EVALUATING THE IMPACT OF MEP SERVICES ON ESTABLISHMENT PERFORMANCE:

A PRELIMINARY EMPIRICAL INVESTIGATION

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Abstract

This work examines the impact of manufacturing extension services on establishment productivity. It builds on an earlier study conducted by Jarmin in the 1990s, by matching the Census of Manufacturers (CMF) with the Manufacturing Extension Partnership (MEP) customer and activity datasets to generate treatment and comparison groups for analysis. The scope of the study is the period 1997 to 2002, which was a period of economic downturn in the manufacturing sector and budgetary challenges for the MEP. The paper presents some preliminary findings from this analysis. Both lagged dependent variable (LDV) and difference in difference (DiD) models are employed to estimate the relationship between manufacturing extension and labor productivity. The results presented are inconclusive and paint a mixed picture as they demonstrate the benefits and limitations of using Census microdata in program evaluation. They also point to the need to conduct analyses that could help to better understand the dynamic impact of MEP services.

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1. Introduction

The aim of this paper is to examine the productivity growth of manufacturers assisted through the Manufacturing Extension Partnership (MEP), which is administered by the National Institute of Standards and Technology, with a comparison group of unassisted manufacturers in the 1997-2002 time period. The paper seeks to replicate a study conducted by Jarmin (1999) of MEP assisted and unassisted manufacturers in the 1987-1992 time period, which was before the MEP was fully established as a national program. The paper summarizes work to replicate the Jarmin study by using updated MEP customer and project information, more recent data from the Census of Manufacturers, a similar modeling approach, and an extension of the analysis to entire United States. The paper summarizes the methods, data sources, and results of this work.

2. Prior Research: the Jarmin study

Jarmin's 1999 study represented a special analysis for the MEP to understand the effect of services on productivity growth of assisted firms. His work identified MEP assisted manufacturers in the Longitudinal Research Database (LRD) which contains results from prior Census of Manufacturers, enabling him to construct "treatment" and "comparison groups." These firms were assessed in terms of productivity growth, specifically labor productivity (value-added per employee). The manufacturers were from eight manufacturing assistance centers in Pennsylvania and Ohio. Jarmin's study also controlled for selection bias, or the tendency of manufacturers with a distinctive profile (for example, those having high levels of productivity prior to being assisted) to self-select into the MEP program.

Jarmin calculated the effect of MEP services on productivity growth. He concluded that "participation in manufacturing extension is associated with between 3.4 and 16 percent higher labor productivity between 1987 and 1992."[1] Jarmin again used OLS and two-stage models to estimate this impact. Using simple OLS, Jarmin estimated that clients receiving MEP services increased productivity by about 3 percent, results that were significant at the 5 percent level. Jarmin used a two stage model to control for selection bias, with the model using location within a metropolitan statistical area with an MEP center as an instrument to proxy the likelihood that a manufacturer would be assisted by an MEP center. Jarmin estimated that the impact of MEP services on productivity growth ranged from 7 percent to 16 percent. Since Jarmin's estimates from both the simple OLS and two-stage models were positive and significant, he concluded that having received MEP services between 1987 and 1992 was associated with an increase in productivity of between 3 and 16 percent. This finding demonstrates that the MEP does have a significant positive effect on increasing labor productivity of assisted manufacturers.

This study is to replicate and expand on Jarmin's analyses using more recent data at the national level. The results are presented for the model as a whole, as Jarmin did, using an OLS approach. In addition, a parallel analysis involving a lagged dependent variable is provided. The outcome of efforts to control for selection bias by using the same instrument as Jarmin did, as well as trying other instruments, is presented; in addition, the analysis presents the results of propensity score matching findings as an

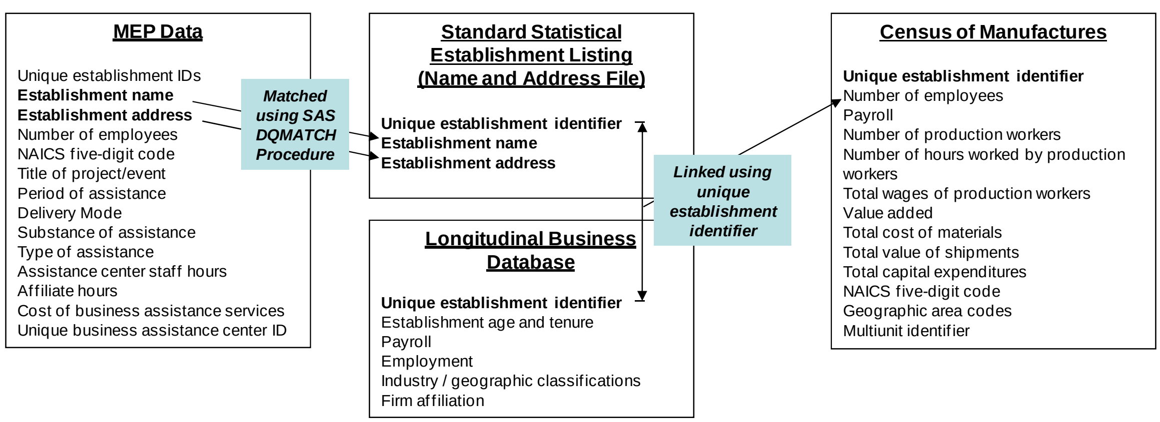
[1] Jarmin (1999), p.99

alternative method of addressing selection bias. Results broken down by company size are also presented.

3. Method

3.1. Data. To estimate the impact of the NIST MEP program, we linked the four datasets shown in Figure 1. Each dataset contains records at the establishment level. The first dataset, derived from data provided by NIST MEP, includes all MEP clients receiving services between 1999 and 2002 and a fraction of clients receiving services in 1997 and 1998 due to the fact that MEP did not have comprehensive data prior to 1999, the year in which centers began reporting directly to NIST MEP. The data includes data on the levels and types of services received as well as establishment names and addresses used to link this data to the Standard Statistical Establishment Listing (SSEL) and thereby to other Census datasets. The SSEL is a comprehensive list of business establishment names and addresses that is used as the sampling frame for Census Bureau surveys. After matching MEP data to the SSEL, we linked the matched dataset to the Longitudinal Business Database (LBD) which contains establishment identifiers that are unique over time. This allowed us to link an establishment existing in 1997 with the same establishment existing in 2002. Finally, we linked the combined dataset to the Census of Manufactures (CMF) from 1997 and 2002 using a unique establishment identifier. The CMF contains key outcome measures such as value added, output, and employment. The following sub-sections discuss each of these datasets in more detail.

Figure 1: Data Linkages



NIST provided us with three databases: one with MEP client engagements occurring between 1997 and 2002, another with demographic information for each client, and a final one with MEP center characteristics. While complete data on MEP engagements only dates back to 1999, we include all data available on MEP engagements between 1997 and 2002 in our analyses to ensure we capture as many MEP clients as possible. There were about 47,000 engagements in the MEP database which were delivered to about 20,000 unique establishments between 1997 and 2002[2]. We cleaned and linked the

[2] The 20,000 figure cannot be accurately divided by five to get a per year estimate of the number of manufacturers served. Customer information from 1997 and 1998 is less prevalent because mandatory reporting was not in place

MEP project, client, and center data to ensure that we had a valid entry for each unique MEP client during this time period. A finalized dataset of MEP clients with aggregated levels of MEP services by client was submitted to the Census Bureau's Research Data Center (RDC) in Suitland, MD.

Census Data and Matching. We utilized three datasets available at the Census Bureau's RDC. Each of these datasets contains confidential micro data and is only accessible by researchers who have been granted Special Sworn Status. To access this data, the project team had to submit a proposal outlining the research design and the benefits of this work to the Census Bureau. The three datasets used in our analysis are the SSEL, the LBD, and the CMF.

We began by linking the MEP client data to the SSEL. The SSEL (now referred to as the business register) contains a listing of all known establishments in a given year in the United States.[3] This list serves as the sampling frame for many Census surveys and is available annually from 1974 through 2007. The SSEL contains the name of each establishment, its address (in a given year), and a unique identifier that allows linking of establishments in the SSEL to the LBD in each year. Using a combinatorial matching approach, we matched 70 percent of MEP clients to establishments in the SSEL. We used the SAS DQMATCH procedure to match on combinations of name and address fields available in both the MEP data and the SSEL. SAS DQMATCH is a fuzzy matching procedure that allows for minor variations in names and addresses among matches. We explored many different combinations of fields and matching sensitivity levels before deciding on an optimal approach. Our final approach included performing matches at two sensitivity levels using the same sets of fields and then examining the difference in matches by hand. This allowed us to appropriately balance the match rate and the false positive rate.

After matching the MEP data to the SSEL, we linked the SSEL with the LBD using a unique identifier available in both datasets. The LBD includes nearly all non-farm private establishments existing in the United States in each year with a unique identifier linking them across time.[4] The LBD also includes industry, employment, and payroll data as well as ownership status and the years in which the establishment is first and last observed in the data.

Lastly, we linked the combined dataset to the CMF using a unique identifier that follows each establishment over time. The CMF contains records for nearly all manufacturers existing in economic census years (those ending with a 2 or a 7). The CMF includes key outcome and control variables for use in our analyses such as value added, sales, employment, and capital stock. Linking to the CMF limits our population to only manufacturers, the target of MEP services.

The final dataset linking MEP, SSEL, LBD, and CMF data was cleaned to match the establishments analyzed in official CMF tabulations from the years 1997 and 2002. This was primarily done by removing establishments that had zero payroll. The final dataset used in most of the analyses in this study was further limited to only establishments that existed in both 1997 and 2002. After matching the NIST MEP

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in those years. Thus reporting that the number of assisted firms is 5000 a year underestimates the counts because there are fewer assisted firms in the earlier years and more in the later years.

[3] http://www.census.gov/econ/overview/mu0600.html

[4] Jarmin and Miranda (2002)

client data to the CMF, our dataset contained 7,737 MEP client and 223,520 non-clients that existed in both 1997 and 2002.

3.2. Treatment measure. The MEP data contains information on the level and type of assistance for all establishments receiving assistance between 1999 and 2002 and a subset of establishments in 1997 and 1998. Our core analyses look at the impact of being a MEP client on productivity. This is modeled as a binary variable (Ext) for which a value of 1 indicates an establishment received MEP services between 1997 and 2002 and 0 indicates it did not.[5]

3.3. Models. The models estimated in this study are based on an augmented Cobb-Douglas production function depicted below where Y is output, K is physical capital, L is the number of production workers, and Ext is a measure of MEP services.[6] We have measures of these variables for each establishment (i) in a given year (t).

$$Y_{it} = Ae^{\delta Ext_{it}} K_{it}^{\beta} L_{it}^{\eta} e^{\varepsilon_{it}}$$

The main focus of this paper is on the impact of MEP services on productivity. Productivity is the relationship between inputs and outputs. An establishment that produces more output with fewer inputs is said to be more productive. In this study, as in previous studies of MEP, we utilize single-factor labor productivity as our key outcome measure. Also consistent with previous studies, we measure productivity as value added per production worker.[7] Both value added and the average number of production workers in a given year are directly available in the CMF. We chose to use the number of production workers as our measure of labor because this was the standard used in previous studies.[8] Future work might explore MEP impact on value added per employee, as some MEP services are thought to have benefits away from the factory floor.

We model productivity by dividing the Cobb-Douglas production function above by the number of production workers (L) and taking the natural logarithm. This results in the linear equation below which can be estimated via ordinary least squares (OLS). The dependent variable in this equation is the log of productivity. The impact of MEP services is captured by the parameter δ, which measures the percentage difference in productivity between those establishments that received services and those that did not after controlling for other factors included in the model.

$$\log\left(\frac{Y_{it}}{L_{it}}\right) = \alpha + \delta Ext_{it} + \beta \log\left(\frac{K_{it}}{L_{it}}\right) + (\mu - 1)\log(L_{it}) + \varepsilon_{it}$$

[5] A range of other treatment measures such as level of treatment, periods of treatment, and types of treatment were also implemented and sent to the sponsor in a separate technical report.

[6] This model is based on the work of Solow (1957) and the augmentation of this function by Griliches (1996) with the stock of research expenditures accumulated by the establishment.

[7] Productivity can also be measured as gross output per worker.

[8] Jarmin (1999)

We begin with two OLS models which are popular in the analysis of panel data: difference in difference (DiD) and lagged dependent variable (LDV).[9] These two approaches take advantage of the fact that we have repeated observations for the same establishment (panel data), which allows us to control for some unobserved factors. Other (cross-sectional approaches) would require that we include controls for all relevant factors that affect productivity since they cannot control for any unobserved factors. Controlling for unobserved factors is important in order to reduce bias due to selection.

As this study aims to replicate some of the analyses in Jarmin (1999), we begin by estimating a DiD model.[10] This model controls for all time-invariant characteristics of each establishment. This includes both observable factors such as industry and location and unobservable factors such as management ability.[11] The equation for the DiD model estimating the impact of MEP services is shown below.

Difference in Difference (DiD) Model:

$$\Delta\log\left(\frac{Y_{it}}{L_{it}}\right)=\Delta\lambda_t+\delta\Delta Ext_{it}+\beta\Delta\log\left(\frac{K_{it}}{L_{it}}\right)+(\mu-1)\Delta\log(L_{it})+\Delta\varepsilon_{it}$$

The DiD model can only control for time-invariant establishment characteristics. It cannot account for baseline differences in productivity between the treatment and control group (beyond those explained by time invariant characteristics), nor can it control for the possibility that the outcome variable is correlated over time. For instance, if productivity is considered as a stock of organizational knowledge, it will be correlated across time.[12] The common alternative to DiD is to include a lag of the dependent variable on the right-hand side of a model as shown in the equation below.[13]

Lagged Dependent Variable (LDV) Model:

$$\log\left(\frac{Y_{it}}{L_{it}}\right)=\alpha+\delta Ext_{it}+\beta\log\left(\frac{K_{it}}{L_{it}}\right)+(\mu-1)\log(L_{it})+\theta\log\left(\frac{Y_{it-1}}{L_{it-1}}\right)+\varepsilon_{it}$$

As discussed in Angrist and Pischke (2009), ideally, we would like to estimate a fixed effects model with a lag term.[14] However, without stronger assumptions and more data,[15] such a combined model leads to inconsistent estimates.[16] Overall, we chose to estimate both the DiD and LDV models separately because

[9] Also referred to as the change score (DiD) and regressor variable method (lag). See Allison (1990)
[10] This is equivalent to a fixed effects model with time controls.
[11] Mundlak (1961)
[12] Allison (1990), p. 107
[13] Angrist and Pischke (2009), pg. 243 and Imbens and Wooldridge (2009), pg. 68
[14] Angrist and Pischke (2009), p. 245
[15] To estimate a model with both differences and a lag, one must have data from more than two time periods and assume that error terms are only correlated across adjacent time periods.
[16] Angrist and Pischke (2009), p.245

each makes different fundamental assumptions that should be considered in interpreting the results. In addition, these two models can be used to bound the impact estimate.[17]

3.4. Selection bias. These models cannot control for all unobservable factors, therefore we also attempt to estimate additional models. These include two-stage models and non-parametric matching models that can reduce bias due to unobserved characteristics and structural assumptions.

A two-stage selection model includes two regression equations to be estimated in sequence. The first stage estimates the probability of being an MEP client (selection equation) and a second stage estimates the impact of receiving MEP services on the outcome of interest (outcome equation). All selection models require that at least one variable included in the selection equation be excluded from the outcome equation. Excluded variables are called instruments. To be a valid instrument, a variable must be strongly correlated with the selection variable (being a MEP client) and must not be correlated with the residuals of the outcome equation (productivity). Jarmin (1999) used whether an establishment was located in a Metropolitan Statistical Area (MSA) with a MEP center as an instrument. Oldsman (1996) attempted to use distance from each establishment to the closest MEP office as an instrument. We attempt to use both of these instruments individually and together. We estimate four different selection models using these instruments including: Heckman's two-stage treatment effects model,[18] an instrumental variables (IV) model,[19] a mixture of the two,[20] and variations of Heckman's approach used in Jarmin (1999).[21] If the models are correctly specified then all of these approaches should yield similar results.

Some of the differences between the DiD and LDV models discussed in the previous subsection are the result of parametric assumptions underlying each model. One way to remove these assumptions is to use a non-parametric estimation approach. The most common of these approaches is propensity score matching. This method involves two stages: (1) estimating the likelihood of each establishment in the dataset being a MEP client (the propensity score) and (2) matching like establishments on the propensity score and calculating the difference in the outcome variable among matches. In order to properly estimate a propensity score model, one must stratify the sample into propensity score blocks and test that each covariate is balanced (no significant difference in means) within the blocks. Only when the balancing property is met is it appropriate to estimate the average difference in outcomes.

4. Results

4.1. Descriptive information. The analysis begins with a simple descriptive comparison of the characteristics of MEP clients and non-clients, before controlling for other factors. Table 1 shows that MEP participants are larger in size, more productive, more capital-intensive, and experience smaller reductions in employment and larger gains in output. This work takes these characteristics into account through the use of separate analyses for small and large employees.

[17] Angrist and Pischke (2009), p.246-247
[18] Heckman (1976)
[19] Angrist and Krueger (2001)
[20] Wooldridge (2002)
[21] Based on Maddala (1983).

Table 1: MEP Client/Non-Client Employment Comparisons

Variable	**Client Median**	**Non-Client Median**
Number of Plants	7,737	223,520
Total Employment		
1997	63	12
2002	61	11
% Change	*-3%*	*-9%*
Production Workers		
1997	43	8
2002	40	7
% Change	*-7%*	*-13%*
Value Added Per Establishment ($2002[22])		
1997	3,980,062	625,035
2002	4,341,000	668,000
% Change	*+9%*	*+7%*
Value Added Per Production Worker ($2002)		
1997	93,559	73,971
2002	107,333	93,250
% Change	*+14%*	*+23%*
MEP Client/Non-Client Capital Intensity Comparisons ($2002)		
1997	57,824	41,780
2002	79,500	58,214
% Change	32%	33%

[22] Value added and sales from 1997 are adjusted to 2002 dollars using BEA price deflators for manufacturing and trade sales.

4.2. Regression models. This section presents preliminary estimates of the impact of MEP services on establishments using both a difference in difference (DiD) and lagged dependent variable (LDV) model. Table 2 shows estimates for MEP impact from both models. The DiD results suggest that having received MEP services between 1997 and 2002 is associated with 6 percent lower productivity growth compared to non-clients, a result that is statistically significant at the 5 percent level.[23] This result contrasts with Jarmin (1999)'s finding of a positive and significant effect estimated using the same DiD model.[24] While the DiD model is able to control for time-invariant establishment characteristics, it cannot account for differences in initial productivity (beyond those captured by time-invariant characteristics) or for the fact that productivity at an establishment is likely correlated across time. In addition, the DiD model cannot address instances in which MEP assistance was provided to comparison group establishments before 1997; pre-base year service was less of an issue in Jarmin's study where the system was in nascent development and broad-based service reach less likely. The LDV model addresses some of these issues in that it can account for baseline differences in productivity between the treatment and control group. The LDV model suggests that having received MEP services between 1997 and 2002 is associated with 2 percent higher productivity growth compared to non-clients, a result that is significant at the 5 percent level. The goodness of fit for the LDV model is significantly higher than that for the DiD model, likely due to the high correlation between productivity across time periods.

Results of LDV model are very similar when including controls for: age, multi-unit status, metropolitan location, and state and 2-digit industry fixed effects or excluding all covariates except MEP treatment. Exogeneity of the independent variables in the LDV model was tested by looking at correlations between the lag variable and the other covariates. Based on the low to moderate correlations between these variables, we made a preliminary determination that this model is appropriate.

The two OLS models estimated in this section produced results that are inconsistent. One model estimates a negative and significant impact of MEP services while the other estimates a positive and significant impact. As previously indicated, the two models have different assumptions underlying them; Did controls for all time-invariant characteristics of each establishment such as industry and location and unobservable factors such as management ability, whereas LDV accounts for baseline differences in productivity between the treatment and control group (beyond those explained by time invariant characteristics), and for the possibility that the outcome variable is correlated over time. The results from these two models can be used to bind the impact estimate.[25] In the case where the treatment group (clients) have higher initial levels of the outcome variable, the did model provides a lower bound while the LDV model provides an upper bound. We present preliminary results from both the DiD and LDV models because there can be debate as to which one is the "correct" model. The results should be considered carefully along with the assumptions made in each of these models. Lastly, while the data

[23] Throughout this paper, the numbers in brackets are absolute t-statistics and statistical significance is indicated by the number of stars indicating significance at the 0.1 (*), 0.05 (**), and 0.01 (***) levels respectively.

[24] Although full knowledge of the differences between the Jarmin and this analysis is not available, the authors hypothesize that the economic downturn and national expansion of the program are part of the explanation.

[25] Angrist and Pischke (2009), p. 246-247

contain a significant number of outliers, we explored the sensitivity of our results to the inclusion of these outliers and found their effect to be minimal.[26]

Table 2: Estimated Impact of MEP Programs on Production Worker Labor Productivity

Variable	**DiD**	**LDV**
Constant	0.075*** [46.70]	1.93*** [206.75]
Impact of Receiving MEP Services on Productivity	**-0.058*** [7.27]**	**0.017** [2.42]**
Log of Capital Intensity	0.21*** [94.89]	0.31*** [147.73]
Log of Number of Production Workers	-0.26*** [92.99]	-0.018*** [21.16]
Log of Productivity in the Previous Period		0.33*** [128.59]
Number of Cases	217,330	217,330
R-Squared	0.1996	0.4518

Note: Labor productivity is measured as value added per production worker (VA/PW)

The two models do demonstrate convergence when results are broken down by establishment size. MEP impact is largest for small establishments, especially those under 50 employees[27]. This finding suggests that MEP services have a particularly strong effect for manufacturing facilities in this size class. In both models, the impact of MEP services on establishments with 0-10 employees is about five percent. (See Table 3.) The impact on establishments with 10-19 employees is also around five percent. Both of these results are statistically significant at the 5 percent level. The impact decreases for establishments with 20-49 employees to a positive one percent in the DiD model and a positive three percent in the LDV model. This result is positive but not statistically significant in the DiD model although remains significant in the LDV model at the 5 percent level. This difference between the two models again reflects the difference in these models' assumptions. For establishments with greater than 50 employees, the MEP impact becomes insignificant from zero in both models.

[26] Outliers were removed in increments from the high and low end of the outcome distribution. With 1-10 percent of the data on each end of the distribution removed, the estimates of MEP impact changed minimally.
[27] Small firm results are more likely to be imputed and therefore have less variability, which could be a factor in the outcome of the model. See White et al (2012).

Table 3: Estimated Impact of MEP Services on Production Worker Labor Productivity, by Establishment Size

Number of Employees	**DiD**	**LDV**
1-10	0.05* [1.91]	0.06*** [2.84]
10-19	0.049** [2.12]	0.047** [2.41]
20-49	0.013 [0.87]	0.03** [2.31]
50-99	-0.002 [0.12]	-0.01 [0.75]
100-249	0.006 [0.36]	-0.013 [0.89]
250-499	0.03 [1.03]	0.01 [0.36]
500-999	-0.06 [1.18]	-0.07 [1.60]
1000-2499	0.01 [0.11]	-0.02 [0.28]
2500+	0.28* [1.72]	0.049 [0.27]

Note: Shading Indicates Significance at the 5 percent level

4.3. Selection bias. While the DiD and LDV models can control for selection bias to some extent, neither model is able to eliminate bias completely. Therefore, we attempted to estimate additional models that have the potential to reduce bias. In this section we discuss our attempts to estimate two types of models: two-stage selection models and propensity score models.

First, we estimated two-stage selection models using two instruments: (1) whether an establishment is in a MSA with a MEP center and (2) the distance from an establishment to the closest MEP center. Table

4 shows the mean differences between clients and non-clients for these two potential instruments. We can see that MEP clients are less likely to be located in a MSA with a MEP office. This is the opposite result found by Jarmin (1999). However, Jarmin's analysis took place before the full MEP system was created in a time period when proximity to a MEP office likely had a greater impact on whether an establishment received services than it does today. We also find that there is no significant difference in the average distance from the closest MEP office between clients and non-clients which is consistent with findings in Oldsman (1996).

Table 4. MEP Client/Non-client Potential Instrument Means Comparisons

Variable	Client Mean	Non-client Mean
Located in a MSA with a MEP Office	58%	65%
Distance from Closest MEP Office (miles)	24	24

Table 5 shows our estimation results for three different probit models. Model (1) includes the log of the distance to the closest MEP office as an instrument. Model (2) includes whether an establishment was in a MSA with a MEP center as an instrument. Model (3) includes both instruments together.

The results from all three models indicate that larger, single-unit establishments, located outside of MSAs, with greater baseline productivity and capital intensity and larger changes in capital intensity and employment during the treatment period are more likely to be MEP clients. These findings suggest that as with many programs, certain kinds of companies self-select into it, indicating the need to consider selection bias in econometric models. The direction of each of these effects, except that for baseline productivity, is consistent with findings in Jarmin (1999) though the magnitudes are much smaller. The low values of the parameters in these models reflect that the actual effect of each of these variables is small and the differences between clients and non-clients as measured by the combination of these variables are practically insignificant. The only coefficients we find with magnitudes larger than 0.1 are on the size group dummy variables for all groups with more than 50 employees. This indicates that the size of an establishment is the only observable practically significant determinant of client selection.

We find that our proposed instruments, both individually and in combination, are too weak to be used in the estimation of a two-stage model. Neither the log of distance to the closest MEP center or being located in a MSA with a MEP center are individually statistically significant in the selection equations. This finding reflects the expansion of the MEP into a national program such that availability to assistance in period of this study is much greater than it was in the time of Jarmin's study. We do find that using both instruments together leads both to be statistically significant at the 5 percent level. However, each instrument has a t-statistic around 2, much lower than desired to estimate a two-stage model. In addition, when we use any of these models as the first stage in any of the two-stage estimation approaches, we obtain inconsistent and unrealistic estimates. Therefore, we do not report the results from the second-stage of the models.

Table 5: Estimated Impact of Establishment Characteristics (Including Instruments) on the Probability to Participate in MEP Programs

Variable	(1)	(2)	(3)
Change in Capital Intensity 1997-2002	0.003*** [10.08]	0.003*** [10.14]	0.003*** [10.10]
Change in Number of Production Workers 1997-2002	0.007*** [16.57]	0.007*** [16.60]	0.007*** [16.57]
Age	-0.00004 [1.05]	-0.00004 [1.06]	-0.00004 [1.05]
Multi-unit	-0.011*** [17.12]	-0.011*** [17.09]	-0.011*** [17.13]
Metro	-0.013*** [16.90]	-0.014*** [13.51]	-0.015*** [13.65]
Instrument = log(distance)	**0.0002** **[1.36]**		**0.0004**** **[2.05]**
Instrument = center		**0.001** **[1.27]**	**0.002**** **[1.99]**
Log of Productivity in 1997	0.0008* [1.89]	0.0008* [1.83]	0.0008* [1.91]
Log of Capital Intensity in 1997	0.003*** [8.59]	0.003*** [8.70]	0.003*** [8.60]
Size Dummies	YES	YES	YES
Number of Cases	216,971	216,971	216,971
Pseudo R-Squared	0.1219	0.1219	0.1219

We also attempted to use propensity score matching to estimate the impact of MEP services. However, we were unable to achieve balance among covariates using a variety of pretreatment variables and the methodology described in Becker and Ichino (2002). We found that multi-unit status rarely balances across all propensity score strata while age, metro, and baseline productivity and labor generally do not balance in the low and high ends of the propensity score distribution. Since we could not achieve balance with our parsimonious models, we added higher-order terms and interaction terms as suggested in Dehejia and Wahba (2002). However, even models containing many higher-order and interaction terms were unable to achieve balance. Since we could not meet the balancing criteria that is key to performing the matching process, we did not pursue this methodology further to calculate the average treatment effect.

5. Summary

This work has explored the impact of manufacturing extension services on establishment productivity by matching the Census and MEP customer data over the 1997 to 2002 period. Lagged dependent variable and DiD models were employed to estimate the relationship between manufacturing extension and labor productivity. The results presented are inconclusive and paint a mixed picture, with the two models differing in magnitude and sign. The exception to this divergence is the analysis by establishment size, in which both models showed positive and significant effects at the smaller establishment end. In addition, we were unable to estimate selection models or perform non-parametric matching that would have allowed us to relax some of the assumptions underlying the DiD and LDV models.

The results of this study point in a number of different directions for further research. One obvious direction is to add data from the 2007 Census of Manufactures. The analyses in this study were performed using data from 1997 to 2002 because that was the most recent Census data available at the time this work is done. Updating this analysis with the 2007 Census of Manufactures is important as the results would both be more relevant to today's policy discussions and would allow assessment of the overall robustness of the preliminary results in this study. The framework for such an analysis is already in place, and NIST administrative data from the time period 2002 through 2007 is more comprehensive. Such data would need to be compiled, cleaned, and linked to the Census datasets using the methodologies established during this study.

This research does not examine the effect of MEP services on establishment survival, an outcome that is of ultimate importance since staying in business is a significant signal of "economic competitiveness."[28] Like productivity, this outcome measure avoids issues of substitution across establishments encountered when comparing output and employment. Estimating the impact of MEP services on survival can be carried out with the datasets created in this study without the need for any new data. We have a dataset containing all manufacturers existing in either 1997 or 2002 and the LBD provides us with a valid estimate of when an establishment ceases to exist permanently. Rigorous methods exist for estimating survival models that can be directly applied to this data. Such an analysis has not been undertaken previously and would add significant value to the breadth of evaluation of MEP impacts.

[28] NIST (2008)

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