Online Appendix

# *Markup Estimation using Production and Demand Data: An Application to the US Brewing Industry*

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# A Data Appendix

In this appendix we describe the various datasets we rely on; i.e., the three demand datasets (IRI, NielsenIQ and Dominick's Finer Foods), the Census production data and the Compustat data. We also present some data from Consumer Reports in 1996, which provides some external information about beer markups.

## A.1 External Info: Consumer Reports Data

Table A1: Decomposing Retail Prices (1996)

| | Mass Brewers | | Craft Beer | | Overall | |
|---|---|---|---|---|---|---|
| Component | Item | cum | Item | cum | Overall | cum. |
| Retail | 0.80 | 4.01 | 1.29 | 6.45 | 1.05 | 5.23 |
| Distributor | 0.66 | 3.21 | 1.19 | 5.16 | 0.93 | 4.19 |
| Tax/shipping | 0.69 | 2.55 | 0.62 | 3.97 | 0.66 | 3.26 |
| Brewer profit | 0.24 | 1.86 | 0.67 | 3.35 | 0.46 | 2.61 |
| | | | | | | |
| adv/manag | 0.33 | 1.62 | 0.54 | 2.68 | 0.44 | 2.15 |
| labor | 0.47 | 1.29 | 1.06 | 2.14 | 0.77 | 1.72 |
| packaging | 0.66 | 0.82 | 0.83 | 1.08 | 0.75 | 0.95 |
| ingredients | 0.16 | 0.16 | 0.25 | 0.25 | 0.21 | 0.21 |
| | | | Markups | | | |
| Brewer-low(*) | 1.44 | | 1.57 | | 1.52 | |
| Brewer-high(**) | 2.27 | | 3.10 | | 2.74 | |
| Distributor | 1.26 | | 1.30 | | 1.28 | |
| Retailer | 1.25 | | 1.25 | | 1.25 | |

Notes: (*) Excluding advertising and management costs (i.e., treated as fixed costs). (**) Labor, advertising, and management costs treated as fixed costs. Source: own calculations using Consumer Reports (1996).

## A.2 Demand Data

**IRI and NielsenIQ** We follow Miller and Weinberg (2017) for the aggregation of the data, and the definition of local markets and products. The empirical analysis focuses on 39 geographic regions in the IRI database. The distinct geographic markets are: Atlanta, Birmingham/Montgomery, Boston, Buffalo/Rochester, Charlotte, Chicago, Cleveland, Dallas, Des Moines, Detroit, Grand Rapids, Green Bay, Hartford, Houston, Indianapolis, Knoxville, Los Angeles, Milwaukee, Mississippi, New Orleans, New York, Omaha, Peoria/Springfield, Phoenix, Portland in Oregon, Raleigh/Durham, Richmond/Norfolk, Roanoke, Sacramento, San Diego, San Francisco, Seattle/Tacoma, South Carolina, Spokane, St. Louis, Syracuse, Toledo, Washington D.C., West Texas/New Mexico. We use the counties that compose these regions to create the equivalent markets in the NielsenIQ data. The potential market of each region is computed by assuming that the market size is 50% greater than the maximum unit sales within each region. Following MW, a product is defined as the combination of brand and size (e.g., Budweiser 6 pack) with three size categories (6, 12, and 24/30 packs). The market shares are measured in terms of 144-ounce equivalent units, and accordingly, prices are measured in USD per 144 ounces. Following MW, prices are converted to 2010 dollars using the CPI (All Urban Consumers) from the US Bureau of Labor Statistics. We aggregate the scanner data from the original UPC-store-week level to the product-region-month level.

We supplement the retail scanner data with two datasets. First, household-level income draws come from the Public Use Microdata Sample (PUMS) of the American Community Survey. Incomes were also converted to 2010 dollars using the CPI. Second, for identification of demand, we use MW's data on driving miles between each market and the nearest brewery and information on diesel fuel prices. For more details about the variables and data aggregation, see MW and their supplementary material.

Table A2 provides an overall comparison of the two main demand datasets used in the analysis in the main text, where we compare the number of stores, markets and products over time. NielsenIQ's sample of stores is quite different in 2017. Some of our figures dropped this year from the time series; we note when this is the case.

Table A2: Overall Comparison of the Datasets

| | IRI Dataset | | | | NIELSENIQ Dataset | | | |
|---|---|---|---|---|---|---|---|---|
| Year | Stores | Markets | Products | Units | Stores | Markets | Products | Units |
| 2005 | 1256 | 39 | 38 | 21.9 | | | | |
| 2006 | 1213 | 39 | 39 | 20.8 | 4689 | 38 | 39 | 102.9 |
| 2007 | 1211 | 39 | 39 | 21.0 | 5013 | 39 | 39 | 111.5 |
| 2008 | 1181 | 39 | 39 | 21.4 | 5067 | 39 | 39 | 111.7 |
| 2009 | 1157 | 39 | 39 | 21.6 | 5156 | 39 | 39 | 114.7 |
| 2010 | 1155 | 39 | 39 | 19.5 | 5175 | 39 | 39 | 108.8 |
| 2011 | 1091 | 39 | 39 | 17.2 | 5177 | 39 | 39 | 102.5 |
| 2012 | | | | | 5159 | 39 | 39 | 94.9 |
| 2013 | | | | | 5209 | 39 | 39 | 91.5 |
| 2014 | | | | | 4929 | 39 | 39 | 90.3 |
| 2015 | | | | | 4870 | 39 | 39 | 90.0 |
| 2016 | | | | | 4756 | 39 | 39 | 91.1 |
| 2017 | | | | | 2838 | 33 | 39 | 51.2 |
| 2018 | | | | | 5847 | 39 | 39 | 102.2 |
| 2019 | | | | | 5885 | 39 | 39 | 98.5 |

Notes: The units sold are in millions of 12-packs. The number of stores corresponds only to the stores selling at least one unit of beer. The segment of the stores is supermarkets (IRI) and food (NielsenIQ).

### A.3 Production Data

The Census of Manufactures sends a questionnaire to all manufacturing plants in the United States with five or more employees every five years. Labor inputs are measured by total production hours. Materials inputs are measured by total expenditure on materials including grains, malt, packaging, electricity, and fuel. Capital is measured using a question on total assets. Capital, materials, and sales were deflated using the NBER-CES industry-level deflators into 1997 dollars. Our output measure is the total value of product shipments (deflated).

We construct our panel of establishments (plants) as follows. First, we collect all years of data for any establishment listed as having a primary or secondary industry affiliation in NAICS 312120 or SIC 2082. Then, we look at the number of years where that establishment has "good" data. An establishment-year qualifies as "good" if all of the following criteria are met: at least three employees, at least $50,000 in sales, materials and capital inputs are non-missing and non-zero, and the observation was included in tabulations of official census statistics. An establishment is included in our panel only if it has at least two consecutive census years of good data, and, over the sample, at least 50% of its sales come from sales of beer.

# B Demand System Details

In this section, we review some important details of Miller and Weinberg's demand model and explain our alternative estimation strategy relying on the same IRI data.

MW's main specification involves twelve instruments, each of which is interacted with the product-market demand shock $\xi_{jdt}$ to form a moment:

1. An indicator for Anheuser-Busch InBev and MillerCoors products following the MillerCoors merger
2. Distance from the market to the product manufacturer's closest brewery
3. Sum of the above distances for all products in market $(d, t)$
4. Number of products in market $(d, t)$
5. Interaction of 1 and 3
6. Interaction of 1 and 4
7. Indicator for Anheuser-Busch products interacted with 3
8. Indicator for Anheuser-Busch products interacted with 4
9. Mean income in market $(d, t)$
10. An indicator for imported products interacted with 9
11. Calories interacted with 9
12. Package size interacted with 9

MW also include fixed effects for each product and time period. We follow MW in dropping the merger period of June 2008 through May 2009, so the post-merger indicator is equal to 1 for June 2009 onward for products owned by either Anheuser-Busch InBev or MillerCoors.

When we drop the cost-shifters from estimation, we drop the moments associated with 2, 3, 5, and 7. When we drop the BLP instruments, we drop moments 4, 6, and 8.

Table 4 was generated using a modified version of MW's code. Because we want to illustrate the difference that adding and/or dropping moments makes, rather than presenting differences resulting from changes in how the moments are weighted, we avoid changing how moments are weighted from column to column. To be precise, column 1 is estimated using standard two-step GMM estimation, following MW. For the other columns, we start with the same weighting matrix used in the second step for column 1's (MW's) estimation. To produce columns 4 and 5, we simply drop the rows and columns corresponding to the dropped moments, and then we run the second-step GMM estimation. For columns 2 and 3, we do the same thing, but we also add another row and column to the weighting matrix for the production-based markup moment. The elements of the new row and column are set to zero, except for the diagonal element, which is set equal to the inverse of the variance of the fitted values of the new moment, evaluated at the first-step parameter estimates. That is, the weighting matrix is given by

$$\begin{bmatrix} W^{MW} & \mathbf{0} \\ \mathbf{0}' & Var\left(\mu_{jdt}^{MW} - \hat{\mu}\right)^{-1} \end{bmatrix},$$

where $W^{MW}$ is the second-stage weighting matrix from MW's main specification, selecting the rows and columns that correspond to moments we are using in our estimation, and $Var\left(\mu_{jdt}^{MW} - \hat{\mu}\right)^{-1}$ is the variance of our markup moment, evaluated at MW's first-stage parameter estimates.

The addition of the markup moment calls for a subtle but important change to the typical strategy for implementing differentiated products demand estimation following Berry et al. (1995). Demand parameters are typically divided into "linear" and "nonlinear" parameters, where the nonlinear parameters must be explicitly searched over when minimizing the GMM objective function, and the linear parameters can be concentrated out, or solved for algebraically given the candidate nonlinear parameters—see section 6.5 of Berry et al. (1995). Normally, parameters controlling heterogeneity in price sensitivity are nonlinear parameters, and the mean price sensitivity parameter is a linear parameter. However, with the inclusion of the markup moment, the linear price parameter must be treated as a nonlinear parameter because it affects the markup moment, which means we no longer have linear first-order conditions for the optimal value of the mean price parameter.

A final detail is accounting for uncertainty in the production-based moment when computing standard errors for the demand estimates. We do this by simulating the asymptotic distribution of the demand estimates, using the asymptotic distribution of the production-based markups. That is, we start by simulating the asymptotic distribution of production-based markup estimates, drawing 40 points from the estimated distribution. For each of these draws of a production-based markup, we implement our modified estimation of MW's model imputing the drawn markup value in the new moment. The standard errors in column 2 of Table 4 are then computed by integrating over these 40 points and the standard GMM asymptotic distribution associated with the demand estimates for each draw.

# C Wholesale-Retail Pass-Through

Applying the implicit function theorem to equation (22) results in the following expression for retail-wholesale pass-through:

$$\frac{d\boldsymbol{P}^R(\boldsymbol{P};\gamma)}{d\boldsymbol{P}} = \left[\left(\sum_{j=1}^{J} \frac{\partial}{\partial \boldsymbol{P}^r} \left( \left.\frac{\partial \boldsymbol{q}_j^r\left(\boldsymbol{P}^r,\boldsymbol{P}^{r'};\gamma\right)}{\partial \boldsymbol{P}^r}\right|_{\boldsymbol{P}^{r'}=\boldsymbol{P}^r} (\boldsymbol{P}^r - \boldsymbol{P} - c^r)\right)\right) + \left(\frac{\partial \boldsymbol{q}^r\left(\boldsymbol{P}^r,\boldsymbol{P}^{r'};\gamma\right)}{\partial \boldsymbol{P}^r}\right)' + \frac{d\boldsymbol{q}^r(\boldsymbol{P}^r,\boldsymbol{P}^r;\gamma)}{d\boldsymbol{P}^r}\right]^{-1} \left(\frac{\partial \boldsymbol{q}^r\left(\boldsymbol{P}^r,\boldsymbol{P}^{r'};\gamma\right)}{\partial \boldsymbol{P}^r}\right)',$$

which we evaluate with $\boldsymbol{P}^r$ and $\boldsymbol{P}^{r'}$ equal to the observed retail price vector. To understand this equation, it is important to distinguish between the derivatives

$$\frac{d\boldsymbol{q}^r\left(\boldsymbol{P}^r,\boldsymbol{P}^r;\gamma\right)}{d\boldsymbol{P}^r}$$

and

$$\frac{\partial \boldsymbol{q}^r\left(\boldsymbol{P}^r,\boldsymbol{P}^{r'};\gamma\right)}{\partial \boldsymbol{P}^r}.$$

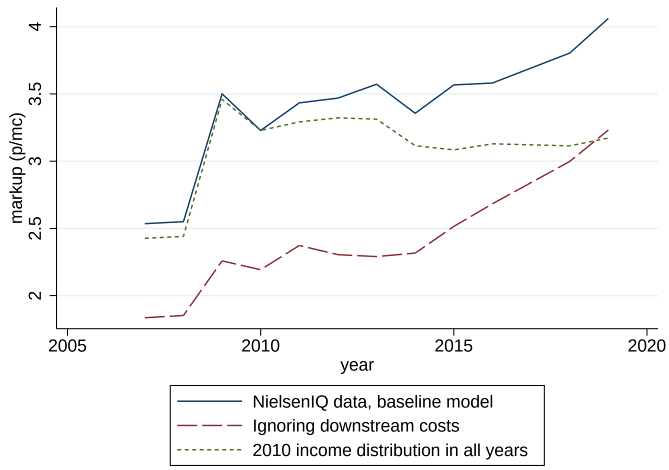
The former involves changing prices at a store and its competitor in the same way, thus introducing no changes in store-level market shares—it corresponds to the derivative of the product-level demand system. The latter is a partial derivative, changing a store's own prices while holding its competitor's prices fixed. The second derivatives of $\boldsymbol{q}^r$ involve derivatives of both product shares $\boldsymbol{s}$ and derivatives of store shares $\widetilde{s}$. The model of store shares, equation (21), allows us to compute the latter.

The pass-through matrix $\frac{d\boldsymbol{P}^R(\boldsymbol{P};\gamma)}{d\boldsymbol{P}}$ converges to an identity matrix as $\gamma \to 1$ (as retail becomes perfectly competitive). This can be seen from the fact that the Jacobian term $\frac{\partial \boldsymbol{q}^r\left(\boldsymbol{P}^r,\boldsymbol{P}^{r'};\gamma\right)}{\partial \boldsymbol{P}^r}$ grows without bound as the market becomes more competitive. The other terms remain bounded, and so the above expression converges to the Jacobian term times its inverse.

# D Additional Results

## D.1 Markups Time Series and the Role of Assumptions

Figure D1: Demand-Based Markups under Alternative Assumptions



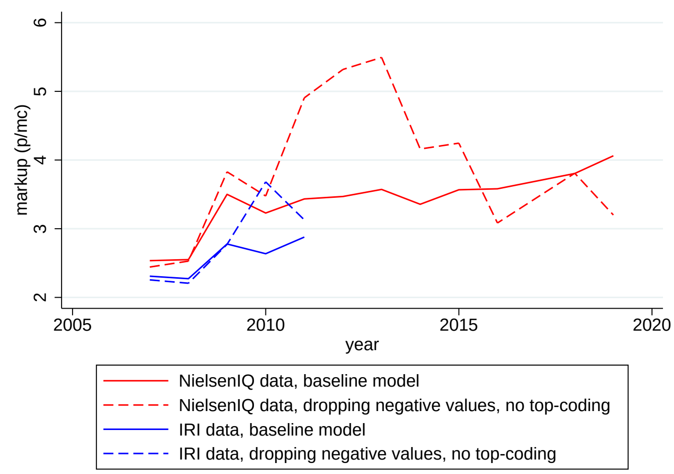

Notes: We plot sales-weighted average demand-based markups using the NielsenIQ data. Following MW, the merger period of June 2008 to May 2009 is omitted from these calculations. 2017 was dropped because the sample of stores was very different in that year.

Using the NielsenIQ data, Figure D1 shows how the time series of demand-based markups depends on modeling assumptions. First, the figure shows that accounting for downstream costs (retail and distribution costs and taxes) makes a substantial difference in the level of markups. Furthermore, we compute a time series in which we use the 2010 income distribution for all years, shutting down changes in markups that are driven by demographic shifts and the associated changes in demand parameters. In this case, markups are largely flat after the merger, and the merger is the only substantial reason that markups increase during this period.

Another feature of our baseline markup calculations is that we top-code markups at 15 and replace negative markups with a markup of 15. The motivation for doing this comes from the fact that, as a single-product firm's own-price elasticity of demand approaches $-1$ from below, the markup asymptotes to infinity. However, an own-price elasticity of slightly larger than $-1$ (or smaller than 1 in absolute value) implies negative markups. This discontinuity in the mapping from demand elasticities to markups can lead to strange comparative statics, in the sense that something that makes demand less elastic will tend to increase markups, except when elasticities cross a threshold that discontinuously makes the markups jump from very large positive numbers to negative numbers. Our top-coding strategy avoids such discontinuities.

Figure D2 shows the markup time series without top-coding. While top-coding makes a modest difference in the time series based on the IRI data, the NielsenIQ-based series illustrates that results can be implausible and unstable without top-coding. Average markup levels are sensitive to the possibility that a single product can have an astronomical markup (e.g., in the case of a single-product firm, when the own-price demand elasticity is slightly larger than 1 in absolute value).

Figure D2: Demand-Based Markups with and without Top-coding




<u>Notes</u>: We plot the sales-weighted average demand-based markup using the IRI and the NielsenIQ data. The baseline calculations impose a maximum markup of 15 and set all negative markups to 15. The versions without top-coding do not impose a maximum, and negative markups are dropped. Following MW, the merger period of June 2008 to May 2009 is omitted from these calculations.

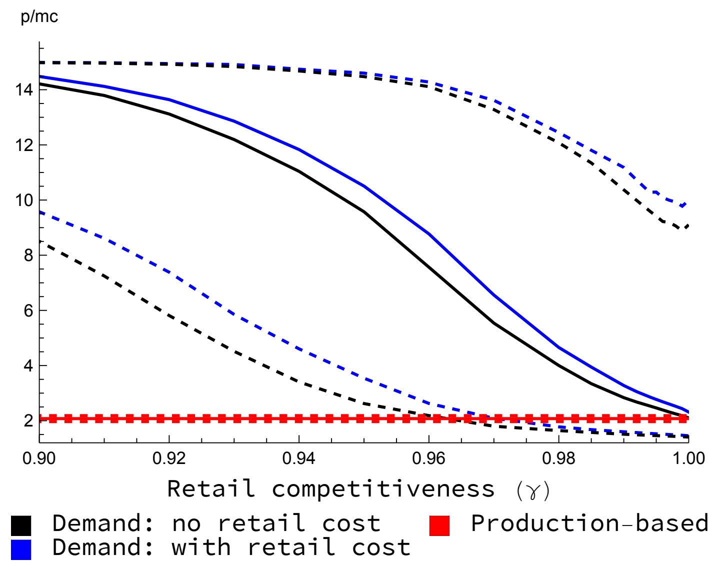
### D.2 Retail Competition Without Costs of Retailing

Our main results in Section 5.2.3 impute (small) retail costs as described in Section 3.1.2. Figure D3 adds a specification with zero cost of retailing.

### D.3 Demand-Based Markups with Alternative Models

Our earlier draft estimated demand using the Dominick's Finer Foods dataset, which covers an earlier time period (1992-1995). These data cover only the Chicago area, and come from one retailer, but these data have been used extensively to study the beer market, and they have a few important advantages, chief among them reporting both retail and

Figure D3: Markups, Retail Market Structure, and Costs of Retailing




Notes: The solid blue line represents implied markups for different values of the retail competitiveness parameter ($\gamma$), with costs of retailing imputed as described in the text. The black line displays the analogous demand-based results imputing a cost of retailing of zero. The red line displays average markups using the production approach (using the Leontief-Cobb-Douglas specification). Dashed lines indicate 95% confidence intervals.

wholesale prices. For details about the data, model, and estimation, see the subsumed draft `https://www.nber.org/papers/w22957`. Figure D4 adds the mean demand-based markups from that draft (in 1992, which corresponds to a census year on the production side) to our markups time series.

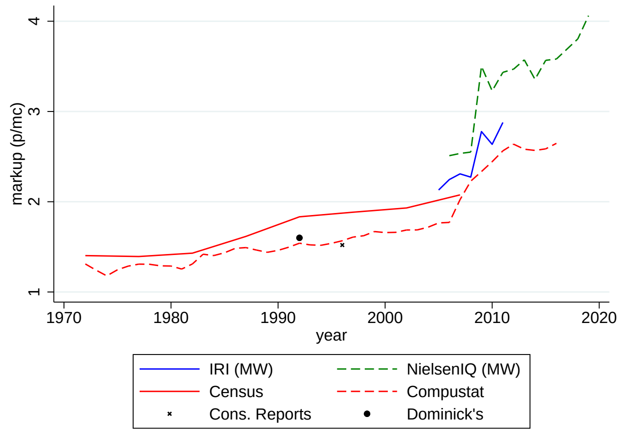
This draft uses the Dominick's data only to measure the average gap between retail and wholesale prices as a measure of the costs of retailing, as described in section 3.1.2.

Comparing markups across the two approaches for 1992 yields a very similar conclusion to what was presented in the main text for 2007. Table D1 reports, for each approach, the implied markups for the years where we have census data as well as demand estimates.

Table D1: Markup Estimates Across Approaches, Data Sources, and Years

| Year | External | Production | | Demand | | |
|---|---|---|---|---|---|---|
| | Cons. Rep. | Census | Compustat | Dominick's | IRI | NielsenIQ |
| 1992 | | 1.83 | 1.54 | 1.53 | - | - |
| 1996 | 1.52 | - | 1.57 | - | - | - |
| 2007 | | 2.08 | 2.02 | - | 2.31 | 2.54 |

Figure D4: Aggregate Markups Across Methods and Datasets




Notes We plot the sales-weighted average markup across firms using the production approach on the census and Compustat data (red lines), and using the demand approach on the IRI and NielsenIQ data (blue and green lines). The black dot indicates the average demand-based markup from our earlier draft, which used a different demand specification and Dominick's data. We also include the Consumer Reports (1996) markup for comparison. Demand-based markups are aggregated from product-level; production-based markups, from plant-level. All demand-based markups are computed assuming passive retailing, correcting for the downstream retail and wholesale costs as described in the text. Following MW, the merger period of June 2008 to May 2009 is omitted from demand-based calculations. 2017 was dropped from the NielsenIQ time series because the sample of stores was very different in that year.

Hidalgo (2023) features a beer demand model with richer consumer heterogeneity. The demographics include income, a dummy variable indicating whether the individual belongs to either the Millennial or Gen Z generation, and a dummy variable indicating whether the individual self-identifies as being of Hispanic ethnicity. He produces a time series of markups for US brewers that is similar to ours. For further details about the dataset, demand model, and identification, see Hidalgo (2023), particularly Sections 2.4, 4.1.2, and 5.1.

### D.4 Production Function Parameters

Table D2: Production Function Parameter Estimates

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| betal | 0.125 | 0.298 | 0.436 | 1.390 | 0.538 | 1.615 | 0.749 | 0.766 |
| | (0.110) | (0.185) | (0.075) | (0.216) | (0.058) | (0.241) | (0.118) | (0.359) |
| betam | 0.700 | 0.717 | | | | | | |
| | (0.148) | (0.248) | | | | | | |
| betak | 0.177 | 0.164 | 0.538 | -0.152 | 0.489 | -0.106 | 0.300 | 0.235 |
| | (0.061) | (0.124) | (0.098) | (0.196) | (0.065) | (0.200) | (0.123) | (0.259) |
| betal2 | | 0.042 | | 0.127 | | 0.168 | | 0.271 |
| | | (0.048) | | (0.028) | | (0.027) | | (0.272) |
| betam2 | | 0.054 | | | | | | |
| | | (0.023) | | | | | | |
| betak2 | | 0.008 | | 0.094 | | 0.102 | | 0.084 |
| | | (0.025) | | (0.019) | | (0.019) | | (0.076) |
| betalm | | -0.124 | | | | | | |
| | | (0.056) | | | | | | |
| betamk | | -0.048 | | | | | | |
| | | (0.046) | | | | | | |
| betalk | | 0.052 | | -0.230 | | -0.279 | | -0.287 |
| | | (0.044) | | (0.042) | | (0.045) | | (0.267) |
| betalmk | | 0.001 | | | | | | |
| | | (0.002) | | | | | | |
| Specification | GO | GO | VA | VA | LEO | LEO | LEO | LEO |
| Technology | CD | TL | CD | TL | CD | TL | CD | TL |
| Labor IV | $l_t$ | $l_t$ | $l_t$ | $l_t$ | $l_t$ | $l_t$ | $l_{t-1}$ | $l_{t-1}$ |

Notes: Standard errors in parentheses. Technology is either Cobb-Douglas or translog. Specification is either gross output, value added, or Leontief. Instruments include $k_t$ and either $l_t$ or $l_{t-1}$. Instruments also include $m_{t-1}$ for gross output specifications and interactions for translog specifications. All specifications shown here assume that expected productivity is linear in lagged productivity.

## References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