Auburn University
Department of Economics
Working Paper Series

Capital Investment and Employment in the Information Sector

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AUWP 2013-14

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Abstract: Estimation of the employment effects of changes in capital investment is a standard tool in public policy debates. Typically, such predictions are based on employment multipliers derived from Input-Output analysis. In this paper, we measure the employment effects of changes in capital investment in the U.S. information sector by econometrically estimating an "employment multiplier" from historical data. The estimated multiplier is 10 information sector jobs for each million dollars in expenditure, and perhaps 24 new jobs per million dollars invested across the entire economy. Employment multipliers derived from the Input-Output methodology average about 16 jobs per million, but the multiplier includes jobs outside the information sector. Including employment spillovers, our estimates suggest the multipliers from Input-Output models are plausible. We also note that information sector jobs have substantially higher median earnings than the private sector average, so the economic significance of changes in information sector employment are greater than might first appear. Our findings may be useful in debates over changes in industry regulation that could affect investment.

I. Introduction

The very poor state of the US economy has focused policy analysts' attention firmly on job creation. The information sector, which is one of the few "bright spots" in a dismal employment landscape, has figured prominently in these discussions. Many studies of information sector employment have concluded that employment both in and outside the communications industry is highly responsive to capital expenditures by communications firms. Consequently, it is argued that, depending on the response of firms to regulatory interventions, public policy has significant employment effects. The consistency of these findings is unsurprising – these studies typically rely exclusively on employment multipliers calculated by the U.S. Bureau of Economic Analysis' ("BEA") Regional Input-Output Modeling System ("RIMS II") (Erlich 1997).[1] RIMS is a general equilibrium model of the U. S. economy sponsored by a federal government agency and, unlike private-sector models, the RIMS output is available at low cost to the research community. For these reasons, RIMS is a popular tool for the estimation of regional jobs impacts. Thus, although numerous studies suggest similar employment

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[1] http://www.bea.gov/regional/rims/index.cfm. Use of the RIMS multipliers to size employment gains and losses is attractive for many reasons: (a) RIMS is a general equilibrium model of the economy, so it can estimate employment effects for the entire economy of expenditures in just one sector; (b) the multipliers are calculated by a government agency and thereby are unaffected by any alleged researcher bias; and (c) these numbers can be looked up rather than calculated or estimated directly, thereby making it easier for researchers to produce estimates of employment effects.

multipliers for the information sector, this unanimity may be quite misleading, since it represents a single initial source.

In recent studies, the use of employment multipliers in U.S. communications policy is varied. Crandall, Jackson and Singer (2003) use multipliers to estimate the effect of broadband adoption and expanded investment in the technology on the U.S. economy. The study used the RIMS-based multiplier of 18.1 jobs for each $1 million in capital expenditures (Crandall, Jackson and Singer 2003: 14). More recently, Crandall and Singer (2009) updated their study, employing a RIMS-based multiplier of 16.7 jobs per million in investment. In an effort to encourage government investment in broadband technology as part of the American Reinvestment & Recovery Act, the Communications Workers of America (CWA 2009) claimed that 97,500 jobs would be created for each $5 billion in investment (using a RIMS-based multiplier of 19.5). Davidson and Swanson (2010) used a multiplier-based approach to argue that Network Neutrality regulation will reduce employment by curbing the incentive to invest in communications networks, applying the RIMS-based multiplier from Crandall and Singer (2009) of 16.7 jobs per million in investment. Eisenach, Singer and West (2009) employ a multiplier of 19.7 ($19,744 jobs for 3 billion in investment in fiber connections to the home, while Singer and West (2010), leaning on estimates for non-fiber investments from the Eisenach, Singer and West (2009), predict 39,961 on $2.72 billion in investment for an implied multiplier of 14.7 jobs per million. Bazelon (2010) also considers the employment effects of reduced investment from Network Neutrality regulation but uses the IMPLAN Input-Output model to estimate employment effects rather than relying on the RIMS multiplier tables. The implied multiplier (averaged over five years) is smaller than the prior studies at 13.6 jobs per million of investment. These few studies are a small sample from a voluminous literature using employment multipliers to influence communications policy generated over many decades, almost all of which apply a multiplier from Input-Output models.[2]

In this paper we attempt to provide some relevant evidence on employment effects using an entirely different methodology. Specifically, we estimate a type of "employment multiplier" directly from historical data using time-series econometrics (Rosen and Mathur, 1973). This econometric approach offers several benefits. First, while the Input-Output models provide uniform, annual employment effects, the time series approach is dynamic, thus permitting the estimation of both the immediate and delayed effects of a shock. Second, the causal connection between jobs and expenditures (at the margin) can in principle be statistically tested. Third, and most importantly, the most studies of employment effects in the industry are national in scope, but the BEA makes clear that the RIMS multipliers are, in fact, regional, and caution that "[d]ifferences in industry-specific regional multipliers are not meaningful or appropriate for use in a national context."[3] Additionally, the BEA lists a number of reasons why the RIMS

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[2] In many cases, the multipliers used are for telephone equipment manufacturing and construction, the latter having very large multiplier effects (Eisenach, Singer and West 2009).

[3] http://www.bea.gov/regional/rims/index.cfm (emphasis supplied).

multipliers "are likely to be upper bound estimates," including the assumptions of: (1) no supply constraints; (2) fixed patterns of purchase; and (3) the use of local inputs when available.[4] As a check on the validity of the common use of the multipliers to evaluate public policy, the multipliers obtained from econometric estimation can be compared to the IO-based multipliers used in prior studies, providing policy-makers with either independent support for current estimates, or else reason to apply the current estimates with caution. For both historical and practical reasons, the IO multiplier methodology has become standard, and we do not claim the statistical approach is superior. We do suggest, however, that the nearly universal reliance on the IO framework means the apparent "consensus" on employment effects should be seen for what it is - a reflection of the use of a common methodology.

Our approach, however, is not without important limitations. For example, our analysis is limited to "Information" sector capital expenditures and jobs. Clearly, capital expenditures in the sector may create employment opportunities outside of the information sector, so we suspect our "multipliers" could be smaller than those found using RIMS or other Input-Output models, which take a broader view of the economy. Consequently, our directly-estimated (information sector) multipliers are probably conservative estimates relative to those found in these prior studies. We make an effort to assess the impacts of such limitations, but the reader should keep these caveats in mind.

Our findings are mostly reassuring: we calculate investment-employment multipliers that are similar to, but smaller than, those often borrowed from RIMS and similar models. In the first year, a one million dollar shock to capital spending will "create" six information sector jobs (one-year multiplier of 6). Five-years after the shock, the employment multiplier is about 14. This five-year effect is broadly consistent with IO values (see Table 1). This finding is somewhat surprising since the RIMS (and some other) models are specifically designed to provide *regional* employment effects across multiple industries. Whether this pleasant discovery is purely fortuitous, or is result of some peculiarity of the information industry, is an interesting question beyond the scope of the present paper.

II. The Multiplier Method

The development of input-output analysis is attributed largely to the work of Leontief for which he won a Nobel Prize (Carter and Petri, 1989), though some economic historians may track back the idea to Quesnay's Tableau economique (Ekelund and Hebert, 2007). The input-output model is primarily used as a tool for estimating the impacts -- measured in output, income and employment -- of an economic activity on a particular regional economy, and does so by a detailed accounting of inter–sectoral relationships within a regional economy (country, region or county) using an input-output matrix populated with observed data (Miller and Blair, 1985). As described by Fjeldsted (1990: 1), the term regional impact multiplier "refers to the

[4] https://www.bea.gov/regional/rims/RIMSII/illustrativetables.aspx

ratio of the size of the total effect on a regional economy of some initial direct exogenous impact to the size of the direct impact itself." The capacity to estimate employment effects of spending programs make the input-output tool exceedingly useful for public policy purposes (Baumol and Wolff, 1994).

The standard procedure in "jobs studies," including those mentioned above, is to assume that policy affects jobs *indirectly* via capital expenditures (or, in some cases, industry revenues). That is, a policy change leads to either more or less investment by firms, and, in turn, this change in expenditure is what leads to more or fewer jobs. More formally, let the number of jobs of interest be J, and let capital expenditures be E (which we measure in millions of constant-value dollars). For some assumed change in policy, we have a change in expenditures (ΔE), and then a subsequent (and implied) change in jobs (ΔJ):

$$\Delta Policy \rightarrow \Delta E \rightarrow \Delta J \ , \tag{1}$$

In most cases, the relationship between jobs and expenditures is measured by the RIMS multipliers (or multipliers from some other Input-Output model such as IMPLAN), so that

$$\Delta J = m \cdot \Delta E \ , \tag{2}$$

where m is a "multiplier" that relates changes in capital spending to changes in employment levels. Notably, this "multiplier" effect is not the same as the multiplier effect between fiscal spending and Gross Domestic Product. Coughlin and Mandelbaum (1991) and Erlich (1997) provide detailed discussions of the use of employment multipliers of the form used here.

From Expressions (1) and (2), we see that estimating a "jobs delta" involves two key inputs: (1) how big is the expenditure change? and (2) what is the relationship between jobs and expenditures? As many "jobs studies" are released prior to the implementation of a policy initiative (indeed, these studies are typically aimed at influencing the policy choice), it is impossible to credibly estimate the resulting investment effect before specific rules are written, litigated, and "digested" by the industry. As a result, researchers typically consider a range of plausible expenditure changes.

In the standard course, the multiplier "m" is taken from Input-Output models, whether RIMS, IMPLAN, or some other model. Table 1 summarizes the assumed multipliers from a number of recent studies released to influence policy debates in the U.S. telecommunications sector. All of these studies, with the exception of Bazelon (2009), use multipliers obtained from the RIMS program. (The difference between Crandall et al. (2003) and Crandall et al. (2010) is due to an increased variety of industry-specific multipliers that were updated after the earlier study.) Davidson and Swanson (2010) rely on Crandall and Singer (2010) for the size of the multipliers, so by implication they also use RIMS. CWA (2009) expressly uses RIMS multipliers. Bazelon (2010) uses the IMPLAN Input-Output model for the computation of employment effects, which results in slightly smaller effects.

The credibility of studies using RIMS and similar models would be enhanced if some independent evaluation of the employment multipliers were available. This is a primary purpose of our estimation in this paper. We utilize a vector error-correction time series technique in an attempt to isolate the effects of innovations in capital expenditure in the information industry on sector employment. Our estimation supports calculation of impulse responses, allowing us to investigate the time evolution of employment in reaction to shocks to capital investment. Our analysis lets us derive employment effect multipliers using a credible method which is, however, wholly unlike the structure of assumptions underlying the Input-Output approach.

III. Econometric Approach

Looking at Expression (2), it seems that, given data on J and E, we can m (for some sectors) directly from historical data. We will attempt to do so here. It should also be possible to size m and to test whether or not changes in expenditures (ΔE) can be said to "cause" changes in employment (ΔJ), at least in the ordinary (i.e., operative) statistical sense. Moreover, with appropriate time series techniques, it is possible to estimate the capital expenditure and employment effects in an extended, dynamic context, and to evaluate a hypothetical shock of interest, such as a change in capital expenditure arising from a change in regulation.

A. *Data*

We begin by considering the available data. The Bureau of Labor Statistics ("BLS") provides industry-specific employment data, but the availability of older historical data depends on the industry of interest. Data on the "Information" sector (NAICS 51), which includes telecommunications, cable, broadcasting, publishing, and data processing, is available annually back to 1939.[5] Investment data (E) is provided in the BEA's Fixed Assets Tables.[6] We match the investment figures to the employment data, thereby including BEA Industry Codes 5110, 5120, 5130, and 5140. The investment data is available through year 2008. In 2008, total investment in this sector was $122.3 billion. Telecommunications and broadcasting firms (BEA Code 5130) accounted for about $100 billion (82%) of this total, so it is reasonable to conclude that the estimated employment multiplier mostly reflects the telecommunications and broadcasting sector.[7] We convert the *nominal* "Investment" data to *real* values using either the Producer Price

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[5] For a description of the industry, see http://www.bls.gov/iag/tgs/iag51.htm. More narrow industry classifications, though, only have about twenty years of data in the current industry definitions. Efforts to patch together the earlier data with current data was, in our view, unsatisfactory. Consequently, we use data on the information sector, broadly defined.

[6] http://www.bea.gov/national/index.htm#fixed.

[7] The Publishing Industries (5110) and the Information and Data Processing Services industry (5140) each represent about 8% of the total. Motion Pictures and Sound Recording Industries (5120) is a little over 1% of the total.

Index ("PPI") as provided by BLS.[8] All values are expressed in 2009 dollars to aid in interpreting the results. While we have data going back to 1939, we restrict our analysis to the last forty years in hopes of doing less injury to the assumption of parameter stability. The time-frame covered is thus 1969 through 2008. (We also estimated the model with a shorter sample covering the last thirty years to evaluate the robustness of our findings. The results were very similar.)

B. *Data Issues*

We are dealing with time series data, so standard least squares econometric approaches are unlikely to be valid. Some preliminary evaluation of the properties of the data is required prior to choosing the estimation approach. First, we need to evaluate whether the two series are stationary. We do so using the Augmented Dickey-Fuller Test ("ADF"). The results, including a test version with a constant term ("ADFc") and a constant term and trend ("ADFτ"), are summarized in Table 2. The logarithms of the two variables are found to be stationary in first differences.

Second, we evaluate whether the two series have a cointegrating relationship. If we can answer in the affirmative, then a long-run ("equilibrium") relationship exists between the two. This long-run dependency is important for evaluating the employment effects through time. As shown in Table 2, the Engle-Granger, Hausman-Type (Engle and Granger 1987; Choi et al., 2008), and $H(p, q)$ tests proposed by Park (1992) indicate that the two series are, in fact, cointegrated.[9] Given the results summarized in Table 2, we conclude that the employment and expenditure series are difference stationary random variables (that is, they are individually I(1)) and are cointegrated. Our estimation proceeds accordingly.

C. *Estimation Details*

The details of the estimation strategy are as follows. Let $y_t = [y_{1,t} \quad y_{2,t}]'$ be a vector of difference stationary random variables where $y_{1,t}$ and $y_{2,t}$ denote the number of information industry jobs (J) and real capital expenditures (E) in the industry at time t, respectively. All variables are measured in natural logarithms. We assume that $y_{1,t}$ and $y_{2,t}$ are cointegrated with a cointegrating vector $\gamma = [1 - \beta]'$, that is, jobs (J) and expenditures (E) share a stable long-run relationship. For instance, if β were to equal 0.5, a 10% decreases in expenditures would result

8 http://www.bls.gov/ppi (Commodity PPI). Converting to constant dollars using the BEA's chained GDP deflator has very little impact on the results. We do not use the BEA's quantity index of investment, since our primary interest is to compare our findings with that of the standard multipliers, which are based on dollars of investment. Using dollars rather than quantity-based measures of investment also permits an opportunity-cost analysis among investments in different sectors. We are grateful to an anonymous referee for comments on this question of deflators.

9 Critical values (5%) are generated for 40 observation case by 100,000 Monte Carlo simulations.

in a 5% decrease in jobs in the long-run. Jobs and expenditures have the following triangular representation (Phillips 1991):

$$y_{1,t} = \alpha + \beta y_{2,t} + \varepsilon_t \tag{3}$$

$$\Delta y_{2,t} = \delta + u_t, \tag{4}$$

where Δ is the difference operator, α is an intercept, δ denotes a drift, ε_t and u_t are mean-zero white noise processes. The cointegrating parameter β can be estimated by the (static) least squares estimation ("SOLS"). However, the least squares estimator $\hat{\beta}_{LS}$ is asymptotically biased and inefficient. Furthermore, its asymptotic distribution is non-normal (Phillips 1991; Stock 1987). Therefore, statistical inference based on the least squares estimator may not be reliable. Recognizing these potential problems, we employ two alternative estimators for the cointegrating vector: (i) Park's (1992) CCR method and (ii) Stock and Watson's (1993) dynamic Ordinary Least Squares ("DOLS") estimator (Park 1992; Stock and Watson 1993). These estimators are more efficient and perform better than the least squares estimator in finite samples.

Given the cointegrating vector estimate for γ = [1 - β]′ from (3) and (4), we construct the following bivariate vector error correction model ("VECM"). Abstracting from deterministic components,

$$\Delta y_t = \rho\gamma' y_{t-1} + \sum\nolimits_{j=1}^{k} \theta_j \Delta y_{t-j} + Ce_t \tag{5}$$

where $\rho = [\rho_1 \;\; \rho_2]'$ is a 2 × 1 speed of convergence parameter vector, C is a matrix that defines the contemporaneous structural relationship among employment and investment expenditures, and $e_t = [e_{1,t} \;\; e_{2,t}]'$ is a vector of mutually orthogonal structural shocks to these variables. We interpret $e_{2,t}$ as a structural shock that is caused by some external events that disturb investment expenditures but not employment. However, we allow $e_{2,t}$ to have an immediate effect on jobs. (This happens when the (1,2)th element of C has a non-zero value.) For example, $e_{2,t}$ may be interpreted as a policy change that may result in a decrease in firms' capital expenditures, which may result in a job loss in that industry as firms re-optimize their production with reduced capital expenditures.

To study the effect of $e_{2,t}$ on jobs and investment expenditures in both the short- and long-run, we employ the generalized impulse-response analysis based on our bivariate VECM described in Equation (3) (Pesaran and Shin 1998). For this purpose, we rewrite Equation (5) as the following state-space representation:

$$z_t = Fz_{t-1} + \xi_t \tag{6}$$

where

$$z_t = [y_t \;\; y_{t-1} \;\; \dots \;\; y_{t-k}]', \tag{7}$$

$$F = \begin{bmatrix} \vartheta_1 & \vartheta_2 & \dots & \vartheta_{k+1} \\ & & & 0 \\ & I_{2k} & & \vdots \\ & & & 0 \end{bmatrix}, \tag{8}$$

$$\xi_t = [Ce_t \ \ 0 \ \dots \ 0]', \tag{9}$$

and

$$\vartheta_1 = I_2 + \rho\gamma' + \theta_1, \tag{10}$$

$$\vartheta_j = \theta_{j+1} - \theta_j, j = 2, \cdots, k, \tag{11}$$

$$\vartheta_{k+1} = -\theta_k, \tag{12}$$

and I_p is the p-dimension identity matrix. The r^{th} period impulse-response functions, then, are obtained by,

$$(S'F^r S)C \tag{13}$$

where $S = [I_2 \ \ 0 \ \cdots \ 0]'$ is a 2(k + 1)×3 selection matrix and the contemporaneous matrix C can be obtained by the Choleski factor of the least squares variance-covariance matrix of Expression (5). With regards to the responses of employment to a capital expenditure shock, the generalized impulse-response function coincides with the orthogonalized impulse-response function with expenditures the first variable in the ordering (Kim 2009). Our forecast of information sector job changes due to the real capital expenditure shocks, and our other estimates, are mostly obtained from the estimates for Expression (13).

IV. Results

Our analysis was conducted using a purpose-built program written in the GAUSS language, although many of our estimations are supported by popular statistical packages.[10] Once the relevant parameters are estimated, it is possible to simulate the effects on jobs of a shock to capital expenditures. We do so here, but first we address the question of causality from expenditures to jobs, or the reverse, using the standard Granger Causality test. (Note, however, that the Granger test is short-run in nature and our cointegration analysis indicates that the two series do have a long-run relationship. (Never-the-less, causation testing is an obvious step in building a model of this sort.)

A. *Short-Run Granger Causality*

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10 Our code and detailed results are available on request.

In order to evaluate short-run causality, we apply the standard approach of bivariate Vector Autoregression ("VAR"). Given that our series are I(1), we use first-differenced data and estimate the following general equations

$$\text{Expenditure } \textit{Granger causes} \text{ Jobs: } \Delta J_t = f(\Delta J_{t-1}, \Delta E_{t-1}), \tag{14}$$

$$\text{Jobs } \textit{Granger Cause} \text{ Expenditure: } \Delta E_t = f(\Delta J_{t-1}, \Delta E_{t-1}), \tag{15}$$

where the one period lag specification is selected by minimizing the Bayesian Information Criterion ("BIC"). The F-statistic on the null hypothesis that *Expenditure does not cause Jobs* is 3.10, which is statistically significant at the 5% level (i.e., the null hypothesis is rejected). Therefore, the evidence suggests that there is a causal relationship flowing from changes in capital expenditures to employment. In contrast, we cannot reject the null hypothesis that *Jobs do not cause Expenditure*, with an F-statistic of only 0.24. As such, we appear to have a one-way causal relationship, in a Granger sense, flowing from changes in capital expenditures to jobs. We find these results sensible, although we note that this sort of analysis ignores the cointegrating relationship between the two series. On the other hand, a contrary finding would be troubling for our purposes, as well as for the economic logic underlying much of the IO approach.

B. *Vector Error Correction Model* ("*VECM*")

We begin our examination of the VECM results in Table 3, which reports our speed-of-convergence estimates. This information provides measures of the degree to which each variable (jobs and investment) contributes to the adjustment process to the underlying, long-run equilibrium relationship. In other words, if a shock disturbs the equilibrium relationship between employment and investment, how will the two variables participate in the adjustment process necessary to eventually return the system to equilibrium? While both variables will adjust, the speed at which these two variables change is evidently quite different. Table 3 shows that the primary source of such adjustments is changes in capital investment expenditures. This is perhaps unsurprising: capital investment is volatile and flexible, at least when compared to employment, especially for sectors that offer high pay to skilled workers.

Next, we turn to our primary findings: the cointegrating vector estimation results reported in Table 4. We offer three different estimates based on three statistical criteria: ordinary least squares (SOLS), dynamic ordinary least squares (DOLS) (Stock and Watson, 1993), and canonical cointegrating regression (CCR) (Park, 2002). The point estimates all appear quite similar, although this must be regarded as primarily a fortuitous result: SOLS is not statistically appropriate. These coefficients provide estimates of the long-run effects of shocks on the equilibrium values of the variables. In particular, referring to the CCR finding for example, our analysis indicates that a 10% reduction in capital expenditures leads, in equilibrium, to an approximately 4.5% reduction in information sector jobs, when all feedbacks between these variables are taken into account. This is a very significant effect. The reason for the large effect is that a shock to capital expenditures in one period affects employment and capital spending in the next period, which in turn affects these variables going forward, and so on. This complex interdependence over time is precisely the kind of information which is potentially useful, but is not available from ordinary multiplier analysis.

C. *Simulating the Employment Effects*

Using the estimates from the VECM we can conduct a variety of simulations to measure the effect on jobs from a change in capital expenditures. Our simulations assume a negative shock to capital expenditures (in 2009 dollars) ranging from 1% to 30%. (For the point estimates, the fact that the assumed shocks are negative is immaterial- positive shocks produce corresponding positive effects.) In Table 5, the simulated reductions in capital expenditures are provided. Note that the assumption in the simulation is a one-time shock (a shift in the expenditure-time curve), but this reduction persists over time. Since each series is I(1) with drift, each series eventually recovers from the initial decline. When the shock is large, both expenditures and jobs decline for more than one period, after which they start to recover, following their stochastic trends in line with their cointegrating relation. Thus, a negative expenditure shock causes the level of jobs to actually fall in the short run. This employment shock is persistent despite the fact that over time secular growth in the economy raises employment. In other words, the economy exhibits lower levels of sector employment, compared to the no-shock case, indefinitely.

The effects on jobs from these reductions in capital expenditures are summarized in Table 6. As expected, as the size of the shock increases, so does the magnitude of the job loss. For a 5% negative shock, job loss is estimated to be 31,425 jobs, whereas a 10% shock reduces employment by 62,518 in the first year. In five years, that same 10% shock has reduced sector employment by 156,850 (in the fifth year). Over the first five years, the average annual job loss is 128,392 jobs. (See the Appendix for annual changes.) These losses are information sector jobs only; our estimates do not capture the employment (or capital expenditure) effects on other sectors. As such, the job-loss estimates here do not include the full extent of the expected job loss, and quite plausibly understate the effects.

With these estimates of investment and employment changes, we can compute the jobs multipliers implied by the VECM. These multipliers are summarized in Table 7. To understand this table, one should note that the multipliers given refer to actual numbers of jobs lost per one million dollars in lost capital investments in the base year. Thus, for example, a 10% negative shock will, after say 5 years, result in an observed loss of 13.5 jobs per million dollars in lost investment. The non-monotonicity of these values, as can be observed in the table, is a consequence of the relatively rich dynamic process of adjustment described earlier. Importantly, the most severe consequences of the loss in investment are seen to occur in the "middle term"—i.e., in the 3-5 year time horizon. However, the effects are persistent for a very long time.

D. *Multiplier Stability*

The reported results use observations spanning the period 1969 to 2008, discarding early data on the information sector from 1939 to 1968. By including the all the data back to 1939, we can provide some evidence on parameter stability and the relationship between capital and labor in the information sector over time. In alternate DOLS estimations, we estimate 30-year and 40-year rolling regressions beginning in year 1939, and find that rolling window estimates for β in both windows are increasing over time. Figure 1 shows the estimates from the 30-year rolling window, and Table 4 shows the estimate of β used to construct the multiplier (= 0.4379). Thus, the analysis suggests a stronger connection between capital and labor in the information sector in more recent data. Consider, for example, the estimates at the extremes of the data series. Using the data between 1939 to 1978 (40-year window) or to 1968 (30-year window), we obtained estimates of β of about 0.10, noting that the β estimate was statistically insignificant at the 5% level for the 30-year window. As we move to the latest sample period (1969 to 2008 for 40-year window, 1979 to 2008 for 30-year window), we obtain much larger estimates of around 0.43 for β. In light of these experiments, we recognize that there appears to be secular change, but we believe the results suggest smooth changes rather than a structural break and imply, if anything, a rising influence of investment on jobs. We believe this analysis justifies our original sample period that focuses more on recent data.

E. *Indirect Job Impacts*

By the nature of the data, the econometric analysis described above only describes the relationship between expenditures and employment in the information sector of the economy. However, it seems certain that expansion (contraction) in the information industries leads to employment (unemployment) in other sectors, including both directly related industries such as manufacturing and construction, and indirectly related industries that merely sell goods or services to employees. Using econometric methods to estimate these sorts of ancillary effects is very difficult, for many reasons. We can, however, offer some rather informal evidence on employment effects in other sectors, and we do so next.

1. *Econometric Analysis of Indirect Effects*

As stated above, given our underlying assumptions and approach, we cannot simply extend the VECM to all employment sectors. We can, however, selectively look at a few other industries with strong ties to telecommunications. For example, the BLS provides employment data on "Power and communication system construction (NAICS 23713)," though this series is available only since year 1990 (we label this jobs series as ΔJ^{PCSC}). Applying a simple VAR to the limited available data (17 periods), we find

$$\Delta J_t^{PCSC} = 0.04 - 0.35\Delta J_{t-1}^{PCSC} + 0.40\Delta E_{t-1} + e_t\,, \tag{16}$$

where the coefficient on ΔE_{t-1} is statistically significant at the 5% level (t = 3.2), indicating a causal connection between capital expenditures in the information sector and employment in the "power and communications system construction" sector (which is a component of the Construction Industry). Similarly, we can look at employment in "Communications Equipment

(NAICS 3342)," which again is limited to data from 1990 through 2009. The estimated relationship is

$$\Delta J_t^{CE} = 0.04 + 0.11\Delta J_{t-1}^{CE} + 0.31\Delta E_{t-1} + e_t \,, \tag{17}$$

where again the null hypothesis of "no Granger causality" between ΔE and ΔJ is rejected (asymptotically; the t-statistic is 1.92, Probability = 0.076). These simple regressions are suggestive of employment effects outside the industry, but we note that the data is very limited and this analysis should be viewed as highly speculative in nature. The validity of the asymptotic statistical tests are questionable in such small samples. As we observed with the information sector data, employment and capital expenditures have a long-run relationship and the econometric procedures should account for that fact. With such limited data, however, we do not apply the VECM to these series.

Moreover, we must emphasize that our approach is *not* a general equilibrium one. By looking at one, or a few, sectors in isolation, one cannot make economy-wide forecasts. Over time, many resources do become employed somewhere, so job losses in one sector presumably trigger employment reallocation into other sectors. However, this process is by no means instantaneous, and the current high rates of unemployment in the U.S. illustrate the practical difficulty such reallocations entail.

I. Other Considerations

A. Corroboration with Prior Studies

Part of the purpose of this study was to compare econometric estimates of employment effects with those calculated using multipliers from Input-Output models in a policy-relevant and topical way. The multipliers from a few of the more recent studies are summarized in Table 1. Consider, for example, the study by Davidson and Swanson (2010). While numerous scenarios are provided in that study, one such scenario estimates that 152,400 jobs would be lost per year (over the 2010-2015 period) as a result of a hypothetical $9.12 billion reduction in capital expenditures (implying a multiplier of 16.7, commensurate with the BEA Type II multiplier).[11] We choose this example because our multipliers vary by year and Davidson and Swanson (2010) provide a five-year average effect. Using the VECM to simulate the jobs reduction from the same hypothetical $9.12 billion shock, we estimate about 87,000 average annual job loss (over the five year period) for the information sector, implying a five-year average multiplier of 9.58.

Comparing these multipliers with those used in Davidson and Swanson (2010), we see that the information-sector specific multiplier is smaller (about 9.5), which is expected since it

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[11] Davidson and Swanson, *supra* n. 2 at 60.

measures only information-sector employment effects. It is possible to crudely estimate a more general employment effect using the multiplier approach of Bivens (2003), in which one job in the communications sector is "associated" with 2.52 jobs elsewhere in the economy. Given Bivens' (2003) estimate of 2.54 jobs per communications job, the total effect on employment from an investment shock is about 24 jobs per million dollars of investment. Comparing this value to those in Table 1, we see that the multipliers used in some recent studies are, if anything, conservative. We note, however, that this calculation depends on the accuracy and continued relevance of the values provided in Bivens (2003). Assuming Bivens (2003) overstates the multiplier by as much as 40%, our estimates still support a multiplier of about 16 jobs per million dollars in capital expenditure. Indeed, the employment "spillover" to other sectors needs only to be 0.6 jobs per information sector jobs for our estimated multiplier of 10 to get to the commonly-used multiplier of about 16. So, even if Bivens (2003) is extremely optimistic, the implied employment effects from our analysis will equal or exceed those from prior, multiplier-based studies. The implied multiplier from Bazelon (2010) is arguably the best comparison, since that study estimates the employment effect from the IO model rather than simply rely on published multiplier values. Bazelon's multiplier of 13.6 for all sectors is closer to our information-sector only multiplier of 10.

B. *Information Sector Jobs are Not Average Jobs*

In the typical study of employment effects, jobs are discussed without reference to the levels of income they offer to workers. In this regard, at least, information industry jobs are not typical. In the U.S., the average median weekly earnings for private industry generally are $753.[12] In the information sector, the average weekly median earnings are $1,073, and for Telecommunications that figure is $1,096. Thus the median weekly earnings of information sector employees are 42% higher than those of typical private sector workers. Earnings in the more narrow telecommunications sector are slightly higher still, being 45% above the typical private sector rate. Accounting for income differences, one telecommunications job lost is the equivalent of nearly 1.5 "average" jobs. Our analysis above suggests we should expect a change of 10 telecommunications jobs per million dollars in capital expenditures, but these jobs are equivalent, in income terms, to 15 average private sector jobs.

C. *Caveats*

There are a number of important caveats to work of this type, some of which we have mentioned above. First, while one is tempted to exploit the linkage between capital expenditure and job creation for public policy goals, such plans must be economically coherent. For example, we could perhaps increase employment in the telecommunications sector by prohibiting the use of the digital switch and returning to the days of operator-based switching, or we could forbid the use of heavy machinery to dig trenches, thereby creating many jobs for

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12 www.bls.gov; www.unionstats.gsu.edu.

shoveling dirt. Indeed, it is quite possible for regulation or legislation to promote inefficiently high levels of capital expenditures and/or employment, thus reducing overall welfare. Historically, rate-of-return regulation has been criticized for to its tendency to promote excess reliance on capital in production (Averch and Johnson 1962).

Furthermore, capital is portable, so a reduction in investment in one sector may simply shift much of that investment to another sector, presumably having employment impacts there as well. As a matter of policy, the relevant question may be the net effect of capital on employment, not just the partial effects in a single industry or sector. The communications sector is unique in many respects, including its role as a general purpose technology and its potential for significant spillovers. Thus, capital in the information sector may have a higher social payoff than capital in other sectors, but a simple jobs analysis fails to take this into account.

V. Conclusion

In this paper, we estimate the relationship between investment and employment in the information sector of the United States using time-series econometrics. This investment-employment relationship has figured prominently in some recent regulatory policy discussions, and a number of researchers have provided studies that critique regulatory initiatives at least partially from the point-of-view of their effects on employment. Further, these recent analyses have uniformly relied on multipliers "borrowed" from IO models, such as RIMS. It is therefore desirable to attempt some evaluation of the plausibility of the RIMS multipliers outside of the IO framework, and we do this in this paper.

Applying a VECM type estimation and calculating Impulse Response Functions for changes in capital investment, we are able to establish several useful results. First, our findings on the size of the employment multiplier, at least for the information sector, are broadly consistent with some of the values used in recent studies. We find a multiplier of about 10, i.e., a million dollar shock to investment creates about 10 permanent jobs. If one considers spillovers to other sectors, our results are mostly consistent with received practice. Second, our estimation provides evidence that investments "cause" jobs, and not the converse. Finally, we point out that information sector jobs are not typical, generally paying a large premium over average private sector jobs.

For policy purposes, our findings provide cautious support for previous claims as to the size and significance of the multiplier. On the other hand, this result does not, in itself, support policy interventions that increase capital spending. Rather, we offer a measurement of one likely consequence of such policies, and this finding must be combined with, and weighed against, the numerous other effects of regulatory intervention. Regulation has numerous effects, good and bad, of which changes in employment are only a part.

References

Averch, H. & Johnson, L. (1962). Behavior of the Firm Under Regulatory Constraint. *American Economic Review*, 52, 1052-70.

Baumol, William J. and E.N.Wolff, (1994). A Key Role for Input-Output Analysis in Policy Design, *Regional Science and Urban Economics*, 24, 93-113.

Bazelon, C. (2010). *The Employment and Economic Impacts of Network Neutrality Regulation: An Empirical Analysis*, Consulting Report by The Brattle Group (available at: http://mobfut.3cdn.net/8f96484e2f356e7751_f4m6bxvvg.pdf).

Bivens, J. (2003). *Updated Employment Multipliers for the U.S. Economy*, Economic Policy Institute Working Paper (available at: http://www.epi.org/page/-/old/workingpapers/epi_wp_268.pdf).

Carter, Anne P. and Peter A. Petri, (1989). Leontief's Contributions to Economics, *Journal of Policy Modeling*, 11, 7-30.

Choi, C., Hu, L. & Ogaki, M. (2008). Robust Estimation for Structural Spurious Regressions and a Hausman-type Cointegration Test. *Journal of Econometrics*, 142, 327-351.

Communications Workers of America (2009). *Proposals to Stimulate Broadband Investment* (available at: http://files.cwa-union.org/speedmatters/CWA_Proposals_Broadband_Investment_20081209.pdf).

Crandall, R., Jackson, C. & Singer, H. (2003). *The Effects of Ubiquitous Broadband Adoption on Investment, Jobs and the U.S. Economy*, Consulting Report by Criterion Economics, L.L.C.

Crandall, R. & Singer, H. (2010). *The Economic Impact of Broadband Investment*, Study Sponsored by Broadband for America (available at: http://www.broadbandforamerica.com/press-releases/broadband-america-study-shows-importance-investment-0).

Davidson C. & Swanson, B. (2010). *Net Neutrality, Investment & Jobs: Assessing the Potential Impacts of the FCC's Proposed Net Neutrality Rules on the Broadband Ecosystem*, Advanced Communications Law & Policy Institute, New York Law School (available at: http://www.nyls.edu/user_files/1/3/4/30/83/Davidson%20&%20Swanson%20-%20NN%20Economic%20Impact%20Paper%20-%20FINAL.pdf).

Ehrlich, E. (1997). *Regional Multipliers: A User Handbook for the Regional Input-Output Modeling System (RIMS II)*, U.S. Department of Commerce, Economics and Statistics Administration (available at: http://www.bea.gov/scb/pdf/regional/perinc/meth/rims2.pdf)

Eisenach, J. A, Singer, H. J., and West, J. D. (2009). Economic Effects of Tax Incentives for Broadband Infrastructure Deployment. Prepared on Behalf of the Fiber-to-the-Home Council (January 5, 2009).

Ekelund Jr., Robert B. and Hebert, Robert H. (2007). A History of Economic Thought and Method, Waveland Press: Long Grove, IL.

Engle, R. F. & Granger, C. W. J. (1987). Co-integration and Error Correction: Representation, Estimation, and Testing. *Econometrica*, 55, 251-276

Fjeldsted, Boyd L. (1990). Regional Input-Output Multipliers: Calculations, Meaning, Use and Misuse, *Utah Economic and Business Review*, 50, 1-20.

Kim, H. (2009). *Generalized Impulse Response Analysis: General or Extreme?* MUNICH PERSONAL REPEC ARCHIVE WORKING PAPER NO. 17014 (available at: http://mpra.ub.uni-muenchen.de/17014/1/gircheck09.pdf).

Park, J.Y. (1992). Canonical Cointegrating Regressions. *Econometrica*, 60, 119-143

Pesaran, H. & Shin, Y. (1998). Generalized Impulse Response Analysis in Linear Multivariate Models. *Economic Letters*, 58, 17-29

Phillips, P. (1991). Optimal Inference in Cointegrated Systems. *Econometrica*, 59, 283-306.

Rosen, H. S. and Mathur, V. K. (1973). An Econometric Technique Versus Traditional Techniques for Obtaining Regional Employment Multipliers: A Comparative Study. *Environment and Planning*, 5, 273-282.

Singer, H. J. and West, J. D., (2009). Economic Effects of Broadband Infrastructure Deployment and Tax Incentives for Broadband Employment. Prepared on Behalf of the Fiber-to-the-Home Council (March 2, 2010).

Stock, J. (1987). Asymptotic Properties of Least-Squares Estimators of Cointegrating Vectors. *Econometrica*, 55, 1035-1056 .

Stock, J. H. & Watson, M. W. (1993). A Simple Estimator of Cointegrating Vectors in Higher Order Integrated Systems. *Econometrica*, 61, 783-820.

Table 1. Multipliers from Recent Studies

Study	ΔE	ΔJ	m
Crandall … (2003)	$3.20B	58,043	18.1
CWA (2009)	$5.00B	97,500	19.5
Eisenach …(2009)	$3.00B	19,744	19.7
Bazelon (2010)	$20.2B	275,358	13.6
Crandall … (2010)	$30.4B	509,000	16.7
Davidson … (2010)	$6.08B	100,600	16.7
Singer and West (2010)	$2.72B	39,961	14.7

Notes: Bazelon based on 5-year average.

Table 2. Statistical Properties of the Data

Aug. Dickey-Fuller Tests.		PPI-Adjusted	
		ADFc	ADFτ
Investment	Level	-1.391	-3.124
	Differenced	-4.713*	-3.997*
Employment	Level	-1.512	-2.395
	Differenced	-3.434*	-3.490*
Cointegration Tests		Statistic	Cointegrated?
Engle-Granger Test		-4.077	Yes
Hausman-Type Test		1078.7	Yes
$H(p,q)$ Test	H(0,1)	0.0491	Yes
	H(1,2)	0.0134	Yes
	H(1,3)	2.5961	Yes

* Statistically significant at the 5% level.

Table 3. Speed of Convergence Estimates

	Estimates	*Standard Error*
E (ρ_1)	1.3320*	0.5465
J (ρ_2)	-0.1618	0.1493

Notes: (i) The point estimates for ρ and associated standard errors are reported; (ii) The superscript * denotes a rejection of the unit-root null hypothesis at the 5% significance level; (iii) Each estimate has a correct sign that implies that both *E* and *J* contribute to the adjustment process toward the long-run equilibrium. However, *E* plays more dominant role that that of *J*, because its speed of adjustment parameter is relatively bigger and significant at the 5% level.

Table 4. Cointegrating Vector Estimation Results

	Constant (*a*)	*CAPEX* (β)
SOLS	9.9407 (0.1867)	0.4271 (0.0165)
DOLS	9.8282 (0.0279)	0.4379 (0.0279)
CCR	9.6854 (0.1437)	0.4497 (0.0127)

Notes: (i) SOLS denotes a static ordinary least squares estimator; (ii) DOLS is the dynamic ordinary least square estimator proposed by Stock and Watson (1993); (iii) CCR is Park's (1992) canonical cointegrating regression estimator; (iv) The quadratic spectral kernel with automatic bandwidth selection was used to obtain the long-run variance matrix; (v) Standard errors are reported in parentheses. All variables are significant at the 5% level.

Table 5. Annual Real Investment Change (ΔE)
(Million of 2009 Dollars)

Shock Size	1 Year	5 Year	10 Year	20 Year	30 Year
1%	1,109	1,205	1,394	1,646	1,991
5%	5,438	5,903	6,822	8,059	9,747
10%	10,610	11,505	13,281	15,700	18,987
15%	15,531	16,822	19,396	22,943	27,747
20%	20,211	21,868	25,186	29,810	36,051
30%	28,898	31,203	35,859	42,492	51,388

Table 6. Annual Employment Change from Shocks (ΔJ)
(Information Sector Jobs Only)

Shock Size	1 Year	5 Year	10 Year	20 Year	30 Year
1%	6,312	16,059	15,242	16,671	18,152
5%	31,425	79,457	75,487	82,559	89,894
10%	62,518	156,850	149,192	163,159	177,657
15%	93,284	232,232	221,155	241,847	263,338
20%	123,726	305,655	291,419	318,669	346,988
30%	183,652	446,828	427,006	466,888	508,384

Table 7. Annual Employment Multipliers
(Information Jobs Only)

Shock Size	1 Year	2 Year	3 Year	4 Year	5 Year	10 Year	20 Year	30 Year
1%	5.7	7.2	9.4	11.7	13.3	10.9	10.1	9.1
5%	5.8	7.3	9.5	11.9	13.5	11.1	10.2	9.2
10%	5.9	7.5	9.8	12.1	13.6	11.2	10.4	9.4
15%	6.0	7.7	10.0	12.3	13.8	11.4	10.5	9.5
20%	6.1	7.9	10.2	12.5	14.0	11.6	10.7	9.6
30%	6.4	8.3	10.7	12.9	14.3	11.9	11.0	9.9

Figure 1. Estimate of β in 30-year Rolling Regressions

Appendix: Annual Employment Change from Shocks

Year	Forecast	Reduction in Jobs from Forecast Trend			
		ΔE = -5%	ΔE = -10%	ΔE = -20%	ΔE = -30%
1	2,984,000	-31,425	-62,518	-123,726	-183,652
2	3,002,790	-57,478	-113,855	-223,394	-328,779
3	3,019,456	-75,094	-148,321	-289,357	-423,464
4	3,036,641	-81,296	-160,416	-312,357	-456,272
5	3,058,074	-79,457	-156,850	-305,655	-446,828
6	3,083,980	-75,170	-148,509	-289,866	-424,416
7	3,112,322	-72,367	-143,051	-279,528	-409,731
8	3,140,963	-72,140	-142,623	-278,771	-408,736
9	3,168,839	-73,628	-145,545	-284,404	-416,886
10	3,195,978	-75,487	-149,192	-291,419	-427,006
11	3,222,916	-76,873	-151,913	-296,665	-434,595
12	3,250,150	-77,637	-153,419	-299,597	-438,874
13	3,277,885	-78,046	-154,233	-301,209	-441,270
14	3,306,081	-78,423	-154,985	-302,705	-443,500
15	3,334,600	-78,944	-156,020	-304,739	-446,501
16	3,363,331	-79,620	-157,356	-307,349	-450,326
17	3,392,241	-80,375	-158,847	-310,255	-454,573
18	3,421,350	-81,134	-160,344	-313,173	-458,840
19	3,450,695	-81,860	-161,779	-315,973	-462,939
20	3,480,304	-82,559	-163,159	-318,669	-466,888
21	3,510,183	-83,249	-164,523	-321,335	-470,796
22	3,540,330	-83,948	-165,905	-324,036	-474,756
23	3,570,737	-84,663	-167,319	-326,798	-478,804
24	3,601,403	-85,393	-168,760	-329,613	-482,927
25	3,632,327	-86,131	-170,219	-332,461	-487,100
26	3,663,515	-86,874	-171,687	-335,328	-491,300
27	3,694,970	-87,620	-173,163	-338,211	-495,524
28	3,726,696	-88,372	-174,648	-341,112	-499,775
29	3,758,696	-89,130	-176,146	-344,037	-504,060
30	3,790,971	-89,894	-177,657	-346,988	-508,384