

The Micro Elasticity of Substitution and Non-Neutral Technology*

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Abstract

This article provides evidence on the micro capital-labor elasticity of substitution and the bias of technology. Using data on US manufacturing plants, I find several facts inconsistent with a Cobb-Douglas production function, including large, persistent variation in capital shares. I then estimate the elasticity using variation in local wages, and several instruments for them, for identification. Estimates of the substitution elasticity using all plants range between 0.3 and 0.5, with similar estimates across

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industries. I use these elasticity estimates to measure labor augmenting productivity, and find that labor augmenting productivity is highly persistent, and correlated with exports, size and growth.

The elasticity of substitution between capital and labor is central for several policy questions in economics. It determines how firms' usage of labor and capital respond to policy changes that affect factor prices, such as investment subsidies (Hall and Jorgenson (1967)), tariffs on capital goods (Cai et al. (2015)), changes in trade barriers (Dornbusch et al. (1980)), minimum wages (Aaronson and French (2007)), and firing costs (Petrin and Sivadasan (2013)). The elasticity is also important to understand both some of the reasons why firms innovate (Acemoglu (2010)), as well as how technological change affects relative factor intensities, either through non-neutral productivity (Hicks (1932), Sato (1975)) or investment specific technical change (Greenwood et al. (1997)).

Most of the recent empirical literature on production function estimation using micro data (Olley and Pakes, 1996; Levinsohn and Petrin, 2003) sets the elasticity of substitution to one by estimating Cobb-Douglas production functions. Beyond setting the elasticity to one, the Cobb-Douglas production function implies that all productivity differences are neutral, and so productivity improvements affect all factors proportionately. This assumption on productivity thus excludes automation technologies that both improve productivity and decrease the amount of labor used in production. It means that productivity has no effect on factor shares.

In this article, I first develop a set of stylized facts to evaluate the credibility of the Cobb-Douglas assumption at the industry level using US micro data on manufacturing plants. Plants with a Cobb-Douglas production function should have a constant capital share. How-

ever, plants within the same industry exhibit substantial variation in capital shares that are persistent over time. Second, at least for the largest plants, capital shares are correlated with plant revenue. Finally, capital shares fall when the average wage in a locality rises.

Given these facts, I estimate the elasticity of substitution between capital and labor that a manufacturing plant faces. Cost minimization implies that the elasticity of substitution measures how the ratio of factor costs responds to changes in factor prices. I identify the elasticity using this relationship; no assumptions on demand or information about output quality or prices are needed. For factor price variation, I use cross-sectional differences in wages across US localities.¹ Because local wage differences are highly persistent over time, this approach should identify the average effect of a long run change in factor prices on plant factor shares.

The main identifying assumption I make is that location specific wages are uncorrelated with differences in labor augmenting productivity and rental prices across plants. This assumption might be violated if more productive areas have higher wages, or if the price of capital varies across locations due to locally built capital or firm specific interest rates. I address the concern of endogenous wages by instrumenting for the local wage using three sets of instruments. The first set of instruments are cross-sectional differences in amenities from [Albouy et al. \(2016\)](#); locations with greater amenities should have lower wages ([Rosen](#),

¹An earlier literature used cross-sectional differences in wages across countries or US localities to estimate aggregate or industry elasticities. See, for example, [Arrow et al. \(1961\)](#), [Minasian \(1961\)](#), [Solow \(1964\)](#), [Lucas \(1969\)](#), [Dhrymes and Zarembka \(1970\)](#), and [Zarembka and Chernicoff \(1971\)](#).

1979; Roback, 1982). I also use two sets of instruments for labor market conditions based on the interaction of local industry shares and nationwide shocks due to Bartik (1991) and Beaudry et al. (2012).

Using OLS regressions, I estimate a plant-level elasticity of substitution to be between 0.3 to 0.5 using all manufacturing plants. When I allow the elasticity to vary across two digit industries, estimates range between 0.15 and 0.75 for most industries. Using each of the three sets of instruments, or all instruments together, leads to similar estimates of the elasticity.

These estimates are robust to several potential concerns. To address the concern of correlation between rental prices and wages, I estimate the elasticity between labor and equipment capital, because buildings likely to have much more local construction than equipment capital. I also estimate specifications with firm fixed effects to control for differences in rental prices or productivity across firms. To control for industry clustering, I separately examine a set of narrowly defined industries which have plants located in almost all US localities. I find broadly similar estimates to my baseline specification in these robustness checks, except for slightly higher estimates of the elasticity after including firm fixed effects.

I then apply my estimates of the micro elasticity of substitution to identify labor augmenting productivity. I identify labor augmenting productivity without placing any assumptions on demand. Instead, cost minimization allows me to identify labor augmenting productivity using expenditures of each factor; I construct two productivity measures, the first using

capital and labor, and the second using materials and labor.

Using these measures, I revisit some of the stylized facts of the productivity literature looking at labor augmenting productivity. In order to account for measurement errors in productivity, I employ a repeated measures IV strategy, instrumenting for one measure of productivity using the other measure. I find that a plant with a one standard deviation increase in labor augmenting productivity could produce 40 to 50 percent more output. Labor augmenting productivity is quite persistent over time and correlated with revenue, exports, and growth. These findings suggest that labor augmenting productivity is an important dimension of firm differences in productivity; productivity differences affect factor shares.

Misallocation frictions provide an alternate explanation for differences in capital shares across plants. For example, [Hsieh and Klenow \(2009\)](#) identifies misallocation frictions – output and capital taxes – from factor cost and revenue shares; in their framework, differences in capital shares across firms are due to capital taxes. [Midrigan and Xu \(2014\)](#) and [Asker et al. \(2014\)](#) develop models for misallocation frictions due to financing frictions and adjustment costs, respectively. These alternative explanations can be distinguished in multiple ways. First, persistent differences in labor augmenting productivity would generate long run differences in capital shares across plants, whereas financing frictions or adjustment costs would have more short run effects.² Second, auxiliary data on either a source of misallocation frictions, such as a firm’s weighted average cost of capital, or on signals of labor augmenting

²For example, [Midrigan and Xu \(2014\)](#) show that, in the long run, firms overcome collateral constraints in financing by funding capital through internal saving.

productivity, such as adoption of automation technology ([Acemoglu and Restrepo, 2017](#)) or management practices ([Bloom and Van Reenen, 2007](#)), would be helpful to tell apart the two explanations.

This article is related to the empirical literature on the capital-labor elasticity, which has focused on elasticities at the industry or country level of aggregation. We know from [Houthakker \(1955\)](#) that elasticities can be different at different levels of aggregation; [Oberfield and Raval \(2014\)](#) show why the aggregate elasticity should be larger than the micro elasticity for the US. Three other articles estimate the long run micro elasticity using different sources of identifying factor price variation. [Chirinko et al. \(2011\)](#) use the effects of long run movements in the user cost of capital on US public firms in order to identify the elasticity. Their estimate is close to mine at 0.40. Using US plant level data on equipment capital and a cointegrating regression, [Caballero et al. \(1995\)](#) find estimates ranging from 0.00 to 2.00 across different manufacturing industries, with an average of about 1. [Doraszelski and Jaumendreu \(2018\)](#) use panel variation in the ratio between labor and materials prices in a structural model in which the elasticity of substitution is equal between capital, labor, and materials, and find estimates ranging between 0.45 and 0.65. Despite using different factor price variation and data, my estimate is thus very similar to two of these articles.

This article is also related to the literature on production function estimation and productivity; most of the literature since [Olley and Pakes \(1996\)](#) has focused on neutral technology and the Cobb-Douglas functional form. Like my article, three recent articles examine dif-

ferences in production technology, either due to more general production functions, endogenous technology, or non-neutral technology. [Gandhi et al. \(2017b\)](#) develop a methodology to estimate many production functions by using the revenue share equations, provided that productivity differences are neutral. [Doraszelski and Jaumendreu \(2013\)](#) build a model that generalizes the knowledge capital model by allowing R&D to affect future plant productivity. [Doraszelski and Jaumendreu \(2018\)](#) is the article closest to mine; they extend their previous model to include non-neutral productivity, and find that labor augmenting technical change is required to explain productivity growth for Spanish manufacturing firms.

The article proceeds as follows. [Section 1](#) develops a set of stylized facts inconsistent with a Cobb-Douglas production function. [Section 2](#) builds a model of the firm’s production problem. [Section 3](#) discusses my estimates of the elasticity. [Section 4](#) revisits stylized facts on productivity using measures of labor augmenting productivity. [Section 5](#) concludes. The Web Appendix contains data notes and additional robustness checks.

1 Stylized Facts

Economists estimating production functions on micro data have typically assumed a Cobb-Douglas production function at the industry level ([Olley and Pakes, 1996](#); [Levinsohn and Petrin, 2003](#)). One strong implication of this assumption is that technological differences are neutral, so factor shares should not vary with productivity. In addition, the elasticity of substitution between factors is one under the Cobb-Douglas production function, so factor

shares should not vary due to factor price differences either. On the other hand, non-neutral productivity differences, and factor prices given a non-unitary elasticity, would affect plant factor shares. In this section, I develop a set of stylized facts on the dispersion, persistence, and correlation with size of the plant ratio of capital costs to labor costs, or factor cost ratio, inconsistent with a Cobb-Douglas production function. These facts then motivate a CES production function with non-neutral technology.

Data on Factor Costs

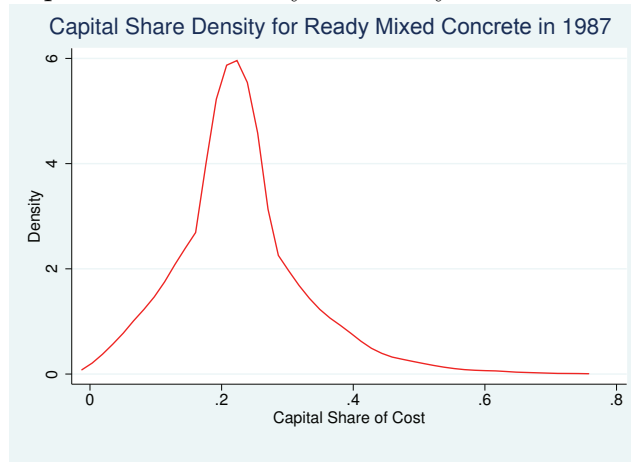
For plant factor costs, I use the 1987 through 2007 US Censuses of Manufactures, which are censuses of all US manufacturing plants taken every five years. Following common practice in the literature, I remove Administrative Record plants, which are typically less than five employees and lack data on capital or output. A typical Census sample has more than 180,000 plants and considerable variation across plant age, location, and industry, which I use to control for confounding factors in my empirical specifications.³

I measure labor costs as the total salaries and wages for the plant. I measure capital using a perpetual inventory measure of capital developed by the Census. Capital costs are these capital stocks multiplied by rental rates based upon an external real rate of return as in Harper et al. (1989).⁴ For robustness checks, I use the subsample of the Census included

³I drop manufacturing plants with missing or outlier data from my main estimates, although my results are not sensitive to these outlier corrections. I also exclude Alaska and Hawaii as amenity instruments are not available for these states. I detail these procedures in the Web Appendix.

⁴Because both the capital deflator and rental rate are fixed within industry for a given year, however, these are often captured in industry fixed effects. These measures of capital costs do not include industry

Figure 1 Capital Share Density for Ready Mixed Concrete in 1987



in the Annual Survey of Manufactures (ASM), which tracks about 50,000 plants over five year panel rotations. The ASM plants also have information on machinery rents and non-wage labor benefits.

Persistent Within Industry Variation

I first document substantial variation in capital shares across plants within the same industry. **Figure 1** depicts the smoothed density for the capital share of the ready mixed concrete industry in 1987. The mode of the capital share distribution for ready mixed concrete is slightly above 0.2. However, many plants have capital shares below 0.1 or above 0.3, and a long tail of plants have even higher capital shares.

This within industry dispersion in plant capital shares exists across manufacturing industries. I measure the magnitude of this dispersion by the 75/25 and 90/10 ratios of the

rental payments, except for ASM samples where I also include machinery rents.

capital share distribution across plants for a given industry. I calculate these ratios for all SIC 4 digit industries, and report the value of both ratios for the median, 25th percentile, and 75th percentile industry for each ratio, where each percentile is defined relative to the distribution of the given ratio across industries. [Table 1](#) contains these results.

For the median industry in 1987, the capital share for the 75th percentile plant is almost double that of the 25th percentile plant; the 90th percentile plant has a capital share almost four times that of the 10th percentile plant. Moreover, the 75/25 ratio and 90/10 ratios of the capital share vary slightly between the 25th percentile industry and 75th percentile industry. For example, the 75/25 ratio for the capital share is 1.6 for the 25th percentile industry, 1.7 for the median industry, and 2.0 for the 75th percentile industry.

This variation is similar for the factor cost ratio, which is the ratio of the capital share to the labor share. From now on, I report statistics for the factor cost ratio because the factor cost ratio better maps to the theory in [Section 2](#) and my identification strategy for the elasticity of substitution in [Section 3](#).

Within industry differences in factor cost ratios are persistent across time. I examine persistence in order to demonstrate that factors that cause temporary variation in capital shares, including idiosyncratic measurement errors and factor adjustment costs, cannot explain the degree of dispersion in plant factor shares.⁵ [Table II](#) contains estimates of the 10 year autocorrelation coefficient for the factor cost ratio after controlling for industry fixed ef-

⁵Because factor adjustment costs would lead to temporary persistence, the level of persistence observed is not consistent with standard models of adjustment costs.

Table I Dispersion in the Capital Share and Factor Cost Ratio in 1987

Variable	Statistic	Industry Percentile		
		Median	25th	75th
Capital Share	75/25 Ratio	1.7	1.6	2.0
	90/10 Ratio	3.6	2.8	4.4
Factor Cost Ratio	75/25 Ratio	2.1	2.0	2.5
	90/10 Ratio	5.7	4.8	6.9

Note: The table contains the 75/25 ratio and 90/10 ratio of each variable for the median industry, 25th percentile industry, and 75th percentile industry in the 1987 Census, where each percentile is defined relative to the distribution of the given ratio across 4 digit SIC industries. The capital share is the capital share of capital and labor costs, and the factor cost ratio is the ratio of the capital share to the labor share.

fects. The factor cost ratio is substantially autocorrelated over time with a coefficient of 0.37 over ten years in 1997, 0.36 in 2002, and 0.26 in 2007. The implied one year autocorrelation coefficients given an AR(1) model of persistence range from 0.87 to 0.90.⁶ I also examine the same 10 year autocorrelation using value added weights to measure the autocorrelation of the largest manufacturing plants. The factor cost ratio is even more persistent for the largest manufacturing plants, with a ten year correlation of 0.51 in 1997, 0.47 in 2002, and 0.41 in 2007 and implied AR(1) one year autocorrelations between 0.91 and 0.93.

The factor cost ratio has the same order of magnitude of persistence as revenue TFP, which is well known to be highly persistent ([Bartlesman and Doms \(2000\)](#)). If productivity differences are neutral, as the Cobb-Douglas production function implies, then persistent productivity differences cannot explain persistent differences in factor shares. On the other hand, persistent non-neutral productivity differences would explain persistent differences in TFP and factor shares.

⁶Under an AR(1) model the one year coefficient is the ten year coefficient to the power $\frac{1}{10}$.

Table II Persistence in Factor Cost Ratio

Ten Year Persistence			
1987-1997	0.37 (<i>0.004</i>)	0.51 (<i>0.013</i>)	
1992-2002	0.36 (<i>0.004</i>)	0.47 (<i>0.013</i>)	
1997-2007	0.26 (<i>0.003</i>)	0.41 (<i>0.024</i>)	
Weights	No	Value Added	

Note: All regressions control for four digit SIC or 6 digit NAICS industry.

Correlation with Size

I next examine whether large manufacturing plants have higher capital shares than the norm for their industry. I do so because, given the neutral productivity differences implied by a Cobb-Douglas production function, high productivity plants would be larger than low productivity plants, but would have the same capital shares. On the other hand, if productivity differences differentially affected factor shares, large plants would also have different average factor shares.

Figure 1 displays the nonparametric relationship between the plant factor cost ratio and value added for 1987, in the left figure, and 2002, in the right figure. Each variable is calculated as a log deviation from its industry mean in order to control for industry effects. In both 1987 and 2002, the factor cost ratio increases with value added for plants whose value added is above the industry mean, with an increase of about 35 to 50 percent between plants with value added at the industry mean and the largest plants in the industry.

For plants with value added below the industry mean, the factor cost ratio falls in 1987 and rises in 2002. One explanation for the dip in 1987 is mismeasurement of capital utilization

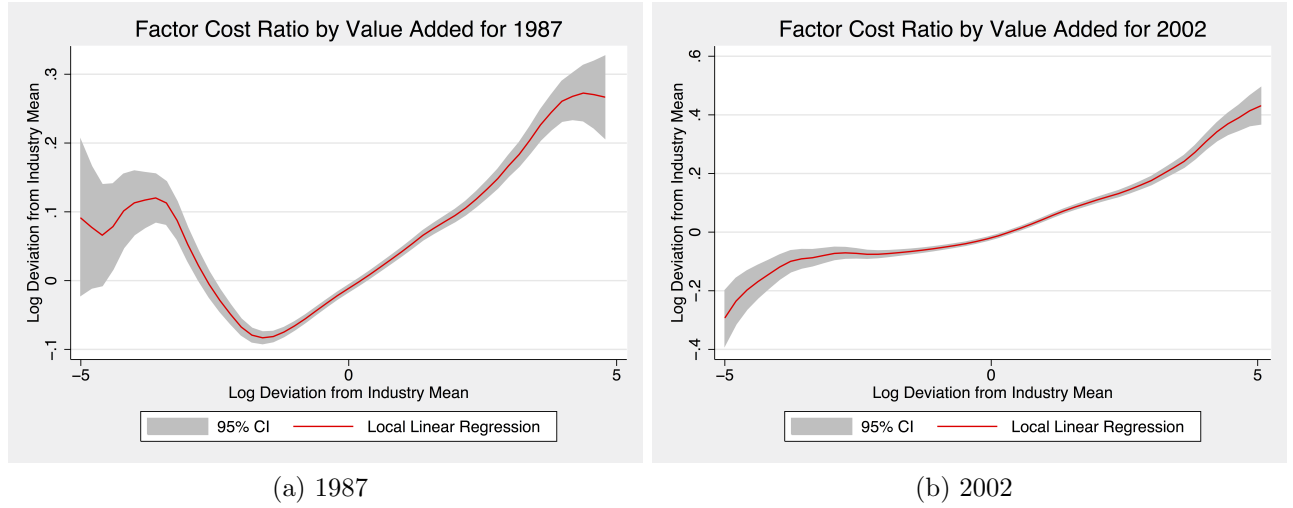


Figure 2 Factor Cost Ratio by Value Added

Note: Each graph depicts a local polynomial regression of the log factor cost ratio on log plant value added, after adjusting all variables for industry effects by subtracting the log industry mean.

for small plants. Accounting for utilization would lower the factor cost ratio for low output firms and raise the factor cost ratio for high output firms.

I then examine whether the relationships with plant value added hold through regressions with controls for plant level age through a set of dummy variables, plant single establishment status, and the state in which the plant is located. Table III reports the coefficient on log value added for regressions with this extensive set of controls. I examine both the full Census sample as well as the ASM subsample, as for the ASM sample I can include machinery rents and non-wage benefits in factor costs.⁷

The relationship between the factor cost ratio and value added ranges from a 3 percent decrease to a 2 percent increase across years with a 100 percent increase in value added using

⁷All specifications using the ASM sample include the ASM sampling weights. When weighting by value added, I multiply value added by the ASM weight.

the full Census sample. It decreases between 2 to 5 percent with a 100 percent increase in value added using the ASM subsample, primarily because of the inclusion of machinery rents. Including machinery rents reduces the coefficient on value added because more small plants rent their machinery; these small plants may be more subject to the unobserved capital utilization problem discussed earlier.

However, the correlation between the factor cost ratio and value added is always positive and of larger magnitude for the largest plants in manufacturing. I examine the largest plants by weighting for value added, which puts much greater weight on the largest plants in these regressions. After weighting for value added, the factor cost ratio increases between 5 and 9 percent across years with a 100 percent increase in value added using the full Census sample, or 6 to 11 percent using the ASM subsample. Thus, even though the relationship between the factor cost ratio and value added is ambiguous and possibly negative for all plants, it remains positive and sizeable when looking at the largest plants.⁸ If productivity differences were neutral, productivity cannot explain these patterns.

2 Theory

Given the evidence of differences in the factor cost ratio across plants in the previous section,

I assume a constant elasticity of substitution (CES) production function. The production

⁸In [Appendix B.1](#), in order to show how the size relationship varies by the size of the plant, I run regressions weighting around a given value of log value added, and continue to find a substantial positive correlation between value added and the factor cost ratio for large plants.

Table III Correlations of Factor Cost Ratio with Value Added

	CMF	CMF	ASM	ASM
1987	0.02 (0.002)	0.06 (0.005)	-0.03 (0.009)	0.06 (0.006)
1992	0.02 (0.001)	0.09 (0.006)	-0.05 (0.006)	0.08 (0.007)
1997	-0.03 (0.001)	0.07 (0.006)	-0.02 (0.006)	0.11 (0.01)
2002	0.004 (0.002)	0.05 (0.009)	-0.04 (0.006)	0.08 (0.01)
2007	-0.03 (0.002)	0.06 (0.009)	-0.02 (0.005)	0.10 (0.009)
Weights	No	Value Added	ASM Weight	ASM Weight * Value Added

Note: Each cell contains the coefficient from a regression with log value added as the independent variable and the factor cost ratio as the dependent variable, and includes controls for dummy variables for age and state, single establishment status and four digit SIC or six digit NAICS industry. Reported standard errors are robust to arbitrary degrees of heteroskedasticity.

function for the plant is then:

$$Y = A(\alpha_k(K)^{\frac{\sigma-1}{\sigma}} + (1 - \alpha_k - \alpha_m)(BL)^{\frac{\sigma-1}{\sigma}} + \alpha_m(M)^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}} \quad (1)$$

The elasticity of substitution is σ . Plant level technology has two components. The first component, A , is neutral productivity, and the second component, B , is labor augmenting productivity. An increase in labor augmenting productivity B is equivalent to having more labor. The physical output produced by the plant is Y . The distribution parameters α_k and α_m govern how much capital and materials contribute to output relative to labor.⁹ Returns to scale are constant.

A cost minimizing plant sets marginal products equal to factor prices. Assuming com-

⁹When σ is one, we have the familiar Cobb Douglas production function; all productivity is neutral, α_k is the elasticity of output with respect to capital, and α_m is the elasticity of output with respect to materials.

petitive factor markets, this implies that:

$$\frac{Y}{L} = \left(\frac{w}{C}\right)^\sigma (1 - \alpha_k - \alpha_m)^{-\sigma} (AB)^{1-\sigma} \quad (2)$$

$$\frac{Y}{K} = \left(\frac{r}{C}\right)^\sigma (\alpha_k)^{-\sigma} A^{1-\sigma} \quad (3)$$

where C is the marginal cost.¹⁰ Thus, the average product of labor depends on the ratio of the wage to marginal cost through the elasticity of substitution, as well as on both neutral productivity A and labor augmenting productivity B . By dividing the two equations above and rearranging, the plant capital cost to labor cost ratio, or factor cost ratio, is:

$$\frac{rK}{wL} = (B)^{1-\sigma} \left(\frac{r}{w}\right)^{1-\sigma} \left(\frac{\alpha_k}{1 - \alpha_k - \alpha_m}\right)^\sigma \quad (4)$$

$$\log \frac{rK}{wL} = (1 - \sigma) \log(B) + (1 - \sigma) \log\left(\frac{r}{w}\right) + \sigma \log\left(\frac{\alpha_k}{1 - \alpha_k - \alpha_m}\right) \quad (5)$$

I use the above equation to estimate the elasticity of substitution σ . Wage increases reduce the factor cost ratio when σ is less than one, and increase the factor cost ratio when σ is greater than one.

The elasticity of substitution also determines how productivity affects the plant factor cost ratio; the elasticity of the factor cost ratio to changes in labor augmenting productivity B is $1 - \sigma$. The intuition is the following. Because the increase in labor augmenting productivity

¹⁰The marginal cost is the Lagrange multiplier on the production function in the cost minimization problem.

B is akin to more labor, the plant will increase K to exactly match the increase in efficient labor BL . However, the increase in B also reduces the cost of an efficient unit of labor, which is $\frac{w}{B}$. The plant will then substitute towards relatively cheaper labor, with the ratio of capital to efficient labor $\frac{K}{BL}$ changing by $-\sigma$ given the change in the ratio of prices $r/(w/B)$. Hence K/L increases 1 by a direct effect and decreases σ by a substitution effect. When capital and labor are gross complements, so σ is less than one, the direct effect is stronger than the substitution effect.¹¹ Neutral productivity A has no effect on the factor cost ratio.

3 Elasticity of Substitution

I identify the elasticity of substitution by using the log-linear relationship between the plant factor cost ratio and plant factor prices from [equation \(4\)](#):

$$f_i = \beta_0 + \beta_1 \log(w_{l(i)}) + \delta_{n(i)} + \gamma X_i + \varepsilon_i. \quad (6)$$

In this equation, f_i is the log factor cost ratio, $w_{l(i)}$ is the local wage, $\delta_{n(i)}$ are controls for the 4 digit SIC or 6 digit NAICS industry of the plant, and X_i are additional controls in the form of age fixed effects and an indicator for the multiunit status of the plant. The industry fixed effects control for industry level differences in rental rates as well as in the capital and

¹¹I use the same definition of gross complements as [Acemoglu \(2002\)](#), who defines two inputs as gross complements if the demand for one input falls in response to another input's price rising holding its own price and the quantity of the other input fixed.

materials distribution parameters α_k and α_m .

The main coefficient of interest is β_1 , which identifies the elasticity of substitution through the wage that the plant faces; the elasticity σ is $\beta_1 + 1$. I use cross-sectional variation in the local wage for identification. The local wage is the price of an efficiency unit of labor: plants with higher plant level wages in the same location are assumed to have higher skilled workers. By using the local wage instead of the plant wage, I avoid biases from plant level skill differences.¹² In addition, I avoid division bias, in which the same variable is present on both sides of the regression specification and measured with error. The wage data on the left hand side of [equation \(6\)](#) are total labor costs in the Census data for the plant, whereas the wage on the right hand side is an average local wage from either Census surveys of workers or information on all establishments, not just manufacturing plants, in the locality.

The identification strategy based on [equation \(6\)](#) still identifies the capital-labor elasticity when a number of the assumptions in [Section 2](#) are relaxed. Although [Section 2](#) examines a production function with the same elasticity of substitution across capital, labor, and materials, my identification approach for the capital-labor elasticity requires separability between materials and a CES capital-labor aggregate. Returns to scale affect all factor costs to the same degree and so do not affect estimates of the elasticity.

[Section 2](#) also assumes that the static cost minimization conditions on inputs hold in each period, which would be violated if plants face adjustment costs together with demand

¹²In [Appendix B.2](#), I provide a data generating process under which the local wage identifies the elasticity, as well as alternative estimates using the plant level wage.

or productivity shocks. Adjustment costs and a process of demand and productivity shocks together generate an ergodic cross-sectional distribution for the factor cost ratio across all plants at a given location. At any given point in time, a plant will have factor shares within this cross-sectional distribution, and will move within the distribution over time. As I show in the next section, the local wage differences I use for identification are highly persistent across time. Thus, my estimate of the elasticity of substitution measures how the distribution of factor cost ratios in a location responds to a long run change in factor prices; in that sense, this article estimates a long run elasticity. This elasticity would be relevant to assess the effects on plant factor shares of any policy that causes long run changes to factor prices.

For consistent estimates, the local wage must be orthogonal to the error term ε_i , which will include plant-level differences in the rental rate for capital and labor augmenting productivity. I first show estimates using OLS regressions in [Section 3](#). In [Section 3](#), I discuss estimates using three sets of instruments for the local wage, and in [Section 3](#), I examine further robustness checks to the exogeneity assumption.

Local Wage Data

I use the 1990 Commuting Zone as my definition of local labor market. Commuting zones are clusters of US counties designed to have high commuting ties within cluster and low commuting ties across cluster. Thus, workers in the same commuting zones likely face the same labor market conditions and same wages. In the lower 48 states, there are 722

commuting zones.

I measure local area wages through two independent data sources. My first source of wages is the Census five percent samples of Americans, and American Community Surveys (ACS), available from [Ruggles et al. \(2010\)](#). These surveys collect information on a wide range of attributes for a large sample of workers. I calculate the individual wage as wage and salary income divided by the total hours worked for private sector workers.

I control for differences in worker quality across areas by measuring the local wage as the average residual log wage after controlling for education, experience, industry, occupation, gender, and race of workers.¹³ Wage differences across locations are persistent; the correlation in the log wage between 1990 and 2000 across all commuting zones is 0.93.

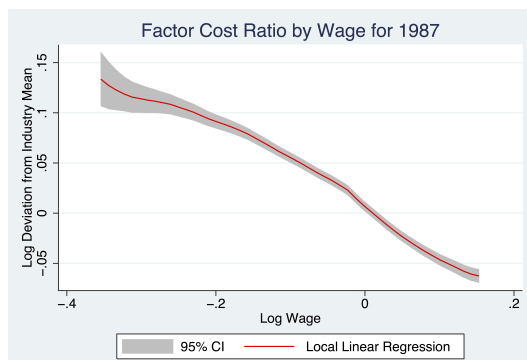
My second source of local wages is the Longitudinal Business Database (LBD), which contains yearly employment and payroll data for all US establishments. I define the wage as payroll divided by employment, and construct average log wages for each commuting zone in the United States after eliminating industry wage premia. LBD wages allow me to match wages to the same year as plant production data, but do not permit adjustment for worker quality differences.

¹³[Appendix A.2](#) contains the details of these procedures. Since the Population Census is conducted every ten years, I match the Census of Manufactures to the closest Economic Census.

Estimates

I first examine the relationship between the factor cost ratio and local wage nonparametrically. **Figure 3** depicts how the industry demeaned factor cost ratio varies with the worker based local wage in 1987. The factor cost ratio falls by 20 percent as the wage increases by about 50 percent, indicating an elasticity of substitution slightly less than one half.¹⁴

Figure 3 Factor Cost Ratio by Local Wage for 1987



Note: The graph depicts the local linear regression of the log deviation of the plant factor cost ratio from the industry mean against the log commuting zone wage adjusted for worker characteristics.

The relationship between the logged values of the factor cost ratio and local area wage is approximately linear, as a constant elasticity of substitution would imply. **Table IV** contains estimates of the elasticity of substitution across all manufacturing industries using **equation (6)** and both sources of wages. I cluster standard errors at the commuting zone level, which adjusts standard errors for the possibility of correlated shocks within local areas. For

¹⁴ To my knowledge, I am the first to examine the relationship between plant factor shares and the local wage.

example, all plants in Detroit can be affected by the same shock.¹⁵

Table IV OLS Estimates of Plant Capital-Labor Substitution Elasticity

Wage Source	Worker Data	Establishment Data	N
1987	0.44 (<i>0.04</i>)	0.54 (<i>0.03</i>)	≈ 185,000
1992	0.47 (<i>0.03</i>)	0.52 (<i>0.03</i>)	≈ 201,000
1997	0.29 (<i>0.05</i>)	0.48 (<i>0.04</i>)	≈ 209,000
2002	0.31 (<i>0.06</i>)	0.48 (<i>0.05</i>)	≈ 186,000
2007	0.45 (<i>0.04</i>)	0.58 (<i>0.03</i>)	≈ 184,000

Note: All regressions are of the log factor cost ratio on the log local area wage, with age fixed effects, a multi-unit status indicator, and 4 digit SIC or 6 digit NAICS industry fixed effects as controls. Standard errors are clustered at the commuting zone level.

My estimates of the elasticity of substitution from the regressions using wages from worker data range from 0.29 to 0.47 across years. Using the wages from establishment data, my estimates of the elasticity of substitution range from 0.48 to 0.58. These estimates are precise.

Estimates that use wages from worker data are below the estimates that use wages from establishment data. The main reason for this difference is that the worker based wages adjust for worker quality differences. If I do not adjust the wages from worker data for worker quality differences, I estimate higher elasticities, similar to the estimates above using wages from establishment data.

I further estimate the elasticity of substitution at the SIC two digit, or NAICS 3 digit, level to examine how the elasticity varies by industry. I find estimates similar to those for the entire manufacturing sector. [Figure 4](#) displays estimates and 95 percent confidence intervals

¹⁵Although there are 722 commuting zones in the lower 48 United States, the number of clusters will be slightly lower and vary from year to year as a few small commuting zones do not have manufacturing plants. Unfortunately, I cannot report the exact number of clusters per year for Census disclosure reasons.

of the elasticity of substitution for each two digit SIC industry for 1987 using worker based wages.¹⁶ Most of the estimates are concentrated between 0.15 and 0.75; in 1987, 18 out of the 19 estimates are in this band.¹⁷ The elasticity of substitution is below one for all industries, and I can reject that the elasticity of substitution is one for 17 of 19 industries. In [Table A6](#) through [Table A11](#), I report the full set of estimates across all years, using both worker and establishment based wages.

Exogenous Wage Variation

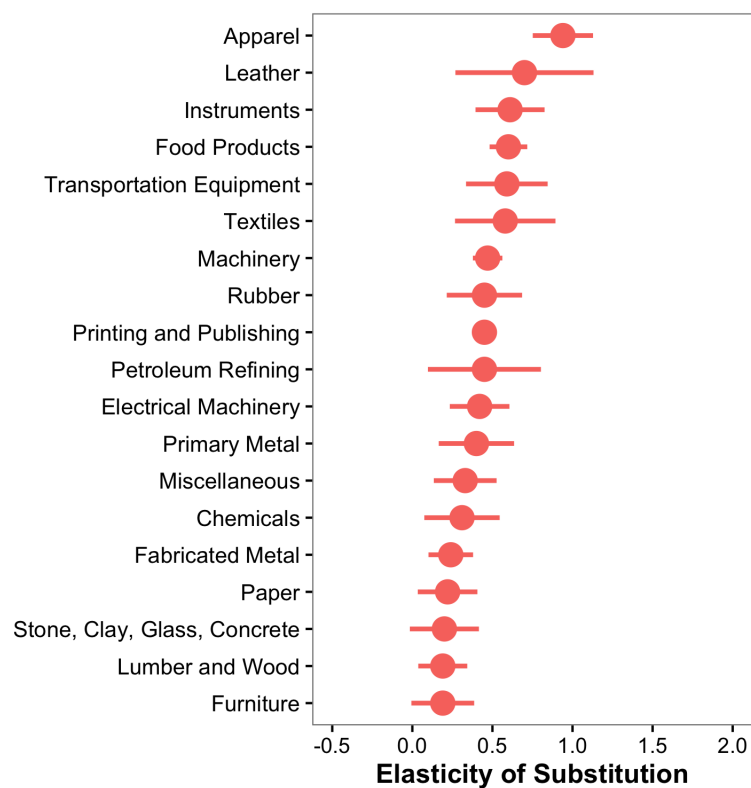
One concern with the OLS estimates is that productivity differences affect local wages. If highly productive areas have high wages and high labor augmenting productivity, my estimates of the elasticity of substitution would be biased upwards. I examine the salience of this bias through three different sets of instrumental variables for the local wage.

The first set of instruments are measures of local amenities from climate and geography that affect labor supply. A model with free mobility of workers and firms and compensating wage differentials implies that locations with greater amenity value should have lower wages ([Rosen, 1979](#); [Roback, 1982](#)). The amenities I use were developed by [Albouy et al. \(2016\)](#) and include measures of the slope, elevation, relative humidity, average precipitation, average sunlight, the number of heating degree days and cooling degree days, and temperature day

¹⁶I include the tobacco industry (SIC 21) as part of Food Products (SIC 20) from the table because it is much smaller than the other two digit industries.

¹⁷Using worker based wages, 18 out of 19 estimates in 1992, 14 out of 19 in 1997 (SIC), 17 out of 21 in 1997 (NAICS), 14 out of 21 in 2002, and 16 out of 21 in 2007 are in this band.

Figure 4 Elasticity of Substitution by Industry for 1987



Note: The figure plots estimates of the elasticity of substitution by two digit SIC industry, as well as 95 percent confidence intervals. Estimates are for 1987 using worker based wages.

bins for each local area. I exclude amenities based on distance to the coast or lakes as these may also affect import and export possibilities, and thus the productivity of the plant and the competition it faces.¹⁸

The second instrument varies labor market conditions through how national level industry shocks affect locations with different initial industries. As in [Bartik \(1991\)](#), I define this instrument as the predicted local employment growth from the interaction between initial local area employment shares of industries and the national employment growth rate of these industries. I restrict the instrument to non-manufacturing industries to avoid any correlation between plant productivity shocks and national level industry demand shocks.¹⁹

I also use a second set of instruments for labor market conditions from [Beaudry et al. \(2012\)](#), which I call the BGS instruments. [Beaudry et al. \(2012\)](#) construct a search and bargaining theory of employment in which the industrial composition of the city – its shares of each industry multiplied by each industry’s wage premium – affects the city-level wage for an industry through workers’ outside options. Although the industrial composition itself is endogenous to productivity shocks, [Beaudry et al. \(2012\)](#) develop two instruments for it: the interaction of predicted changes in industry employment shares and industry initial wage premia, and the interaction of national changes in industry wage premia and predicted

¹⁸The amenities in [Albouy et al. \(2016\)](#) were collected at the PUMA level. I aggregate them to the commuting zone level by taking an average across PUMAs in the same commuting zone, weighting PUMAs by their population in the commuting zone.

¹⁹Because industry definitions change twice in the sample – from 1972 SIC to 1987 SIC in 1987, and then from SIC to NAICS in 1997, I have to alter years slightly, or use the five year instrument and its lag instead of the ten year instrument, depending upon the Census year. Details are in [Appendix A.3](#).

future industry employment shares.

[Table V](#) contains estimates of the elasticity of substitution using these instruments, as well as the F-statistic associated with each instrument. The first two columns contain estimates for the amenity instruments using wages from worker and establishment data, respectively. For the Bartik and BGS instruments, I use wages from establishment data for the same Census year to match the instrument timing. Although these wages do not control for differences in individual worker characteristics, the instruments should be orthogonal to the measurement error in wages. The third and fourth columns use the Bartik and BGS ([Beaudry et al. \(2012\)](#)) instruments, and the last column includes the amenity, Bartik, and BGS instruments together in one specification. The estimates of the elasticity of substitution are similar in magnitude to the OLS estimates in [Table IV](#), ranging roughly between 0.3 and 0.6. I also report F-statistics to examine the suitability of the instruments. The instruments are also typically strong, with most of the F-statistics above 10 and the lowest F-statistic at 7.

In [Appendix B.3](#), I also conduct ex-post instrument specification tests, both through running heteroskedasticity robust Hausman tests and by regressing the residual from an instrumented regression on excluded instruments. I reject exogeneity of the amenity instruments in all years, and exogeneity of the Bartik instrument and BGS instruments in two out of five years each. However, regressions of the residual from an instrumented regression on excluded instruments lead me to conclude that departures from plausible exogeneity of the

instruments are small, and concentrated in a few of the amenity instruments. Small differences in elasticities estimated by varying the set of instruments are consistent with small departures from plausible exogeneity.

Table V IV Estimates of Plant Capital-Labor Substitution Elasticity

Year	Estimate	Amenities		Bartik	BGS	All
Wage Source		Worker	Establish	Establish	Establish	Establish
1987	Elasticity	0.45 (0.07)	0.48 (0.06)	0.52 (0.04)	0.45 (0.09)	0.51 (0.04)
	F-Statistic	15	9	257	8	99
1992	Elasticity	0.57 (0.06)	0.55 (0.05)	0.45 (0.04)	0.48 (0.04)	0.50 (0.03)
	F-Statistic	15	8	46	58	59
1997	Elasticity	0.28 (0.09)	0.40 (0.07)	0.41 (0.11)	0.36 (0.08)	0.41 (0.05)
	F-Statistic	10	8	7	73	39
2002	Elasticity	0.33 (0.13)	0.42 (0.11)	0.31 (0.10)	0.37 (0.06)	0.42 (0.06)
	F-Statistic	10	11	67	35	46
2007	Elasticity	0.49 (0.09)	0.53 (0.07)	0.51 (0.05)	0.56 (0.05)	0.54 (0.04)
	F-Statistic	16	14	48	13	34

Note: Standard errors are clustered at the commuting zone level. All regressions include industry dummies, age fixed effects, and a multiunit status indicator. Instruments are as defined in the text. Wages are establishment based except for column 2, which uses worker based wages.

Robustness

My identification strategy requires that the local area wage, or instruments for the local area wage, are orthogonal to differences in the rental rate of capital and plant level productivity across areas. I now discuss a number of robustness checks that test these assumptions.

Rental Rate of Capital

Any systematic correlation between the rental rate of capital and local wage would bias my estimates. These might be correlated if the capital of the plant was produced in the same locality as the plant, so local labor and materials were factors in its production. Because locally constructed capital is more likely for buildings than equipment, I examine the elasticity of substitution between labor and equipment capital alone for 1987 and 1992 to control for rental rate differences across local areas stemming from structures capital. The elasticity between labor and equipment capital is 0.45 in 1987 and 0.47 in 1992 using the quality adjusted worker wages, almost identical to the estimates using the full capital stock.

The cost of capital could also vary across firms because of differences in lending rates from banks in different locations, or from differences in firm creditworthiness. I include firm fixed effects for plants that belong to multiunit firms to control for variation in the firm rental rate of capital. These firm fixed effects also control for firm level productivity differences. The third column in [Table VI](#) reports these estimates. The estimates of the elasticity of substitution with firm fixed effects are somewhat higher than my baseline estimates in these specifications, ranging from 0.55 to 0.66 across years, about 0.2 higher than my baseline results.

Including firm fixed effects for multiunit plants is the only specification check with a substantially different estimate of the elasticity of substitution. These results could imply

that the plant’s cost of capital is negatively correlated with wages, so controlling for firm level rental rates increases estimates of the elasticity of substitution. Another explanation for this finding is that some multiunit firms may set a uniform wage policy across plants that they own in different local areas, due perhaps to fairness norms. If firms are constrained to pay similar wages across plants in different locations, then I would overestimate local differences in wages for multiunit firms after controlling for a firm effect, which would attenuate the estimate of $1 - \sigma$, and so bias the estimate of σ toward one.

Regulation

Regulations could also vary across local areas that affect both plant productivity and rental prices. For example, states vary in their regulations towards unions, such as right to work laws, and some states provide investment tax subsidies. I control for any such state level differences by including state level fixed effects in the fourth column of [Table VI](#); the elasticity of substitution for 1987 range from 0.3 to 0.5 and are similar to my baseline estimates.

Measurement Errors in Capital

Another concern when using data in capital is that measurement errors in capital bias estimates of the elasticity. The factor cost ratio is the dependent variable, so any measurement error in capital is part of ε_i in [equation \(6\)](#) and must be uncorrelated with the local wage, or instruments for the local wage.

I examine the salience of measurement error in three ways. First, I examine plants in the Annual Survey of Manufactures. These plants generally have more accurate data, both because they have participated in the plant surveys for multiple years and because they have the investment history required to construct better perpetual inventory measures of capital. The ASM plant samples also have data on the value of non monetary compensation given to employees, such as health care or retirement benefits, which I use to better measure payments to labor. The estimates using the ASM plants, in the fifth column of [Table VI](#), are consistent with, albeit slightly higher than my baseline estimates, and range from 0.37 to 0.67 across years.

Second, I replace the perpetual inventory measure of capital with a book value measure of capital using data on book values of structures and equipment (total value of capital after 1992). These estimates are in the sixth column of [Table VI](#) and are slightly lower than the baseline estimates, ranging from 0.22 to 0.42 across years. Third, for 2002 and 2007 I can include both machinery rents and the value of non monetary compensation to my measure of the factor cost ratio.²⁰ I estimate an elasticity of 0.40 in 2002 and 0.49 in 2007 including both rents and non-monetary compensation, within my baseline range of estimates.

²⁰Unfortunately, in earlier years the Census reports total rents, and the building rents reported to the Census include the value of land, which is excluded from Census information on investment and capital stocks.

Industry Clustering and Selection

I have assumed that plant level productivity is uncorrelated with the prevailing wage in the area that the plant locates. However, firms in an industry often co-locate within a few clusters; Detroit is synonymous with the automotive industry and Silicon Valley with the computer industry. If plants with high labor augmenting productivity cluster in areas with high wages, or agglomeration effects increase the productivity of plants within a cluster, the resulting correlation between productivity and the local wage would bias my estimates upwards. Similarly, plants outside the industry cluster could serve a different segment of the industry than plants within the cluster.

I assess the impact of selection by estimating the elasticity of substitution for a set of ten large four digit SIC industries located in almost all US MSAs and states. Ready Mixed Concrete is perhaps the best test case of these industries; because ready mixed concrete cannot be shipped very far, every location must have concrete plants to supply the construction sector.²¹ Elasticities for the unclustered industries are similar to my baseline estimates, with average elasticities of 0.40 for 1987, 0.51 for 1992, and 0.38 for 1997 using the worker based wages, or 0.50 for 1987, 0.57 for 1992, and 0.53 for 1997 using the establishment wages. In [Table A12](#) through [Table A14](#), I report the full set of estimates.²²

²¹For ready mixed concrete, I find an elasticity of substitution of 0.17 in 1987, 0.66 in 1992, and 0.11 in 1997 using the worker based wages, and 0.36 in 1987, 0.82 in 1992, and 0.34 in 1997 using the establishment wages.

²²The weights across industries are as in [Oberfield and Raval \(2014\)](#) and primarily depend upon overall industry size.

Table VI Robustness Checks for Plant Capital-Labor Substitution Elasticity

	Baseline	Equip Cap	Firm FE	State FE	ASM	Book Cap	Rents
1987	0.44 (0.04)	0.45 (0.03)	0.57 (0.07)	0.39 (0.04)	0.40 (0.08)	0.42 (0.04)	
1992	0.47 (0.03)	0.47 (0.03)	0.65 (0.06)	0.31 (0.03)	0.67 (0.07)	0.39 (0.03)	
1997	0.29 (0.05)		0.66 (0.06)	0.32 (0.05)	0.42 (0.09)	0.27 (0.05)	
2002	0.31 (0.06)		0.59 (0.06)	0.41 (0.07)	0.52 (0.09)	0.22 (0.07)	0.49 (0.05)
2007	0.45 (0.04)		0.55 (0.07)	0.48 (0.05)	0.37 (0.07)	0.39 (0.04)	0.40 (0.05)

Note: Standard errors are clustered at the commuting zone level. All regressions include industry dummies, age fixed effects, and a multiunit status indicator. All specifications use worker based wages.

4 Labor Augmenting Productivity Differences

Coupled with the structural model of production, my estimates of the elasticity of substitution allow me to recover labor augmenting plant productivity. I do so to examine the extent of labor augmenting productivity differences across plants, as well as whether these differences are correlated over time and with plant decisions. If labor augmenting productivity differences across firms are significant, productivity shocks will also alter factor shares. Thus, understanding the bias of technology is important both to measure productivity, as well as to predict how productivity changes affect firms.

Cost minimization implies that labor augmenting productivity is a function of the factor cost ratio and factor price ratio.²³ Thus, one can obtain B using either the capital and labor first order conditions, or the labor and materials first order conditions, as below:

²³Rearrange [equation \(4\)](#) to obtain the first expression for B ; the second expression has a similar derivation from the labor and materials first order conditions.

$$\log(B) = \log\left(\frac{w}{r}\right) - \frac{\sigma}{1-\sigma} \log(\alpha_k) + \frac{1}{1-\sigma} \log\left(\frac{rK}{wL}\right) \quad (7)$$

$$\log(B) = \log\left(\frac{w}{p_m}\right) - \frac{\sigma}{1-\sigma} \log(\alpha_m) + \frac{1}{1-\sigma} \log\left(\frac{p_m M}{wL}\right) \quad (8)$$

I then build two different measures for labor augmenting productivity B based on plant expenditures on factors; the first measure, $\hat{B}^K$, uses the capital cost to labor cost ratio as in [equation \(7\)](#). The second measure, $\hat{B}^M$, uses the materials cost to labor cost ratio as in [equation \(8\)](#).

I then revisit some of the standard relationships between productivity and plant level variables using these productivity measures by examining the persistence of productivity and its correlation with size, exports, and growth. For labor augmenting productivity differences across plants to be important, labor augmenting productivity should exhibit some of the same patterns as have been previously found for productivity in general.

To measure labor augmenting productivity, I set the elasticity of substitution σ to the IV estimate for the manufacturing sector in the given Census year using all three sets of instruments. Each measure of productivity is a difference relative to an industry mean, so differences in industry distribution parameters α_k and α_m are removed from productivity measures. Because the wage w is based upon worker wages that control for observed skill differences, observed skill differences are suppressed from productivity.

Both measures are likely measured with error, however, because of either errors in the measurement of capital (for $\hat{B}^K$) or in the materials price across plants (for $\hat{B}^M$).²⁴ Thus, when examining how labor augmenting productivity varies with other variables, I instrument for $\hat{B}^K$ with $\hat{B}^M$ (Bound et al., 2001). This procedure relies on two additional assumptions from the empirical approach for the capital-labor elasticity. First, errors in capital must be uncorrelated with differences in the materials price across plants and with the other variable of interest. Second, the production function must have the same elasticity of substitution between capital, labor, and materials. The intuition behind this IV strategy is that labor augmenting productivity is likely to be high when both capital costs and materials costs are large relative to labor costs.

Unlike my estimates of the elasticity of substitution, these results do depend upon my assumption of a gross output, as opposed to a value added, production function. Although recent work has found substantial differences between gross output and value added productivity estimates (Gandhi et al., 2017a), the CES production function assumed in equation (1) satisfies the functional separability between primary inputs and materials required for a value added production function to correctly measure marginal productivities (Bruno, 1978).²⁵ With a value added production function, I would only have one measure of labor augmenting productivity ($\hat{B}^K$) and so could not undertake the multiple measures IV

²⁴See Atalay (2014) for a discussion of differences in materials prices across plants.

²⁵Stronger assumptions, such as that materials are Leontief with capital and labor in gross output, are required to correctly measure productivity growth. See Bruno (1978).

approach undertaken in this section.

I first examine the distribution of labor augmenting productivity B . Since both of my measures of B are measured with error, simply measuring the variance of each measure will exaggerate the size of productivity differences. Thus, I calculate the covariance of $\log \hat{B}^K$ and $\log \hat{B}^M$, which will measure the variance of B under the assumption that the measurement error in capital and measurement error in materials prices are uncorrelated with each other and with true productivity. The standard deviation of productivity ranges from 0.64 to 0.85 across Census years.

In order to better interpret the degree of differences across plants, I also calculate the variance of each measure of productivity multiplied by the labor share of total cost, which provides the output elasticity for labor augmenting productivity differences. The standard deviation of this measure is between 0.36 and 0.44 across Census years, indicating that a plant with a one standard deviation increase in labor augmenting productivity can produce about 40 to 50 percent more output. Although this variance implies a large effect of productivity on output, it is consistent with the literature on productivity dispersion in TFP. [Bartelsman et al. \(2013\)](#) documents for US manufacturing plants that a plant with a one standard deviation increase in TFP can produce 46 percent more output.

Persistence

I then examine the degree of persistence in labor augmenting productivity, given that the literature has found that productivity is fairly persistent over time. Table VII contains estimates of the ten year autocorrelation of productivity between the 1987 to 1997, 1992 to 2002, and 1997 to 2007 Manufacturing Censuses. For each pair of Census years, I regress $\log \hat{B}^K$ on its 10 year lag, instrumenting for the 10 year lag with the 10 year lag of $\log \hat{B}^M$. I control for industry fixed effects, as well as age and multiunit status, in this and all other regressions in this section; standard errors are robust.

Labor augmenting productivity has a 10 year autocorrelation of 0.28 for 1997 and 2002 and 0.40 in 2007 in the unweighted regressions. The autocorrelation is even higher in the weighted regressions at 0.46 in 1997, 0.43 in 2002, and 0.70 in 2007. The implied one year AR(1) coefficients for labor augmenting productivity range between 0.88 to 0.96.²⁶ Thus, labor augmenting productivity is very persistent over time.

With greater persistence in labor augmenting productivity, capital share differences will be more persistent across firms. In addition, the marginal product of labor depends more upon labor augmenting productivity than the marginal product of capital. Thus, if labor augmenting productivity is more persistent than neutral productivity, the marginal product of labor within a plant should vary less over time than the marginal product of capital, which will affect a plant's investment decisions over time.

²⁶Under an AR(1) model the one year coefficient is the ten year coefficient to the power $\frac{1}{10}$.

Table VII Autocorrelation of Productivity

Ten Year Persistence			
1987-1997	0.28 (0.01)	0.46 (0.04)	
1992-2002	0.28 (0.02)	0.43 (0.05)	
1997-2007	0.40 (0.02)	0.70 (0.07)	
Weights	No	Value Added	

Note: Each regression instruments for the ten year lag of labor augmenting productivity measure $\hat{B}^K$ with the ten year lag of $\hat{B}^M$. All regressions contain four digit SIC or six digit NAICS industry fixed effects, as well as age and multiunit status controls. Standard errors are robust.

Exports

The trade literature has found that exporting plants are both more capital intense and more productive (Bernard et al. (2007)). One explanation for both facts is that exporting plants have higher labor augmenting productivity. To examine the correlations between exports and productivity, I run regressions of logged exports on labor augmenting productivity for exporting plants. Again, I instrument for $\log \hat{B}^K$ using $\log \hat{B}^M$. Table VIII contains the coefficients on productivity.

Labor augmenting productivity is strongly correlated with exports, with an exporting plant with twice as high productivity having between 84 and 157 percent higher exports across years in the unweighted regressions. Although these correlations are lower in the regressions weighting plants by value added, an exporting plant with twice as high productivity still has between 27 and 121 percent higher exports. Thus, labor augmenting productivity differences would generate exporters that are more productive and more capital intensive.

Table VIII Correlations between Productivity and Exports

1987	0.84 (<i>0.05</i>)	0.27 (<i>0.19</i>)
1992	1.16 (<i>0.05</i>)	0.66 (<i>0.13</i>)
1997	1.49 (<i>0.06</i>)	0.89 (<i>0.14</i>)
2002	1.57 (<i>0.07</i>)	1.21 (<i>0.33</i>)
2007	1.19 (<i>0.05</i>)	0.49 (<i>0.10</i>)
Weights	No	Value Added

Note: The log of exports is the dependent variable and all plants without exports are excluded from the estimates. Each regression instruments for labor augmenting productivity measure $\hat{B}^K$ with $\hat{B}^M$. All regressions contain four digit SIC or six digit NAICS industry fixed effects, as well as age and multiunit status controls. Standard errors are robust.

Correlation with Size

Previous work has found that higher TFP plants are larger. I now examine whether plants with greater labor augmenting productivity are also larger by regressing log value added on $\log \hat{B}^K$, instrumenting for it using $\log \hat{B}^M$. In [Table IX](#), I find that labor augmenting productivity is substantially correlated with plant value added. The first two columns examine the full Census, whereas the last two columns examine the ASM plants for which I can include machinery rents and labor benefits in factor payments. A plant with twice the labor augmenting productivity has between 27 to 57 percent higher value added in the unweighted regressions across years and samples, and between 30 to 70 percent higher in the weighted regressions. I do not find significant differences between the Census and ASM samples. Thus, plants with higher labor augmenting productivity are larger in size.

Table IX Correlations between Productivity and Value Added

	CMF	CMF	ASM	ASM
1987	0.27 (0.01)	0.31 (0.05)	0.31 (0.04)	0.33 (0.05)
1992	0.28 (0.01)	0.45 (0.05)	0.56 (0.07)	0.48 (0.05)
1997	0.33 (0.01)	0.60 (0.07)	0.57 (0.05)	0.62 (0.07)
2002	0.41 (0.01)	0.70 (0.08)	0.56 (0.06)	0.69 (0.08)
2007	0.49 (0.01)	0.37 (0.05)	0.46 (0.04)	0.30 (0.05)
Weights	No	Value Added	ASM Weight	ASM Weight * Value Added

Note: Each regression instruments for labor augmenting productivity measure $\hat{B}^K$ with $\hat{B}^M$. All regressions contain four digit SIC or six digit NAICS industry fixed effects, as well as age and multiunit status controls. Standard errors are robust.

Growth

Finally, I examine whether plants with higher labor augmenting productivity have higher growth rates over the next ten years. I define the growth rate in terms of value added, and regress the log growth rate on labor augmenting productivity, instrumenting for $\log \hat{B}^K$ using $\log \hat{B}^M$. **Table X** contains these estimates looking at growth from 1987-1997, 1992-2002, and 1997-2007. I find significantly higher growth rates for plants with higher labor augmenting productivity; a plant with double the labor augmenting productivity has a 12 to 24 percent higher growth rate across years in the unweighted regressions, and a 8 to 13 percent higher growth rate in the weighted regressions. Thus, plants with higher labor augmenting productivity tend to grow faster in size in future.

Table X Correlations between Productivity and Growth in Value Added

	Ten Year Growth Rate			
1987-1997	0.16	(0.001)	0.13	(0.037)
1992-2002	0.24	(0.012)	0.08	(0.046)
1997-2007	0.12	(0.012)	0.08	(0.079)
Weights	No		Value Added	

Note: Each regression instruments for labor augmenting productivity measure $\hat{B}^K$ with $\hat{B}^M$. All regressions contain four digit SIC or six digit NAICS industry fixed effects, as well as age and multiunit status controls. Standard errors are robust.

5 Conclusion

This article has identified the micro elasticity of substitution using differences in wages across local areas in the US. I then estimated that the elasticity of substitution is between 0.3 and 0.5 for manufacturing, with estimates in a similar range across industries. These estimates held up to a number of robustness checks, including instruments for the local wage due to cross-sectional amenity differences and local labor market conditions, controls for firm level differences in productivity or rental prices, state-level differences in regulation, and examination of a set of narrowly defined unclustered industries.

I then used these estimates of the elasticity to identify labor augmenting productivity. I found that the measure of labor augmenting productivity is highly persistent and strongly correlated with plant value added, exports, and growth. These results point to labor augmenting productivity as an important dimension of productivity, and improve our understanding of how productivity affects firms. With labor augmenting productivity, productivity changes will also affect firm factor shares.

This article has examined the micro elasticity of substitution between capital and labor. The cross-sectional identification strategy used in this article could also be used to understand the substitution possibilities of intermediate inputs with capital and labor, and of different varieties of labor or capital with each other and other inputs.

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