PRELIMINARY – COMMENTS WELCOMED

Climate Policy and Labor Markets

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April 26, 2010

1. Introduction:

An important component of the debate surrounding climate legislation in the United States is its potential impact on labor markets. A main concern is about the displacement of jobs from the U.S. to countries without carbon pricing, especially for energy-intensive industries facing import pressure from non-regulated countries. These concerns are rooted in the long-standing debate on the effects of domestic environmental regulations on U.S. industries and economic activity, although the empirical evidence regarding those effects is mixed (see e.g., Jaffe et al. 1995, Berman and Bui 2001, Greenstone 2002).

While concerns that higher energy prices will depress labor demand have received much attention in this debate, theoretically the connection is ambiguous and depends on the sign of cross-elasticity of labor demand with respect to energy prices, which is a priori unknown.[1] Evidence from studies conducted in the 1970s and 1980s indicates that energy and labor are p-substitutes, albeit weakly, suggesting that increases in energy price increase lead to small *increases* in labor demand (see Hamermesh (1993) are references therein).[2] The implication of this is that empirical estimates of the short-run and long-run cross-elasticities of labor demand with respect to energy prices are the key statistics required to assess the employment effects of climate policies that lead to increase in energy prices. This paper provides some new evidence on that question.

To date, most of the research on the potential effects of carbon pricing on employment has been conducted using computable general equilibrium models[3]. The approach typically combine various aggregate data sets with sophisticated computable general equilibrium models of the U.S. economy and simulate the short-run and long-run effects of a setting price on carbon. For example, Ho, Morgenstern and Shih (2008) find that the employment effects of a $10/ton carbon tax decline over time as the economy adjusts to the new energy prices. Taken as a whole, their analysis suggests employment effects ranging from -1% to -2%, although declines in some sectors are larger.

* I thank Michael Greenstone and Peter Kuhn for helpful discussions and Allison Bauer for research assistance. This paper was prepared for the NBER Conference "The Design and Implementation of U.S. Climate Policy" held in Washington DC, May 13-14, 2010.

[1] This presumes firms use other inputs in additional to labor and energy.

[2] There is also a long-standing macroeconomic literature on the effect of energy prices on economic activity (see Hamilton (2008) and Killian (2008) for recent surveys).

[3] See for example Ho, Morgenstern and Shih (2008), Jorgensen et al. (2008).

An alternative approach is to estimate the relationship between economic activity and energy prices using historical data and use these estimates to predict the impact of a carbon price on various measures of economic performance, such as production and employment rates. In this vein, Aldy and Pizer (2009) use annual industry-level data on output, employment, and electricity prices to assess the effects of a $10/ton price on carbon. The advantage of this approach is that it is more transparent and does not hinge on particular assumptions about inter-sectoral and inter-temporal elasticities. Its main disadvantage is that it ignores general equilibrium effects. The findings of Aldy and Pizer suggest overall modest effects of this carbon tax, although some electricity-intensive manufacturing sectors are affected more severely.

This paper provides new estimates of the relationship between real electricity prices and indicators of labor market activity using data for 1976-2007. While the prices of all energy sources are predicted to increase in proportion to their carbon content under carbon pricing policy, I focus only on electricity because it is the largest energy expenditure in most sectors of economy. For example, in the retail trade sector, electricity purchases correspond to roughly 2% of total production costs, but 80% of total energy costs. Thus in principle, a first-order impact channel of climate policy on labor market will be through its effect on electricity prices.

The paper contributes to the literature in two important ways. First I rely primarily on within-state variation in electricity prices to identify the models. Second, I consider all sectors of the U.S. economy (which I classify in 12 categories) rather than focusing only on the manufacturing sector. This distinction is important since the manufacturing sector now represents less than 20% of total employment in the U.S. The resulting cross-sectional and time-series variation allows me to control for unrestricted year, state, and industry shocks, as well as allowing for differential time trends across states or industry. This modeling effort is made in an attempt to minimize the confounding effects of industry-specific or state-specific permanent and/or transitory shocks that may be correlated with electricity prices. It also implicitly controls for state-specific labor demand shocks (as long they evolving 'smoothly' over time) or arbitrary year-specific shocks to labor demand (perhaps because changes in determinants of international trade such as tariffs).

The main finding is that employment rates are weakly related to electricity prices. The implied cross elasticity of full-time equivalent (FTE) employment with respect to electricity prices ranges from -0.15% to -0.08%. By comparison, the average annual change in FTE employment (normalized by population) over the sample period is about 1.5%, so the fluctuations in employment caused by electricity price shocks are well within the range of the normal historical variation. The estimated elasticities are precise with confidence intervals that rule out large short-run declines in employment. An industry-level analysis also reveals that employment in some industries is more responsive to higher electricity prices, although these industries (agriculture, construction, and transportation) only make up 15% of total employment.

I then interpret these empirical estimates in the context of H.R. 2454, the American Clean

Energy and Security Act of 2009. To this end, I use the estimates of the effect of electricity price on employment to simulate the short-run employment response to the higher electricity price implicit in H.R. 2454. I combine these with predictions from the Energy Information Administration on future electricity prices that account for the introduction of the cap-and-trade on GHG in H.R. 2454. These predictions are derived from a CGE-type model that considers various scenarios and time horizons, and indicate that electricity prices will increase by 2.5% to 15% by 2020, depending on the scenario chosen. This approach implies reductions in FTE employment ranging from -0.25% to -3.75% in the short-run, depending on the magnitude of increase in electricity prices.

There are several caveats to this research and its results that need to be emphasized. First, a policy imposing a price on carbon emissions will increase the cost of all energy sources in proportion to their carbon content, and not just increase the cost of electricity. Further research will be required to evaluate the labor market impacts of increase in the cost of other energy sources, and the results in this paper may be affected by such considerations. Second, since the analysis is based on annual variation in electricity prices, it is only relevant for evaluating the short-run employment effects of a possible carbon policy. These short-run effects are important determinants of the initial transitions costs associated with a climate policy. Presumably, the long-run effects will be smaller in magnitude once all the adjustments to the capital stock are made and the sectoral reallocation of labor takes place. Nevertheless, long-run effects can only be determined by using a proper dynamic general equilibrium model. Third, estimates based on historical data are dependent on the set of events, institutions, and regulations that applied during the period observed. As such, these estimates may not be applicable to the 'new' economic environment that would follow climate legislation. Fourth, the observed historical variation in electricity prices may not overlap with the higher energy prices caused by a specific carbon pricing policy.[4] Finally, this analysis does not quantify the effect of the policy incentives that could increase employment in 'green' sectors. In addition, many climate legislation proposals, such as H.R. 2454, contain provisions for job assistance programs aimed at workers displaced by the policy, and industry-specific subsidies designed to counter some of the added costs imposed by the policy. It is possible that such provisions will cause increases in labor demand in some sectors and this possibility is not accounted for in this analysis.

2. Conceptual Framework

A natural starting point to conceptualize the effect of energy prices on labor market is the neoclassical theory of labor demand. In a model where labor and energy are factors of production (along with other factors), the cross-elasticity of labor demand with respect to energy prices is given by $\eta_{LE} = s_E \times \left(\sigma_{LE} - \frac{\rho}{\rho - \theta} \right)$ where s_E is the share of energy in total production costs, σ_{LE} is the partial elasticity of substitution between labor and energy, ρ is a

[4] The largest predicted increase in electricity prices under H.R. 2454 are in the magnitude of 15%, while the average annual change in real electricity prices is about 2%, with a 95 percentile of 7%, and so it is unclear how estimates based on observed historical variation would extrapolate to those higher levels.

measure of market power of the firm (if the firm is a price-taker in the product market $\rho=1$, if the firm is a price-maker, $\rho>1$) , and θ measures the degree of homogeneity of the production function (see Cahuc and Zylberberg 2004 for derivations). The first term in the parentheses is the substitution effect (which may positive or negative in this case) and the second term is the scale effect (which is positive and declines in magnitude as the degree of market power increases). This formula has two key implications: (1) the cross-elasticity of labor demand with respect to energy prices is likely to be small since s_E is small for most industries; (2) the sign of η_{LE} will depend on whether the substitution or the scale effect dominates.

The expression above also highlights three key sources of variation in the cross elasticity of labor demand to energy price across industries. First there are differences in energy intensity (i.e. s_E) across industries. Second there may be differences in market power across industries which determine the degree to which firms in a sector can pass the extra costs associated with the policy to the buyers of their products (either as intermediary inputs, or as final demand). For example, sectors producing goods that face low import pressure are less likely to be affected by carbon pricing, at least in the short run. Finally, differences in the production technology (i.e. σ_{LE}) across sectors will also contribute to differences in the responsiveness of labor demand to shocks to energy prices.

Another important issue in assessing the impacts of GHG-pricing policy on labor markets is the time horizon in consideration. In the short-run, firms may not be able to optimally adjust to higher energy costs or higher input costs because their capital stock or production processes are fixed. Nevertheless, even in the short-run firms should be able to adjust to some degree their variable inputs such as labor and energy. In the longer run, firms will adjust their capital stocks and production technologies towards more energy-efficient ones in response to higher costs of carbon-intensive inputs. These possibilities of adjustment in the short-run, the long-run, as well as the transition paths are likely to differ across industries. Finally, while aggregate employment effects in the long-run may be smaller, the reallocation of workers across sectors may lead to the loss of existing industry rents, and lower real wages due to higher energy prices. And so the long-run costs of the policy may be significant for some industries and segment of the workforce.

3. Data Sources and Preliminary Analysis:

A. Data

The primary data for this paper are taken from the 1977-2008 March Current Population Surveys (CPS), and covers calendar years 1976-2007.[5] The CPS is a monthly household survey conducted by the Bureau of the Census for the Bureau of Labor Statistics and is representative of the civilian non-institutional population. The March supplement to the CPS focuses specifically on sources of income received in the previous year. Importantly, the March CPS also contains information about labor force outcomes (employment status, hours worked, weeks worked in the last year), as well as information on industry affiliation at the three-digit

[5] The data was accessed through IPUMS.

level. Starting in 1976, weeks of work are reported continuously, which explains the choice of the sample period. In addition, the March CPS contains demographic information including state of residence, age, gender, race, education, etc. The state of residence information will be used in conjunction with the survey year to link the CPS with the electricity price data.

The annual worker-level data are then combined with retail electricity prices from the State Energy Data System (SEDS) maintained by the Energy Information Administration. The SEDS data is detailed, and contains prices and expenditures for a dozen primary energy sources (i.e. coal, natural gas, etc), as well as 'transformed' energy sources, such as retail electricity and total energy at the state-year level. The retail electricity price data from SEDS are then merged with the micro-level CPS data by year and state of residence to construct the final samples used in the analysis.

B. Sample Construction and Key Variables:

For the purpose of this analysis, I consider individuals aged 16-65, working for pay (i.e. not self-employed), and residing in the continental United States. I then use the micro data to construct measures of employment (number of full-time and part-time workers; number of full-time equivalent (FTE) workers), as well as other measures of labor supply, such as total hours worked in the previous calendar year.

Previous research has found that the level of industry aggregation matters in measuring the effect of energy price on employment. In practice, there is a tradeoff between a fine industry classification and statistical precision and so for this paper, I consider a 12-industry classification.[6] Full-time and part-time employment variables are obtained by summing the number of full-time and part-time workers in each state-year-industry cell. Full-time equivalent (FTE) employment is obtained by summing annual hours worked in each state-year-industry cell, and then dividing by 2080 (40 hours per week * 52 weeks per year). In all cases, I use the CPS person weight (perwt) variable for these calculations.

C. Preliminary Analysis:

Panel A of Table 1 reports summary information on employment patterns over the whole sample period. The entries are average employment measures taken over state-year cells and reveal that on average, 1.8 million FTE workers were employed in the typical state over the 1976-2007 period, representing 1.3 million full-time workers (defined as working at least 48 weeks per year and at least 35 hours per week) and 0.6 million part-time workers. It also evident that employment as grown over time as the population as grown, and as female labor market participation has increased dramatically in this period, especially in full-time employment. Relative to the population aged 16-65, FTE employment has increased from 49% on average between 1976 and 1989 to 55% on average between 1990 and 2007.

[6] Those are Agriculture, Fishing and Forestry, Mining, Construction, Durable Manufacturing, Non-Durable Manufacturing, Transportation, Utilities, Wholesale Trade, Retail Trade, Finance, Finance, Insurance and Real Estate, Services, and Public Administration.

Panel B shows the distribution of FTE employment across the 12 industries. The percents reported are defined as the average FTE employment in a state*year*industry cell relative to total FTE employment in state*year cell. The service sector is the largest industry, accounting for 33% of total FTE employment, and growing in importance over time, from 29% to 36% between the halves of the sample period. The next largest industry is retail trade, which has remained constant at about 15% of FTE employment, followed by durable manufacturing at 13%. The decline of the U.S. manufacturing sector is evident in these figures, with durable manufacturing and non-durable manufacturing loosing 5 and 3 percentage points of total employment on average between 1976-1989 and 1990-2007.

As discussed earlier, a mandated carbon price is likely to have differential effects across industries, reflecting in part differences in energy intensity. One issue in documenting differences in energy and electricity intensity across sectors is that there are no comprehensive and comparable sources of data on energy expenditure available for each sector. For example, the Manufacturing Energy Consumption Survey contains detailed information on energy consumption in the manufacturing sector, but by definition this covers only roughly 20% of U.S. workforce. Similarly, the Survey of Business Expenses conducted by the Census Bureau omits the agricultural sector, the utility sector and the public administration sector. Finally, Annual Industry Accounts from the Bureau of Economic Analysis only report the total value of energy inputs by industry. So it is impossible to derive a measure of electricity intensity from these data.

Table 2 attempts to fill some of this gap by making use of model-derived sectoral GHG emissions from the Economic Input-Output Life Cycle Assessment model of the Green Design Institute of Carnegie Mellon University. This model is based on the 2002 input-output table for the U.S. economy produced by the BEA, and accounts for all GHG emissions of all primary and intermediate processes necessary to produce a benchmark level of output in 428 NAICS industries, which I recoded to match the 12 industry categories described earlier. Column 1 of Table 2 reports 'direct' GHG emissions for each of the 12 industries. The direct emissions correspond to the emissions generated by economic activity in each sector and by the activity of its suppliers, and ignore the transaction further up in the supply chain. For example, direct emissions in the 'Automobile and light truck manufacturing sector' account for the emissions of its electricity inputs, metal inputs, and any other emissions from its suppliers, as well as emissions generated by the assembly process. It ignores the emissions from all other sectors that use its output as inputs (for example, electricity usage in the Retail sector which sells cars).

The entries show the importance of the utility sector, which is responsible for almost half of aggregate GHG emissions (2312.2 MMTC02E). It is worth noting that since electricity is essentially only used as an input in other sectors, the 'direct' and 'total' emissions for utility are practically the same. The other largest GHG emitting sectors are transportation (613.5 MMTC02E), and non-durable manufacturing (572.2 MMTC02E). It is also useful to normalize sectoral GHG emissions by employment or economic activity to obtain measures of carbon intensity. Columns 2 and 3 provide such statistics, with column 2 reporting GHG emissions per million FTE worker and column 3 reporting GHG emissions per billion of value added ($2002). The information in both columns is highly correlated (0.93) and identifies the most polluting industries. Utilities rank worst in both metrics, at 4464.6 MMTC02E per million FTE workers and 8.74 MMTC02E per billion of value-added, followed by the agriculture, forestry and fishery sector, transportation and mining.

Because of the input-output nature of the model, it is possible to trace emissions caused by electricity usage by sector, and this reported in the last column. This measure of carbon intensity is the most relevant to the present analysis as it details which sectors are most 'electricity intensive', and presumably the most exposed to higher electricity costs under a climate bill. As noted above, it is not possible to compute more direct measures exposure such as fraction of production costs attributable to electricity for all sectors. This analysis indicates that services, FIRE, and trade (both retail and wholesale) are the most electricity-intensive sectors, with electricity inputs accounting for 40%-60% of GHG emissions. To the extent that this tabulation provides a valid measure of 'exposure' to higher electricity costs under a climate bill, these sectors, along with the utility sector itself are the most at risk under a carbon-pricing policy, at least in the short-run. It is also important to note that these 4 sectors are also important in terms of employment as they account for about 60% of FTE employment in the United States.

3. Methods and Results:

In order to estimate the relationship between real electricity price and labor market outcomes I consider group-level regression models of the form:

$$\text{(1)}\quad \mathrm{Log}(Y_{jst}) = \alpha_j + \alpha_s + \alpha_t + \beta P_{st} + X_{jst}\gamma + \varepsilon_{jst}$$

Where Y_{jst} represents a labor market outcome for industry j (when applicable to the outcome considered), located in state s and observed in year t. For example, this might be the log of FTE employment in a state*year*industry cell. The parameters α_j, α_s, and α_t are fixed effects for industries (j), state (s) and year (t). In some models, these fixed effects are also augmented by including industry-specific and state-specific time trends. In addition, I also consider more parsimonious models where the year effects are replaced with a quadratic time trend. P_{st} is the average retail electricity price in dollar per million BTU in state s and year t (deflated to 2005 dollars) and β is the parameter of central interest in this paper: it measures the proportional effect of a 1 dollar change in real electricity prices on the labor market outcomes considered. The vector X_{jst} contains the control variables, most importantly the size of the 16-65 population in the relevant cell. Finally the last term ε_{jst} is an error term. Throughout the paper the standard errors are corrected to allow for arbitrary within-state serial correlation.

Once the semi-elasticity of electricity price is estimated from (1), we can infer employment effects caused by the higher electricity price of a particular climate policy by multiplying the coefficient by the predicted increase in electricity price. For example, the predicted change in

FTE employment would be calculated as follows:

$$(2)\ \ \%\Delta \text{FTE} = \hat{\beta}_{\text{FTE}} \times \Delta \text{P}$$

The credibility of this approach depends on the assumption that the estimation of equation (1) will produce unbiased estimates of the β vector. The key assumption is that there are no residual labor demand shocks that are correlated with electricity price once we control for year, state, and industry fixed effects as well as industry-specific and state-specific time trends. This is a strong assumption, for example, it rules out state-specific labor demand shocks that do not evolve smoothly over time. Below I discuss the limitations of the empirical estimates produced by this analysis.

(A) Effect of Electricity Price on Employment

Table 3 reports estimates of the effect of electricity prices on various measures of employment, corresponding to the coefficient β in equation (1). In all models the dependent variable is expressed in logs, so the impacts are the semi-elasticities associated with $1 change in the real price of electricity. Panel (A) is based on state*year cells and ignores the variation in employment due to differences across states (and/or over time) in industry composition.

Estimates in column (1) are based on models including a quadratic time trend and state fixed effects, column (2) replaces the quadratic time trend with year fixed effects and column (3) adds state-specific time trends to the specification. It is the more general model considered, and allows for differentials shocks to labor demand in each state, provided that these shocks evolve smoothly enough. Four employment measures are considered: The number of full-time workers, part-time workers, number of FTE workers, and total hours worked. With the exception of part-time employment, the impact of electricity price on employment is negative across all employment measures and specification. The point estimates range from -0.0033 to -0.0057, implying that a $1 dollar increase in real electricity prices (in million BTU) lowers employment by 0.3% to 0.6%. The proportional effect on total hours worked is remarkably similar in magnitude, ranging from -0.3% to -0.5%. Notably, the estimates for part-time employment are positive, implying that higher energy costs may lead to a substitution of full-time employment by part-time employment. Finally, most of these estimates are statistically significant at the conventional level, with the estimates in column (1) generally being the largest and most precise.

Estimates in Panel B replicate the analysis, but this time are based on state*year*industry cells. The specification of the models in columns (1)-(3) remains the same, with the exception that industry fixed-effects are included in all specifications, and industry-specific time trends are added to the models in column (3). In general, the same patterns from Panel A emerge. There is a negative relationship between electricity prices and full-time employment, FTE employment and total hours. Estimates from columns (1) and (3) are the largest in magnitude, and the effects on part-time employment are sometimes positive. Across all specifications, the estimates imply that a $1 dollar increase in real electricity prices (in million BTU) lowers employment by 0.4% to 0.6%. It is also important to emphasize that with the exception of column (1), most point estimates in Panel B are not statistically significant at the conventional level, but do rule out 'large' negative impacts, i.e. reductions in employment of more than 1%.

(B) Industry-Specific Estimates

Table 4 reports estimates of impact of electricity prices on FTE employment specific to each to the 12 industry categories considered. These are obtained by fitting variants of equation (1) separately by industry (column 3), or by estimating a pooled regression, with separate electricity price effect for each industry (column 2).[7] Column 1 reports the fraction of FTE employment in each industry. Despite the lack of statistical precision in some cases, it is notable that higher electricity prices reduce employment in most industries. The most affected industries are transportation (-1.5%), construction (-0.7% to -1%) and agriculture (-1% to -1.7%). Importantly, these are smaller industries in terms of overall employment, representing about 15% of total employment in U.S. over the sample period. Other industries where employment is reduced by higher electricity prices are retail trade, service, and FIRE, although those point estimates are not always statistically significant at the conventional level. Finally, there is a positive correlation between electricity prices and employment in the mining and utilities sector, although the point estimates are not statistically significant

Taken as a whole, the evidence in Tables 3 and 4 indicates a relatively weak connection between employment and real electricity prices. FTE employment is reduced by about 0.5% for each dollar increase in the real price of electricity (in million BTUs), with corresponding elasticities ranging from -0.15% to -0.10%. By comparison, the average annual change in FTE employment (normalized by population) over the sample period is about 1.5%, so the fluctuations in employment caused by electricity price shocks are well within the range of the normal historical variation. Although not reported here, I have also considered alternative specifications of equation (1), notably to allow for potential nonlinear effects of energy prices on employment and allow for lagged energy price to enter the contemporaneous employment equation. In general, these considerations did not alter the main results significantly. Finally, the results also suggest that the employment effect of higher electricity price is not constant across industries, although the most strongly affected industries make up a small share of total employment.

(C) Possible Sources of Bias

It is possible that the estimates reported in Tables 3 and 4 are biased if there omitted factors in the model correlated with both electricity prices and labor demand, and under certain

[7] The pooled model in column (2) includes year, state, and industry fixed effects, state-by-industry fixed effects and state and industry time trends. The models in column (3) include year fixed effects and state fixed effects.

assumptions this bias will understate the employment effects of electricity price.[8] A common solution to this problem is to rely on instrumental variables that are correlated with electricity prices but otherwise uncorrelated with labor demand. While a complete implementation is beyond the scope of this paper, it is an approach I am undertaking in continuing work. For example local weather shocks that shift electricity demand may be a valid candidate as instruments, at least in some industrial sectors. I will also explore other instruments that have been used in recent literature measuring the demand price elasticity of gasoline (see e.g., Davis and Killian 2010 and Hughes, Knittel and Sperling 2008). Finally, another issue not directly addressed in this paper is the fact that the location of employment opportunities location is endogenous and may depend local on energy prices, as well as other state-level variables such as taxes, environmental regulations, unionization rates, etc.

4. Implications and Concluding Remarks

Taken literally, the estimates in this paper suggest that the short-run response to the increase in electricity price caused by H.R. 2454 would be a reduction in the total number of FTE workers of 200,000 to 1.2 million, depending on the magnitude of the increase in electricity prices. More precisely, these estimates correspond to the to the first-year response to the higher electricity prices assuming firms did not anticipate the rise in electricity costs and that no production subsidies are given to sectors most affected by the introduction of a price on carbon. In reality, it is probable that a carbon pricing policy will be phased in gradually and accompanied with subsidies to selected sectors. Such adjustment mechanisms should reduce some of the employment loss predicted by the approach in this paper. By comparison, the important recession that started in December of 2007 caused the number employed nationally to decline by 3.1 million between December 2007 and 2008.[9] Using this recent experience as a benchmark, it does not appear that a climate proposal like H.R. 2454 will lead to unprecedented employment loss, even in the short-run.

There are many limitations to this research and its results that need to be addressed in future research. In my view the most significant is that the approach taken here is only informative about short-run employment effects, and ignores general equilibrium effects. Information about the differential dynamic adjustment paths across industries is essential to evaluate the full extent of the implications of climate legislation on labor markets. Insights in this question can be obtained by considering dynamic general equilibrium models. In addition, this paper has only considered the employment impacts of higher electricity prices. Climate legislation such as H.R. 2454 will increase the cost of all energy sources in proportion to their carbon content. These considerations would surely add to the predicted declines in employment.

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[8] Omitting subscripts for simplicity, consider the structural model where $Y = \alpha + \beta*P + \gamma*u + \varepsilon$, where $\beta<0$ and $\gamma>0$. If the variable u is omitted from the model, the OLS estimator of β will be biased by the factor $\gamma*Cov(P,u)/Var(P)$, and so if P and u are positively correlated, β will be biased upwards.

[9] Laura A. Kelter: "Substantial job losses in 2008: weakness broadens and deepens across industries," Monthly Labor Review, March 2009.

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Table 1: Employment Statistics, and Industry Distribution of Employment, 1976-2007

	All Years	1976-1989	1990-2007
A. State*Year Cells			
Number of Full-Time Workers	1,315,300	1,094,361	1,487,141
Number of Part-Time Workers	626,807	589,442	655,868
Number of FTE Workers	1,778,816	1,498,870	1,996,552
Number of FTE Workers Per 16-65 Population	0.52	0.49	0.55
B. State*Year*Industry Cells			
Industry Distribution (Percent of FTE Employment)			
Agriculture, Fishing, and Forestry	1.4	1.5	1.4
Mining	1.0	1.3	0.8
Construction	5.5	5.1	5.8
Manufacturing, Durables	12.8	15.7	11.1
Manufacturing, Non-Durables	7.6	9.2	6.7
Transportation	5.3	5.5	5.2
Utilities	0.9	1.0	0.8
Wholesale Trade	4.1	4.4	3.9
Retail Trade	14.6	13.8	15.0
Finance, Insurance, Real Estate	6.9	6.9	7.0
Services	33.3	28.8	36.0
Public Administration	6.6	6.7	6.5

Notes: Data are taken from the 1976-2007 March CPS and the sample is composed of individuals aged 16-65, working for pay (not self-employed), and residing in the continental United States. Averages in Panel A are taken over 1,568 state*year cells. Entries in Panel B are from 18,471 state*year*industry cells. Shares defined as average FTE employment per industry over total employment in a state*year cell. See the text for more details.

Table 2: GHG Emissions and Percent of GHG Due to Electricity Consumption By Industry

	2002 Direct GHG Emissions (MMTCO2E):			
	Total For Industry	Per Million FTE Worker	Per $Bilion. of Value Added	Percent GHG Emission Due to Electricity Inputs
Agriculture, Fishing, and Forestry	521.2	267.3	3.70	8.4
Mining	191.3	249.8	0.75	15.9
Construction	181.2	22.4	0.29	20.0
Manufacturing, Durables	306.5	32.3	0.34	28.9
Manufacturing, Non-Durables	572.2	61.5	0.55	19.6
Transportation	613.5	120.4	1.59	8.3
Utilities	2,312.2	4464.6	8.74	---
Wholesale Trade	28.3	7.5	0.04	39.2
Retail Trade	23.7	1.3	0.03	59.1
Finance, Insurance, Real Estate	22.2	2.7	0.08	59.0
Services	262.4	5.9	0.07	39.2
Public Administration	147.5	21.6	0.09	10.4

Notes: Data on GHG emissions are taken from the Economic Input-Output Life Cycle Assessment (EIO-LCA) model of the Green Design Institute of Carnegie Mellon University and are derived from the 2002 Input-Output tables from the BEA. FTE employment and value-added also correspond to year 2002. See the text for more details.

Table 3: Short-Run Estimates of the Impact of Electricity Prices on Employment and Hours Worked

	(1)	(2)	(3)
A. Based on State*Year Cells			
Log(Full Time Workers)	-0.0060	-0.0040	-0.0043
	(0.0009)	(0.0011)	(0.0013)
Log(Part Time Workers)	0.0006	0.0025	0.0032
	(0.0013)	(0.0016)	(0.0011)
Log(FTE Workers)	-0.0057	-0.0032	-0.0036
	(0.0008)	(0.0010)	(0.0012)
Log(Total Hours Worked)	-0.0054	-0.0030	-0.0032
	(0.0008)	(0.0009)	(0.0011)
B. Based on State*Year*12 Industry Cells			
Log(Full Time Workers)	-0.0073	-0.0049	-0.0061
	(0.0015)	(0.0019)	(0.0023)
Log(Part Time Workers)	-0.0009	-0.0005	0.0029
	(0.0017)	(0.0023)	(0.0021)
Log(FTE Workers)	-0.0061	-0.0038	-0.0046
	(0.0015)	(0.0020)	(0.0025)
Log(Total Hours Worked)	-0.0056	-0.0037	-0.0044
	(0.0015)	(0.0020)	(0.0024)
Quadratic in Year	yes	no	no
Year Fixed Effects	no	yes	yes
State Fixed Effects	yes	yes	yes
State Trends	no	no	yes
Industry Fixed Effects (Panel B only)	yes	yes	yes

Notes: Estimates from models based 1,568 state*year cells (Panel A) and 18,471 state*year*industry cells (Panel B). Each model controls for the log of 16-65 population in addition to the variables listed at the bottom of the table. The standard errors in parentheses are corrected for within-state serial correlation. See the text for more details.

Table 4: Industry-Specific Short-Run Estimates of the Impact of Electricity Prices on FTE Employment

	Percent of Total FTE	Pooled Regression	Separate Regresssions
	(1)	**(2)**	**(3)**
Agriculture, Fishing, and Forestry	2.74	-0.0103	-0.0165
		(0.0053)	(0.0060)
Mining	0.88	0.0085	0.0046
		(0.0112)	(0.0174)
Construction	6.34	-0.0100	-0.0070
		(0.0039)	(0.0042)
Manufacturing, Durables	11.61	-0.0079	-0.0033
		(0.0039)	(0.0050)
Manufacturing, Non-Durables	6.93	-0.0017	0.0029
		(0.0036)	(0.0053)
Transportation	5.08	-0.0152	-0.0149
		(0.0030)	(0.0037)
Utilities	0.76	-0.0016	0.0065
		(0.0059)	(0.0071)
Wholesale Trade	4.15	-0.0012	-0.0015
		(0.0035)	(0.0040)
Retail Trade	14.96	-0.0047	-0.0027
		(0.0021)	(0.0021)
Finance, Insurance, Real Estate	7.01	-0.0060	-0.0113
		(0.0041)	(0.0049)
Services	33.74	-0.0034	-0.0016
		(0.0017)	(0.0012)
Public Administration	5.78	0.0000	0.0004
		(0.0025)	(0.0024)
Implied Aggregate Estimates		**-0.0050**	**-0.0035**
		(0.0029)	**(0.0031)**

Notes: Columns (1) reports the percent of total FTE employment over 1976-2007. Estimates in column (2) are from on a pooled regression, with separate electricity price effect for each industry and includes year, state, and industry fixed effects, state-by-industry fixed effects and state and industry time trends. Estimates in column (3) are from regression models estimated separately by industry that include year fixed effects and state fixed effects.