu (2025 a,b)

ratios with respect to the input without market power and get the markdowns without any restriction. We would estimate, as in the case of product market power, input market power entirely from the information in the production function. However, we cannot estimate the elasticities without controlling for ω_L (term of l^*) and ω_H. The control for ω_H can be done by dynamic panel methods, but the control for ω_L needs to use the ratio of FOCs, and this reintroduces the parameters of input market power. Hence, what we can easily do is a little more limited.[14] We can control for ω_L using the ratio of the FOCs if we then consider ρ and τ as either constants or unobservables that can be modeled in terms of observables. That is what we do in the empirical exercise.

The method we use to estimate the production function can be viewed as an alternative to the approach of Hall (1988) and Klette (1999). Those papers relied on the simplified equality $\beta_X = \mu S_X^R$, where $\mu = \frac{P}{MC}$ is the markup and S_X^R is the (observed) share of input cost in revenue. We could have used the expression $\beta_X = \mu(1+a_X)S_X^R \exp(\varepsilon)$, but this would introduce two problems: the need to incorporate the presumably highly variable unobservable markup μ into the production function, and the presence of the unobservable error ε in the expressions. Instead, we work with the short-run elasticity of scale parameter ν, which we assume can be safely taken as constant, and our expressions avoid error.

2.2 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 market power across the product and input markets:

$$\ln \frac{R}{VC} = -\ln \nu + \ln \mu + \ln(1 + S_R\rho + S_L\tau) + \varepsilon \simeq -\ln \nu + \ln \mu + S_R\rho + S_L\tau + \varepsilon, \tag{5}$$

where the second approximate equality splits the contributions of each input's

[14]Full identification could be reached by solving a system of three equations for the three unobservables ω_L, ρ, and τ, and replacing the unobservables in (4). While such equations are implied by the model, we feel that the application of this procedure would increase the nonlinearity in a way too demanding with the data we are working with.

market power.[15] Under $\nu < 1$, averages of this equation set an upper bound to the sum of market power effects on profitability (markup and markdowns) for any group of firms.

Proof
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. Plugging the value of ν^*, expression (5) follows.

Discussion
Note that all terms in the decomposition are likely to be positive, and the error ε tends to cancel out, on average. The parameter ν 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 $\ln \frac{R}{VC}$ (plus the log of the elasticity of scale) sets an upper bound to the sum of market power profitability effects (markup and markdowns).

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

2.3 The control for unobserved productivity

To apply equation (4) to the data, we need to determine how to control for unobserved productivity ω_L and ω_H. 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 ω_H 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

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

equation multiplied by the autoregressive parameter. In this method, the autoregressive parameter is estimated, and the resulting composite error includes the innovations of the Markov process, which capture all transitory productivity shocks. This type of estimation generalizes the approach commonly used in production function estimation, referred to as the dynamic panel method.[16]

In estimations dealing with LAP, unobserved productivity ω_L has typically been replaced by expressions in terms of observables based on the FOCs ratio for labor and a materials input. This method was applied by Doraszelski and Jaumandreu (2018) and later generalized by Demirer (2025). Given the unspecified form of the production function that 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

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

where σ is the elasticity of substitution implicit in the production function.[17] From this expression we can get

$$\omega_L = c_0 + r - l - \frac{\sigma}{1 - \sigma} \ln \frac{S_L}{S_R},$$

where $c_0 = -\frac{cons}{1-\sigma} - \frac{\sigma}{1-\sigma}(\tau - \rho)$. The control in ω_L is made from the observable variations in the ratio $r - l$ and the relative shares. What remains, given constant σ and constant markdowns, is a constant. However, we should keep the term ρ and τ in mind as a reference, in case either of the two parameters needs to be modeled as varying.

2.4 Empirical specification

We rewrite the production function (4) to estimate the log-run parameter to scale directly $\lambda = \beta_K + \beta_R + \beta_L + \beta_M$.

[16]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 ω_H with the inverted demand for an input. That seems more problematic in that it needs to yield a solution to the unobservability of marginal cost in the FOC or FOCs used to derive the input demand, and introduces an additional time the presence of the markdown or markdowns.

[17]In practice we are going to do a combination of the intermediate inputs. See subsection 5.2

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

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

where

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

The parameters to be estimated (in addition to the constants β_0 and c_0) are $\rho_{AR}, \lambda, \nu, \sigma, \rho$, and τ. Recall, however, that we may still choose to make ρ and/or τ vary. Once estimated, these parameters can be used to calculate μ_{jt}, which depends on the implicit MC, and perform the profitability decomposition.

3 Identification

The model in equation (6), even without the unobserved productivity terms ω_L and ω_H, is nonlinear in both parameters and variables. It must therefore be estimated using a procedure such as nonlinear GMM, which we implement 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 turn 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 LAP.

3.1 Moments

After controlling for the productivity unobservables, only the transitory unobserved productivity shocks ξ_{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 past 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 will 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 uncorrelated with the shocks, then (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. Therefore, we will use moments based on the (lagged) composite variable SUM, and on a calculation for (lagged) l^* based on a guess for the value of parameter sigma.

We will complement these instruments with three additional external variables: the cattle cycle, the (lagged) employment in the plant as a proportion of total (lagged) employment in the county where 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, which presumably weakens collective bargaining. We continue the discussion of instruments in more practical terms when we list them 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 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. 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 therefore 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 turns out 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 that one market does not exhibit monopsony power). However, without additional information, we will 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 argue later that livestock is, in fact, 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 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).[18] $H(\cdot)$ constitutes a subfunction that is homogeneous of degree ν_H in the variable inputs, whose cost is minimized, and for which all the relationships described above hold.[19] 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 all the other variables are known. We are able to assess the roles of both technology, profitability, and the labor market, but cannot separate the contributions of market power in the product market from monopsony power in the livestock market.

3.3 Monopsony power and labor-augmenting productivity

An important question remains: Can we identify monopsony power separately from LAP? This issue arises because LAP introduces an unobservable into the FOC for labor similar to monopsony power. Even if we substitute an expression for the unobservable ω_L, separating it from the effects of the markdown τ, how can we be confident that these two effects can be clearly distinguished?

To address this question, in Appendix A, we examine in detail 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 value of zero to a positive value. Ceteris paribus, both changes provide an incentive for the cost-minimizing firm to reduce employment. To facilitate comparison, we assume that the increases

[18] Usually, researchers include $exp(\omega_H)$ affecting the composite input H. We ignore this here for simplicity.

[19] 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.

in LAP and monopsony power are such that, in each case, the firm adopts the same new ratio of materials to labor.

The outcomes are as follows. An exogenous increase in LAP induces the cost-minimizing firm to reduce both labor and materials, but labor proportionally more. As a result, the share of labor in variable cost, S_L, decreases. In addition, the productivity improvement leads to a decrease in MC. By contrast, an exogenous increase in monopsony power causes the firm to reduce labor while expanding materials. If the firm adopts a materials-to-labor ratio that matches the case of the ω_L increase, the labor share in variable cost, S_L, diminishes, though more than with the ω_L increase. However, MC increases. The contrasting behavior of MC implies that the firm has incentives to move further in opposite directions: expanding output in response to a productivity increase, and contracting output following an increase in monopsony power, by scaling both inputs up or down in the same newly adopted proportion. Summarizing, when a LAP or an increase in monopsony power shock occurs, we will see the firm increasing or decreasing its output, respectively.

4 The meatpacking industry

We apply the model to the U.S. meatpacking industry. In what follows, we provide background on the industry, discuss substitutability and the role of contracts, also know as alternative marketing arrangements (AMAs). We also report descriptive statistics and evidence of LAP.

4.1 The U.S. meatpacking industry

The meatpacking industry encompasses the slaughtering (or harvesting), 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. Department of Agriculture (USDA), in 2023, 267 beef packing plants slaughtered 1,000 or more head of cattle. Of these, 11 plants each slaughtered over one million head, collectively accounting for 46% of all cattle slaughtered. Similarly, there were 206 pork slaughter plants processing 1,000 or more head, of which 14 slaughtered over 4 million head each, accounting for 60% of all hogs slaughtered. 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, accounting for 39% of all sheep slaughtered (USDA NASS 2024). This yields 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 a few companies operating several plants. According to the USDA, in 2019, four major producers -Tyson, Cargill, JBS, and National Beef- accounted for 85% of all cattle, 67% of hogs, and 53% of sheep and lambs slaughtered (USDA AMS 2020).

Concentration in the industry increased sharply between 1960 and 1990, as plant sizes grew. Facilities moved from the Midwest and Northern Great Plains to the Southern Great Plains. Since then, concentration has grown more slowly. The four-firm concentration ratio (CR4) in beef processing rose from 41% in 1982 to 79% in 2006 and has remained relatively stable since. Similarly, the CR4 for pork processing increased from 36% to 63% over the same period. For a historical overview, see MacDonald and McBride (2009), and for a more recent account, see MacDonald (2024).

Packer conduct has traditionally been a source 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 over the industry's 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).

On the other hand, the high level of buyer concentration in the livestock market, complaints from livestock producers, and the prevalence of AMAs, have raised concerns about the market's competitiveness.

The literature on 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 the oligopsony affects pricing.[20] 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. On the contrary, Wohlgenant (2013) stresses the evidence of reduced processing and

[20] 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.

distribution costs stemming from reorganization, technical innovation, and increased plant size.

Substitutability

Evidence suggests that livestock exhibits some degree of substitutability, and we accordingly assume that it does not enter the production function in fixed proportion. The idea is that, in principle, different combinations of capital and labor, as well as materials, can be used alongside varying amounts of liveweight livestock to produce the same quantity of (standardized) output. Wohlgenant (2013) makes the case for this, and there is substantial evidence on elasticities of substitution across different inputs and outputs (see, for example, MacDonald and Ollinger, 2001). As we show below, our current exercise provides strong support for substitutability.

That may seem unrealistic if one thinks of livestock in the abstract as the essential input to produce meat. But it becomes clear when one takes into account the differences in input combinations determined by the mixes of processed products that the industry sells to further processors, wholesalers, and retailers. In fact, the mix of content of the product has strongly changed over time. Initially, meatpackers shipped entire carcasses for further processing. Over time, the practice was progressively replaced by processed products that were cut, prepared, and packed -the product known as “boxed beef.” It accounted for only 10% of the shipments in the seventies, but that share had risen to 50% by 2000 (MacDonald and Ollinger, 2005). Even with an important degree of homogeneity, it is natural that the product mix/technological diversity determines input substitutability in the cross-section and even over time in our sample.

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. Currently, approximately 80% of livestock procurement is done through AMAs.

Many authors have raised concerns about the impact of these formula contracts on the erosion of the cash market, and their potential effects on competition. 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 yet been established between the spread expansion observed during 2015 to 2020 and the use of AMAs.

In Appendix B, we briefly develop a "neutral" model of AMAs, following the approach 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 pricing of livestock by packers with input market power across two markets (formula contracts and cash) is fully compatible with our modelling. We therefore take our evaluation as a first negative structural assessment of the effects of AMAs. Obviously, more research is needed; Garrido, Kim, Miller, and Weinberg (2024) is research in progress.

4.2 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 final year covered by the NBER-CES data. Our exercise using plant-level data extends through 2020.

Industry output, measured in pounds of meat, grew about 24% over the 22-years period. The livestock input, measured in pounds of liveweight, closely followed the evolution of 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 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.

The fifth line of Table 1 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. The doubling implies faster growth than the price of livestock and other materials (the index of the price of livestock appears on the sixth line). Despite this, the shares of all three variable inputs in total variable cost have remained notably stable, suggesting that LAP had a role.

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 knifes 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, the efficiency of labor should have improved.

Although we should refrain from using the aggregate data for detailed examination due to the possible biases of aggregation, we posit the following.

The moderate evolution of the ratio livestock to labor (17% increase), in comparison to the rise in wage 52% above the price of livestock suggests that the elasticity of substitution 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 the labor's share of variable costs. The fact that this did not occur strongly suggests that LAP was simultaneously driving this labor share down.

The story can be not 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.

The fact that the share of labor has stayed relatively stable over time is good for our identification strategy. As we mentioned above, our specification is particularly adequate to deal with significant firm differences in elasticities, according to levels of LAP, that have tended to remain similar over time.

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, from 1997 to 2018, covering a span of 24 years. We drop plants with abnormal values and those with fewer than five workers. Then, we 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 or plants.

Table 2 summarizes the characteristics of the sample, with plants grouped into size 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), as we believe this helps the analysis of the effects of scale. However, the analysis is primarily driven by the observations for the largest plants, as reflected in column (6), which shows their 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 a variable that computes, for each plant and point in time, the ratio of the plant employment to total county employment in manufacturing. Column (7) reports the average of this variable for each type of plant. Interestingly, there is little difference among 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 it does not significantly impact the panorama of plants. No firm operates more than 30 plants at any moment, and no firm's plants are all very large. So, 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.

5.2 Specification and estimation

We apply model (6), incorporating a few enlargements described 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, as well as the shares in variable cost of livestock, labor and materials, S_R, S_L, and S_M. Appendix C provides the exact definition of these variables. We estimate the six parameters $\rho_{AR}, \lambda, \nu, \sigma, \rho$, τ, and two constants. From the beginning it is clear that the parameters ρ and τ will be the most challenging.

In a series of trials with different instruments and slightly different specifications, it becomes apparent that parameter τ is heterogeneous within the sample, while parameter ρ is consistently not 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 plant size as the log of the number of workers, l. We expect the final estimation to show that the markdown increases with both the plant's impact on meatpacking employment and plant's size. Replacing county meatpacking employment with county manufacturing employment affects the estimation very little, so we keep the first variable. We also attempt to assess whether this relationship varies with the presence of "right to work" laws in the state using the artificial variable RTW_{jt}, but 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 (5), we finally use $l_{jt}^{*} \equiv \omega_{jt} + l_{jt} = cons - \frac{\sigma}{(1-\sigma)}(\tau - \rho) + r_{jt} + m_{jt} - \frac{\sigma}{(1-\sigma)} \ln \frac{S_{Ljt}}{(1-S_{Ljt})}$. Additionally, we estimate imposing the positivity of sigma.

We have expanded the equation by including the modeling for τ, so 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 $1 - RTW_{jt}$. In total, we use 21 moments, resulting in 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 apply the delta method to approximate the standard errors of the elasticities, evaluated at the means of the observed variables.

5.3 Production function estimates

The results of estimating the production function 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 production function estimates 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 incorporating 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, it 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 marginal cost is approximately 10 percentage points higher than the observed average variable cost. This seems reasonable and implies that the difference between short-run marginal cost and average variable cost will explain roughly this number of percentage points of profitability.

We were unable to make parameter ρ, which models market power in the livestock market, statistically significant. We attempted to let ρ vary with the level or concentration or the plant size, 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 ρ 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 the 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 such a situation in the estimates for ν.

The schedule for the labor markdown exhibits substantial heterogeneity, and the plant's share in county employment, *shce*, it emerges as an important determinant of this heterogeneity. The interaction between share and the plant size is positive (the log of *shce* is negative), and the term in the share is clearly increasing. So, both share and the plant size play a role. However, we are unable to ensure that the entire schedule remains nonnegative without imposing a value on the imprecisely estimated τ_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 the 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).

5.4 Decomposition of profitability

The results are reported in Table 4. The numbers are computed under two restrictions. First, we set ρ to zero due to its lack of significance. Second, we impose a value for the constant τ_0 that ensures no negative τ for any plant.

The value of gross profitability is computed 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 the 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 short-run or gross profitability is approximately 20%, with half of this value due to a marginal cost that exceeds 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 perspective of plants with labor market power above 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, meaning their wages tend to be low relative to labor marginal productivity.

Data detailed by periods (not shown) reveals 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.

The first version of this paper, written before we had access to plant data, developed a streamlined version of the model that we applied to aggregate data (49 years of the aggregate NBER-CES database). Although less precise, the estimation notably detected the main patterns that we now confirm (see Appendix D).

6 Relation to other measurements

A reader who has followed the derivations in Section 2 closely, 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 are, generally, even 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 $\widehat{\beta}_X/S_X^R$.[21] 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 resasons. YMH propose 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, say, $\widehat{\beta}_X/\widehat{\beta}_Z/(S_X/S_Z)$.[22] If we apply this measure to our average values for labor and materials, we would obtain a result 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 the usual application of DLW and YMH is that their measures rely on estimating an unrestricted elasticity, that 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

[21]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.

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

are used to assess the change in markups and markdowns.

To give a simple (aggregate) example, recent estimates of market power across all U.S. manufacturing, and even for the overall economy, appear to be far higher than what the data support. Suppose a standard short-run elasticity of scale $\nu = 0.95$ and labor share in variable cost $S_L = 0.25$. Take the average manufacturing markdown of 1.53 estimated by YMH, along with either the 1.21 YMH markup or the 1.61 markup from De Loecker, Eeckhout, and Unger (2021). The implied gross profitabilities are 36% and 65%, respectively. Both numbers are too large to be considered consistent with the existing firm-level profitability data. The accompanying trends over time are based on ignoring part of the evolution of elasticities over time and on aggregation biases (see Jaumandreu, 2025).

7 Concluding remarks

This paper provides a method to simultaneously measure product and input market power (potentially across multiple markets) that is robust to the presence of unobserved labor-augmenting productivity (or other biased variants of technological change). The approach does not rely on assumptions about product demand, competition in the product market, or competition among oligopsonists in input markets. It specifies a semiparametric approximation to each 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. The baseline version of the model assumes that scale elasticities and input market power are constant across firms and over time, but the model can be generalized. Scale elasticities may vary with the inputs, and input market power may be modeled according to observed determinants, as we do in this paper. A method to estimate varying market power without observables is suggested, but left for further research.

The estimated elasticities are robust to input market power and labor-augmenting productivity 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, labor shares and hence labor elasticity may decrease as predicted by Hicks's (1932), when 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, possibly supplemented by some exogenous shifters.

Marginal cost is implicitly estimated up to an uncorrelated error and can be easily computed. 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 the estimation and results.

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. Using an unbalanced panel 1997-2020 of over 500 plants of varying sizes, we successfully estimate the production function while controlling for both neutral and labor-augmenting productivity. We find no evidence of market power exercise in the livestock market; however, some firms exploit their local employment share to set wages with a significant markdown. Firms 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 labor market power and some product market power. 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 detect a modest recent upward trend in market power.

A streamlined version of the model, applied to 49 years of aggregate data from the NBER-CES database before we had access to the plant-level data, was able to detect the main traits involved, albeit with much less accuracy. This suggests that useful econometric analysis for competition policy purposes does not always require a long process with difficult-to-access data.

Compared to other methods of measuring market power, our approach provides unbiased estimates that are both theoretically and practically consistent. It also allows for a decomposition of observed gross profitability into 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 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[23]

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

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

[23]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 are related to the properties of the production function, as represented by the curvature of the isoquant. With the elasticity of substitution σ less than one, the ratio M/L rises and the share S_L falls.

With a nonzero 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 $R_F = \sum_j R_{Fj}$ and $R_C = \sum_j R_{Cj}$ (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, $Q = \sum_j Q_j$, 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, and cash 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 "price 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 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 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 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 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.

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 information from the USDA and BLS, as we detail below.

We use 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.[24] 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 the total expenses in capital reported by the plant lagged one period, and a depreciation rate of

[24] 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.

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 material expenses 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 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).

Appendix D: Aggregate model

The main data source is the CES-NBER Manufacturing Industry Database (available at https://www.nber.org/research/data/nber-ces-manufacturing-industry-database), which has been recently updated to 2018 (see Becker, Gray, and Marvakov, 2021). It aggregates the data from the Census of Manufactures and the Annual Survey of Manufactures. The data is available for the NAICS code 311611 or the SIC code 2011 (Meatpacking Plants), which includes cattle, hogs, and lambs, for 49 years (1970-2018). It includes price deflators for the value of shipments, materials, energy, and investment.

We compute output in million pounds of meat from USDA ERS (2022) and USDA NASS (2022) reports. We use the real capital variable (equipment plus plants) as provided by the CES-NBER database. Labor is measured as the hours of production workers, as given by the CES-NBER database as well. We separate materials into livestock and other (non-livestock) materials merging the energy input into materials. We use the cycle variable defined in Appendix C.

The instrumental variables include the ratio of wages of production workers to total pay, both variables as provided by CES-NBER, and the price of corn, obtained from USDA NASS.

The model is basically equation (3), where neutral productivity is suppressed after checking that modeled by a trend is not significant, and labor-augmenting productivity is modeled by increasing the observed labor by means of a trend that augments it yearly in "efficiency" terms by 2 percentage points. We estimate six parameters: constant, long and short-run elasticity of scale, the two markdowns, and the coefficient for the variable cycle. We use eight instruments: constant, time trend, lagged capital, lagged livestock, lagged share of labor, the lagged price of corn, cattle cycle, and the ratio of wages. The resulting estimation, is reported in column (3) of Table D1.

The results are reasonable. The short-run and long run parameters of scale are estimated to be 0.960 and 1.185, respectively. The parameter of monopsony power in the livestock market is evaluated virtually at zero, and the parameter of monopsony power in the labor market is significant with probability value of 6%. The markdown parameter value (0.666) implies that workers receive 60% of the labor marginal productivity. The mean elasticities for the inputs look perfectly reasonable and market power in the product market is evaluated as very low (average percentage markup is 2.4 percentage points). A Sargan test accepts the specification, giving a positive indication of the validity of the instruments.

Since monopsony power seems non-existent in the livestock market, we reestimate the model imposing the restriction that the parameter of monopsony power of this market is zero, as reported in column (5). A Chi-square test strongly accepts the imposition of this restriction. If we similarly test the imposition of zero coefficient for the monopsony parameter in the labor market, we tend to obtain a significant rejection. Efficiency is slightly improved and the monopsony parameter estimate for the labor market now has a probability value of 4.6%.

Profitability decomposition is carried out in Table D2. Mean profitability throughout the whole period of almost 50 years is moderate, about 10%. An important part of this profitability comes from technology, more specifically from the fact that, in equilibrium, marginal cost lies about four percentage points above average variable cost. Market power in the product market adds very little to this, only 1.5 points, since the markup is very close to the unit value expected under perfect competition. The market power in the labor market adds a contribution as important as technology's to profitability. The fact that production workers are paid only 60% of the value of their marginal productivity implies a contribution to profitability of a little more than 4 percentage points, even though the share of labor in variable cost is relatively small (an average of 6%).

The results show some recent increase in product market power.

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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	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

[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 (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.

Table D1: The production function of meatpacking industry 1970-2018

Parameters and elasticities	Symbol	Values	s.e./s.d.[a]	Values	s.e/s.d.[a]
(1)	(2)	(3)	(4)	(5)	(6)
Long-run scale	λ	1.185	0.100	1.183	0.071
Short-run scale	ν	0.960	0.097	0.960	0.093
Markdown in livestock	ρ	-0.012	0.460	-	-
Markdown in labor	τ	0.666	0.426	0.663	0.392
Markup	μ	1.024	0.029	1.016	0.029
Elasticity of capital	β_K	0.225	0.066	0.223	0.056
Elasticity of livestock	β_R	0.668	0.026	0.670	0.026
Elasticity of labor	β_L	0.102	0.015	0.101	0.015
Elasticity of materials	β_M	0.190	0.027	0.189	0.026
Test (P-value)		$\chi^2(2)=0.348$ (0.825)		$\chi^2(1)=0.068$ (0.794)	

No. of observations: 49

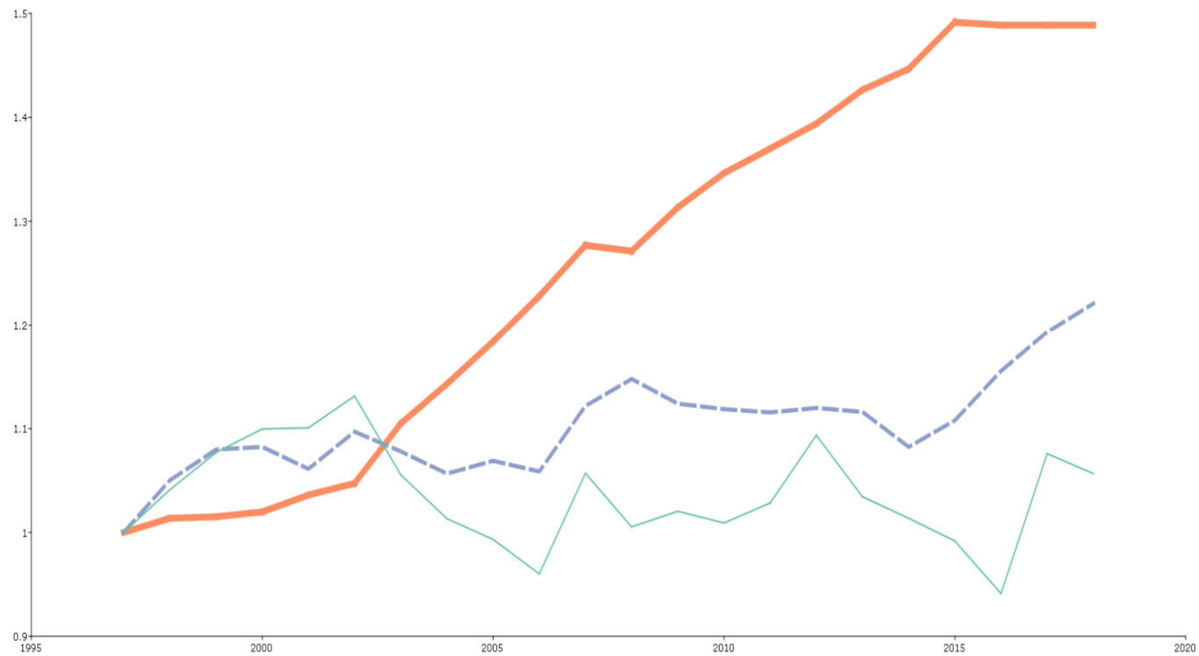
[a] Standard deviation of the elasticities computed in their sample distribution.

Table D2: Decomposition of profitability in the meatpacking industry

	1971-2018	1971-1989	1990-2007	2008-2018
Gross profit (%)	0.099	0.071	0.105	0.139
Technology	0.041	0.041	0.041	0.041
Product market power	0.015	-0.010	0.020	0.052
Labor market power	0.043	0.040	0.044	0.046

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

Indices, 1997=1



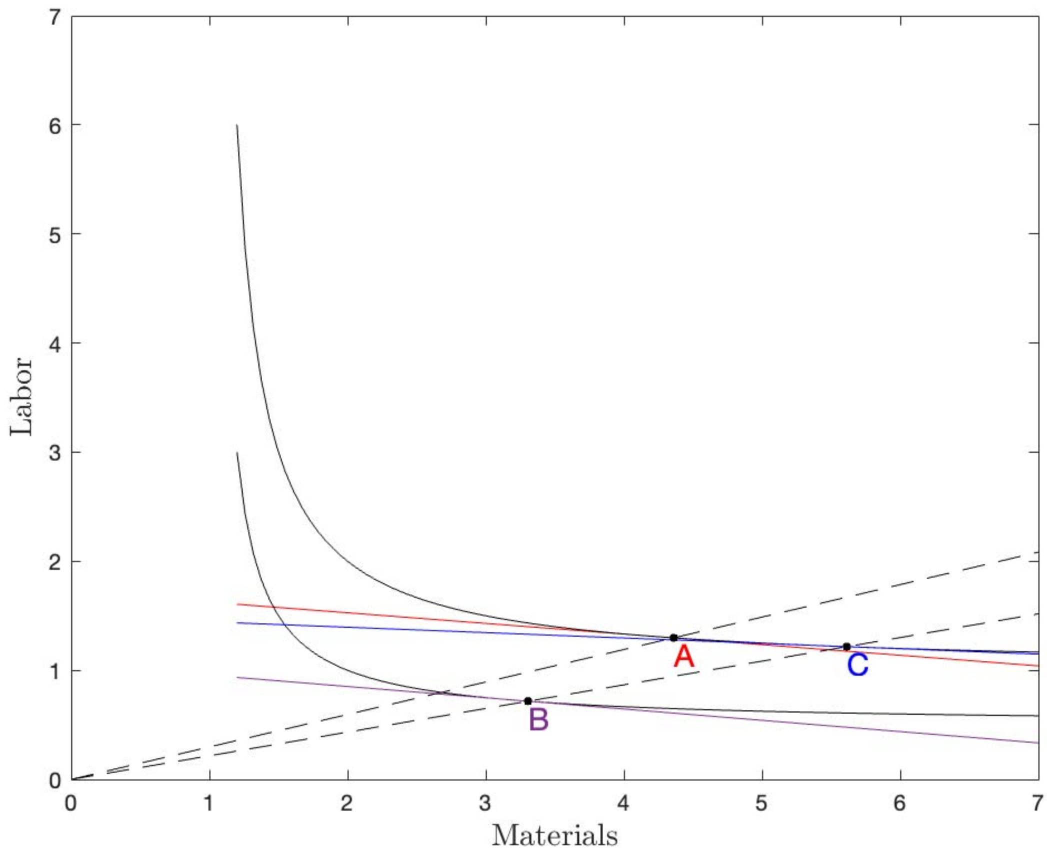
Years

Thick solid line: Capital

Dashed line: Livestock

Thin solid line: Labor

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+τ) flattened by the increase in monopsony power.