Research and Practice

Evaluating the Impact of Manufacturing Extension Services on Establishment Performance

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Abstract

This study examines the effects of receipt of business assistance services from the Manufacturing Extension Partnership (MEP) on manufacturing establishment performance. The results generally indicate that MEP services have had positive and significant impacts on establishment productivity and sales per worker for the 2002 to 2007 period with some exceptions based on employment size, industry, and type of service provided. MEP services have also increased the probability of establishment survival for the 1997 to 2007 period. Regardless of econometric model specification, MEP clients with 1 to 19 employees have statistically significant and higher levels of labor productivity growth. The authors also observed significant productivity differences associated with MEP services by broad sector, with higher impacts over the 2002 to 2007 period in the durable goods manufacturing sector. The study further finds that establishments receiving MEP assistance are more likely to survive than those that do not receive MEP assistance.

Introduction

This study examines the effects of receipt of business assistance services from the Manufacturing Extension Partnership (MEP) on manufacturing establishment performance. The study seeks to advance previous work on the effect of manufacturing extension services on establishment productivity. Examining the determinants of manufacturing establishment performance is important because U.S. industry continues to face challenges due to the increasingly competitive global business environment. Previous work on manufacturing establishment productivity has examined an array of factors, including plant ownership change, technology adoption, and deregulation. This study adds consideration of business assistance services as a potential productivity determinant, specifically services of the MEP program, which is administered by the National Institute of Standards and Technology (NIST). These business assistance services are delivered at the establishment level. To gauge the effects of such services, the measurement of productivity effects must take place at the establishment level; however, publicly available establishment-level productivity information is not accessible. Therefore, this work assesses the performance of MEP-assisted manufacturing establishments by linking establishment-level MEP data on business assistance recipients to establishment-level data from the U.S. Census Bureau.

The methodology used in this study draws on two prior studies that examined the effect of the MEP program on manufacturing establishment performance. The first study, by Jarmin (1999), was conducted on manufacturing performance data for the 1987 to 1992 period. This period was prior to the full rollout of the MEP program in 1999. The second study was performed by a team from SRI International and the Georgia Institute of Technology on manufacturing performance data covering the 1997 to 2002 period (Ordowich, Cheney, Youtie, Fernandez-Ribas, & Shapira, 2012). Both studies assessed the impact of MEP services on manufacturing productivity, sales, and employment growth.

This study extends this body of economic development evaluation studies by using a novel fuzzy logic matching program to confirm that MEP data and census data are linked to the correct establishment and by updating the analysis

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with data from the 2002 to 2007 period. In addition, we also analyze establishment survival by testing the ability of establishments to maintain operations from an earlier to a later period. Generally, we find that MEP services had a statistically significant and positive impact on establishment productivity and sales per worker for the 2002 to 2007 period, with some exceptions. Specifically, we find that (a) smaller establishments receiving MEP services experience statistically significant and positive labor productivity growth across several econometric specifications; (b) durable goods manufacturing establishments receiving MEP services experience statistically significant productivity increases; and (c) receipt of MEP services increases manufacturing establishments' likelihood of survival.

In the section below, we begin with an overview of the MEP program. We then summarize the results of the Jarmin (1999) and Ordowich et al. (2012) studies. This is followed by a description of the methodology used in the study, which involves linking information from MEP project information files (PIF) and customer information files (CIF) to databases from the U.S. Census Bureau. The results of our study are then presented, and we conclude with some implications of the results.

The Manufacturing Extension Partnership

The MEP program provides business, technology, and other forms of assistance, typically to existing (as opposed to start-up), small and midsize manufacturing establishments (Shapira et al., 2015). The program deploys a network of manufacturing experts (also known as manufacturing extension agents) with centers in all 50 U.S. states and Puerto Rico. The aim of the MEP program is to strengthen U.S. manufacturing competitiveness. The program was established through the Omnibus Trade and Competitiveness Act of 1988, which created the first three centers, with additional centers added such that a national system was in place by the mid-1990s.[1]

The total MEP annual system budget is about $300 million (National Research Council, 2013). The federal government awards about one third of funds for the program that the centers match from state funds, client fees, and other sources. Over half (55%)[2] of the centers operate as not-for-profit organizations (under section 501(c)(3) of the Internal Revenue Service code), and the others operate as university-based or state-government–run programs.

The essential rationale for the MEP and similar technology and innovation advisory services in other countries is that existing small and midsize establishments often face market imperfections and other systematic challenges in acquiring and deploying information, expertise, skills, and other resources. These issues lead to difficulties in technological and business upgrading, contributing in turn to lagging productivity, innovativeness, and competitiveness among many of these establishments (National Academy of Public Administration, 2003; National Research Council, 2013). The MEP's underlying program theory seeks to bridge these gaps through services that directly provide expertise, diagnostics, mentoring, training, and other support to help upgrade manufacturing establishments and provide access and referrals to other public and private resources (Shapira & Youtie, 2014). The small and medium-sized firms that engage with the MEP do so because its services are customized to their needs: equivalent private sector sources are either more expensive or not available, the MEP's services are oriented to business outcomes (rather than to research), and it offers independent yet comprehensive access to a range of expertise. If effective, MEP services should prompt intermediate business actions (including, but not limited to, equipment investment, enhanced plant layouts, employee training, process and quality improvements, cost reductions, and new products and marketing strategies) leading to improved business performance outcomes such as enhanced productivity, sustainability, and growth for its clients.

The MEP flexibly operates through a decentralized network in which each center addresses its local conditions and the needs of manufacturers in that region to enhance their productivity. MEP centers deliver services with some mix of in-house specialists and third-party providers. More than 1,400 nonfederal staff and over 2,400 third-party service providers are involved in service delivery (National Research Council, 2013). MEP services are delivered through assessments of all aspects of a company's business or specific functional areas following a variety of outreach activities, one-on-one technical engagements to address problems, hosting manufacturing networks for knowledge and current practice sharing, and training events depending on the needs and preferences of the manufacturer. Currently, the MEP serves about 7,000 to 8,000 clients annually through about 12,000 projects.[3] NIST MEP oversees the governance structure of the system and maintains an extensive program of monitoring and evaluation.

Prior Studies of the MEP and Manufacturing Performance

A series of studies, using a broad range of methods, have examined various aspects of the performance and impact of the MEP in the United States, and other technology extension and advisory services outside of the United States (for reviews of these studies, see Shapira & Youtie, 2014; Youtie, 2013). In this study, we particularly focus on two earlier benchmark national studies of the effects of the MEP on client performance using nonassisted control groups. These benchmark studies are overviewed in the following two sections.

Study 1: Jarmin

Jarmin (1999) estimated the effect of MEP services on the productivity of establishments. His analysis was based on an augmented Cobb–Douglas production function with physical capital, employment, and other plant characteristics, as shown in the equation below.[4]

$$Y_{it} = A e^{\delta Ext_{it}} K_{it}^{\beta} L_{it}^{\eta} e^{\varepsilon_{it}} \qquad (1)$$

This equation serves as the theoretical basis for all of the analyses that follow, where Y_{it} is value added for establishment i in period t, L_{it} is employment for establishment i in period t, K_{it} is book value of the capital stock of plant i in period t, ε_{it} is the error term, and Ext_{it} is a dummy variable equal to 1 if establishment i received MEP services in period t, 0 otherwise.

Jarmin (1999) began his analysis by performing simple ordinary least squares (OLS) analysis. He then used a Heckman two-stage model to control for selection bias (Heckman, 1976). The selection model used a dummy variable for whether the plant was in a metropolitan statistical area that contained a manufacturing extension center as an instrument for the likelihood of being an MEP client. This variable was found to be associated with client standing (Jarmin, 1999).

Jarmin (1999) specified the Cobb–Douglas production function as a linear regression equation by taking the natural logarithm of the Cobb–Douglas equation and rearranging the results. He obtained the following regression equation:

$$\Delta \log \left(\frac{Y}{L} \right)_i = \alpha + \delta Ext_i + \beta \Delta \log \left(\frac{K}{L} \right)_i + \\ (\mu - 1) \Delta \log(L)_i + \varepsilon_i \qquad (2)$$

In Equation 2, the deltas (Δs) reflect changes in the value of a variable between 1987 and 1992, and the parameter μ measures deviations from constant returns to scale. The dependent variable in Equation 2 is the percentage change in labor productivity between 1987 and 1992. (Note that in our analyses, we have measured changes for the periods 1997-2007 and 1997-2002, as well as for 2002-2007.) The impact of the MEP program is measured by the parameter δ that measures the percentage difference in productivity between client and nonclient plants. This formulation assumes that receiving MEP services would increase the productivity of a small plant by the same percentage as it would a large plant. Using Equation 2, Jarmin (1999) estimated two OLS models, one for all plants ($N = 15,263$) and one with plants with 19 to 500 employees ($N = 7,782$).

In addition to estimating the OLS equation above, Jarmin (1999) estimated two more models (using the same plant size delineations) with two-digit standard industrial classification dummies to control for industry differences, as shown in the equation below.

$$\Delta \log \left(\frac{Y}{L} \right)_i = \alpha + \delta Ext_i + \beta \Delta \log \left(\frac{K}{L} \right)_i + \\ (\mu - 1) \Delta \log(L)_i + \lambda_{1 \dots N} SIC_i + \varepsilon_i \qquad (3)$$

Study 2: Ordowich et al. (2012)

Jarmin (1999) faced several limitations. He was only able to measure whether an establishment received MEP services between 1987 and 1992. Data on the level and type of treatment were not of sufficient quality for his analyses. Likewise, his study was situated in a period before nationwide establishment of the MEP, when there were only a few centers funded. To extend the Jarmin modeling effort, Ordowich et al. (2012) studied the effect of MEP services on labor productivity and other outcome variables. Their study used new data to run several additional OLS models, replacing the binary treatment variable in the equations above (Ext_i) with a variety of other measures. The treatment measures used included level of treatment (e.g., number of engagements, cumulative hours of MEP assistance, cumulative dollars amount paid by establishments for assistance), period of treatment, and type of treatment (e.g., delivery mode, type of assistance received, and substance of assistance received).

Ordowich et al. (2012) used three databases: one with MEP client engagements occurring between 1997 and 2002, another with demographic information for each client, and a third data set with MEP center characteristics. While complete data on MEP engagements only dates to 1999, the Ordowich et al. (2012) study included all data available on MEP engagements between 1997 and 2002 to capture as many MEP clients as possible. Their study found about 47,000 engagements in the MEP database that were delivered to about 20,000 unique establishments between 1997 and 2002. Their modeling approaches included difference-in-differences (DiD) models and lagged dependent variable models to estimate the relationship between manufacturing extension and labor productivity. The DiD model for panel data is:

$$\Delta \log \left(\frac{Y_{it}}{L_{it}} \right) = \Delta \lambda_t + \delta \Delta Ext_{it} + \beta \Delta \log \left(\frac{K_{it}}{L_{it}} \right) \\ + (\mu - 1) \Delta \log(L_{it}) + \Delta \varepsilon_{it} \qquad (4)$$

The lagged dependent variable model for panel data is:

$$\log \left(\frac{Y_{it}}{L_{it}} \right) = \alpha + \delta Ext_{it} + \beta \log \left(\frac{K_{it}}{L_{it}} \right) + \\ (\mu - 1) \log(L_{it}) + \theta \log \left(\frac{Y_{it-1}}{L_{it-1}} \right) + \varepsilon_{it} \qquad (5)$$

Their results were mixed and suffered from several data limitations. As discussed in Angrist and Pischke (2009), the ideal situation is to estimate a fixed-effects model with a lag

term.[5] However, as the Ordowich et al. (2012) study correctly pointed out, without stronger assumptions and more data, such a combined model may lead to inconsistent estimates.[6] In addition, the Ordowich et al. (2012) study tried several different instruments based on MEP center locations and other methods to correct for selection bias (such as propensity score matching), but none of these methods was correlated with the likelihood of an establishment being an MEP client in the same way that Jarmin (1999) reported.

This current study, commissioned by NIST MEP in 2012, builds on the Jarmin (1999) and Ordowich et al. (2012) studies by examining these relationships across three different years of Census of Manufactures (CMF) data (1997, 2002, and 2007). This broader timeframe enables us to overcome Jarmin's (1999) focus on the pre-MEP extension period and Ordowich et al.'s (2012) focus on the recession-tainted 1997 to 2002 period. Furthermore, this project builds on the results from these two models to bracket the effect of MEP services on labor productivity and output growth, as well as survival, using multiple methods.[7]

Data and Method

The present study extends the analysis to the CMF for 2007, providing an additional period for observing productivity changes. The focus is on establishments that received MEP services between 1997 and 2007 in two time periods: 1997 to 2002 and 2002 to 2007. The unit of analysis for all analyses is the manufacturing establishment.

Data

NIST MEP Program Data. As an initial step, we processed data on every establishment that received MEP services from 1997 to 2007 from the NIST MEP program. Most of these elements are contained in the NIST MEP PIF.[8] For each MEP client, we received a project-level record containing various data elements, including unique identifications, project titles, the period MEP assistance was received, delivery mode, the type of assistance received, the number of MEP staff hours spent on the project, and the cost of the services provided. We also received a customer-level record that included client name, address, number of employees, and 5-digit North American Industrial Classification System (NAICS) code. In addition, we received data on the MEP centers used to complete each project. Center-level data included the year the MEP center was started, number of staff in each center, total funding from NIST MEP for each center, location of each MEP center, market penetration rate for each center, and type of center (university/501(c)3/state agency).

The location of each center and auxiliary locations (e.g., other offices affiliated with the MEP center) was originally intended to create an instrument for dealing with the problem of selection bias (in which higher productivity growth is a precondition for manufacturers that consider using MEP services). However, this instrument did not resolve the self-selection bias in the models that were estimated. The section on controlling for selection bias describes the other instruments (year of firm establishment, rurality of the county based on firm address) that were used. The distance from each establishment to the location of the nearest center's headquarters and offices was used as a control variable in the survival analysis model.

These establishments were initially labeled as manufacturers using the following process: We (a) created a nonduplicate establishment name list comprising 61,919 records, 55,834 of which were "nonblank" in the "Name" field; (b) selected all establishments that had received service during the time period under analysis, which reduced the record count to 53,647; (c) separated manufacturing establishments from nonmanufacturers based on the former's having NAICS codes in the CIF beginning with 31, 32, or 33 (for those lacking NAICS codes, we looked them up in Dun & Bradstreet's Million Dollar Database and Reference USA); (d) reviewed the list of manufacturers and removed any that had manufacturing NAICS codes but were clearly not manufacturers (this was a manual process); (e) reviewed the list of nonmanufacturers and added back any that appeared to be manufacturers (this also was a manual process, which found a particular clustering of what were actually manufacturers identified as having the NAICS code of "11111"); and (f) linked the resulting list to the PIF data about MEP projects. The resulting database had 38,067 manufacturers served from 1997 to 2007 that received an average of 3.3 project-based assists over this period.

Census Administrative Data. We accessed three databases through the Census Research Data Center in Atlanta, Georgia, after securing approval from the U.S. Census Bureau and the Internal Revenue Service to proceed with the study. These databases were the Standard Statistical Establishment Listing (SSEL), Longitudinal Business Database (LBD), and the CMF. Because 1997 is the first year of our study, NAICS codes were used and there was no need for Standard Industrial Classification code information for establishments. The Annual Survey of Manufactures also was not used because small and midsize manufacturers are not fully represented in this database.

SSEL and matching. The SSEL contained many data elements for all establishments listed in the Business Register. For this analysis, we used data elements such as employer identification number, legal form of organization, NAICS code, state, county, business name, mailing address, and ZIP code for all establishments listed in the Business Register between 1997 and 2007.

The project linked Census Bureau data to the MEP business assistance recipients. This was done using fuzzy logic

Table 1. Distribution of Matched MEP Clients and Nonclients by Employment Size (2007).

Employment size category	Matched MEP clients	Nonclients	Raw MEP records
1 to 19 employees	25%	70%	31%
20 to 99 employees	46%	22%	37%
100 to 249 employees	19%	6%	18%
250 to 499 employees	6%	2%	9%
500 or more employees	4%	1%	5%

Note. MEP = Manufacturing Extension Partnership. MEP clients, $N > 7,500$; non-MEP clients, $N > 300,000$; MEP records, $N = 39,349$.

code in the R programming software to match each establishment in the MEP data set to a unique establishment identifier in the SSEL. Generally, the researchers removed certain characters, such as commas, ampersands, slashes, and periods, to leave only letters in the address field. Then, after standardizing common features such as "street," which may appear as "St." or "Street" or "St," as well as other features such as "road" and "avenue," the algorithm sought matches on combinations of establishment name and address to obtain the highest quality and number of matches. The R matching code enabled real-time review of individual matches. This process took from April 2014 to August 2014. During our review process, we observed that any record with a fuzzy matching score below 90% was likely not a true match. This high, but accurate, threshold resulted in a match rate of 20% (approximately 7,500 establishments). This match rate is like that in the Ordowich et al. (2012) study in terms of the number of MEP client establishments (7,737 MEP client establishments) that were matched in both the LBD and the CMF data sets. Indeed, after a visual inspection of the matched data at the 90% and lower scores, we are very comfortable with the quality of the matches using the 90% score as the threshold vis-à-vis some other score threshold.[9] Nevertheless, we acknowledge that it is highly likely that unmatched MEP clients exist in the control group (non-MEP clients), which means our results could be biased toward zero.

As we expected, the employment size distributions differed between matched and unmatched MEP clients. Looking only at the universe of establishments that received MEP services (from the raw MEP records), we find that most establishments have fewer than 250 employees. We subsequently used the unique establishment identifiers in each file (i.e., the Census file number and LBD number) to link the MEP business assistance records to the CMF and LBD data sets. Because of the linkage of multiple data sets, we are left with approximately 7,500 matched MEP client establishments. For this subset, we see in Table 1 that 71% of matched MEP clients fell into three employment categories (20-99, 100-249, and 250-499). By contrast, we see that nonclients were more concentrated among smaller establishments, particularly the 1-to-19 employment category. Table 1 shows the

distribution of MEP clients and nonclients from the pool of matched establishments across different employment size categories, as well as the distribution of MEP clients across employment size categories before any matching occurred. That the distribution of establishments across employment size categories is somewhat consistent across the raw MEP records and the matched MEP clients suggests that the matching algorithm did not discriminate in favor of any particular size of establishments.

Census of Manufactures. The CMF includes all establishments in the manufacturing sector in years ending with a "2" and a "7." The most recent CMF data available for analysis at the Census Bureau at the time of our initial proposal to the bureau were from the 2007 Census. Our analyses used data from the 1997, 2002, and 2007 CMF. The key variables obtained from the CMF include employer identification number, legal form of organization, NAICS code, state, county, total employment, number of production workers, total value of shipments, value added, total capital expenditures, and salaries and wages.

The primary use of the CMF data was to provide key information on the establishments that was needed for the analysis, such as total employment (full-time equivalent), number of production workers, value added, and capital expenditures (used in the capital-to-labor ratio). To meet Census Bureau disclosure requirements, the Total Value of Shipments (TVS) variable was kept to conduct all disclosure analyses to enable release of the results from the Atlanta Census Research Data Center.

Longitudinal Business Database. The LBD comprises information to enable access to prior CMFs. This database was used to link to information from CMFs in 1997, 2002, and 2007. The project also used the LBD to link establishments across time to analyze survival as well as changes in key variables (such as sales growth) to obtain a measure of the establishment's age, and to identify establishments that are part of single-unit or multiunit firms. LBD variables used included employer identification number, first year establishment is observed, last year establishment is observed, and single–multiunit identifier.

Figure 1 illustrates the linkages between each of these data sets.

Variables

The information in these MEP and Census Bureau databases was used to calculate variables to be used in our analyses. These variables are classified as either outcome, treatment, or control variables. Each variable and how it is calculated is described in Table 2. All dollar values were converted into 2007 dollars using the Consumer Price Index for All Urban Consumers.
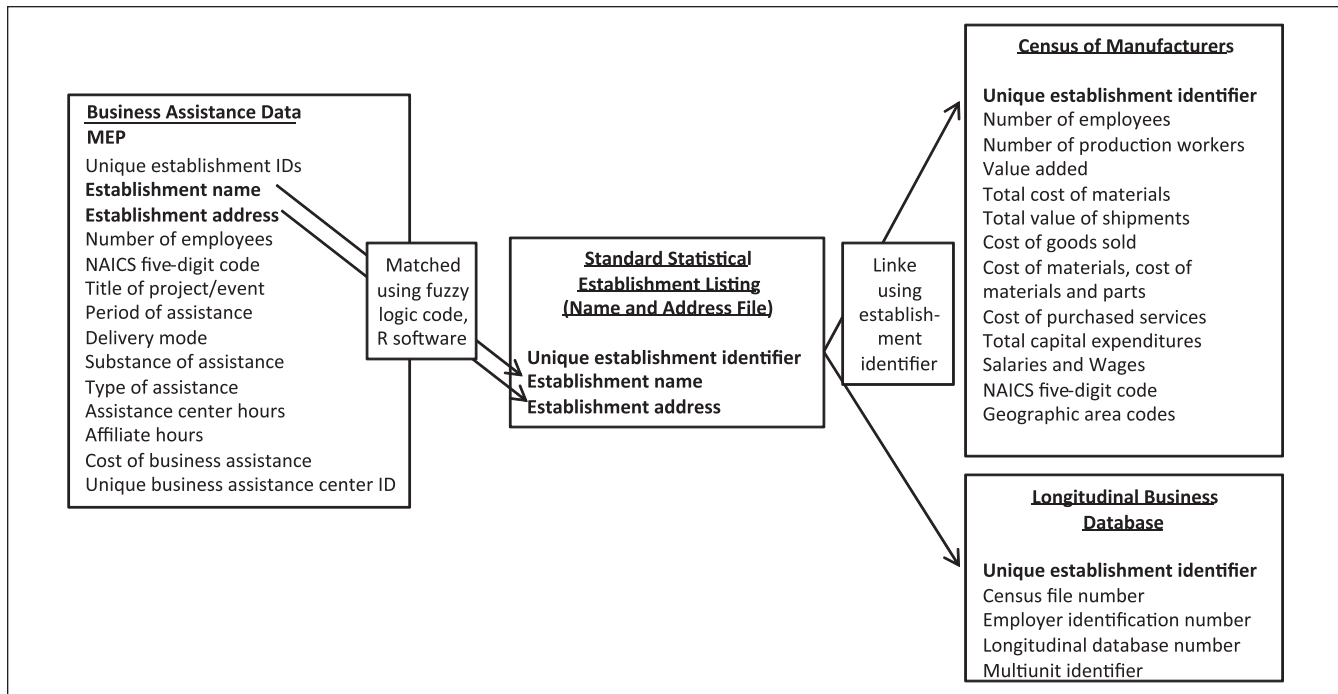
Figure 1. Data sets and links.

Models

Our analyses examine changes in productivity as a function of other variables and MEP assistance. In replicating and enhancing the analyses of the effect of MEP services on establishments performed by Jarmin (1999) and Ordowich et al. (2012), we encountered many of the same issues, including selection bias, the possibility of different methodologies giving us mixed results, limited time coverage, an overemphasis on quantitative measures of productivity, sales, and employment numbers that do not fully capture the effect of MEP in recessionary or slow economic growth periods. In addition to replicating the prior analyses, we performed new analyses (e.g., survival analysis) and considered additional CMF data from 2007 that had been previously unavailable. The models we utilize in this evaluation are described below.

Controlling for Selection Bias. Generally, several interrelated issues need to be addressed when evaluating the effect of MEP services on establishment outcomes. First, establishments are likely more heterogeneous in terms of their characteristics than can be captured by a single-line OLS regression equation. Second, selection bias occurs because establishments are not randomly assigned to the treatment and control groups; establishments select whether or not to become MEP clients. Jarmin (1999) found that companies with high sales growth but lower than average productivity self-select into the group of MEP clients.

To control for self-selection bias, both Jarmin (1999) and Ordowich et al. (2012) used a Heckman two-stage model, which is also commonly referred to as an instrumental variable approach. For his instrument, Jarmin (1999) used a dummy variable to indicate whether an establishment is in a metropolitan statistical area with a manufacturing extension center. Ordowich et al. (2012) used a similar variable. The instrument was successful at controlling for self-selection bias in the Jarmin (1999) study (as it was correlated with client standing), but not in the Ordowich et al. (2012) study.

The current study also estimates an instrumental variable model using the age of the establishment and the 2003 USDA-ERS Rural–Urban Continuum Code (rurality) as instruments. The latter instrument ranges from 1 (*counties with 1+ million population*) to 9 (*completely rural counties with less than 2,500 population, not adjacent to a metro area*). These instruments are correlated with the likelihood of an establishment being a client but are not correlated with labor productivity growth. In early testing, we also considered distance to the nearest MEP center as an instrument, but that variable failed to control for self-selection bias as it did not sufficiently distinguish client standing. We did use this variable in the survival analysis model to account for center effects based on distance from the closest MEP office alone. Table 3 shows, for matched establishments, the distribution of MEP clients and nonclients across the various rurality classifications.

In preliminary analyses, the Heckman correction for selection bias produced mixed results. For the DiD regression model that examined productivity differences between

Table 2. Variables Used in the Analyses.

Variable	Description	Source	Calculation
Outcome variables			
$\dfrac{Y_{it}}{L_{it}}$	Value added per employee at establishment i in period t	CMF	• Y: Value added in 2007 dollars
			• L: Number of production workers
$\dfrac{S_{it}}{L_{it}}$	Sales per employee at establishment i in period t	CMF	• Y: Value of shipments in 2007 dollars
			• L: Number of production workers
$Surv1$	Firm survival from one period t to period $t + 1$	LBD	Coded as 1 if establishment is not operating and 0 if establishment is operating (used in Cox model)
Treatment variables			
$Ext_{i,X\to Y,Z}$	Binary variable for whether a plant received MEP services between years X and Y^{a}	NIST-MEP	Coded as 1 for received services (all records from NIST MEP) and 0 for all other establishments (control group from LBD/CMF)
$Substance_i$	Substance of MEP treatment	NIST-MEP	Calculated based on summary statistics by MEP center
$CumHours_{i,X\to Y,Z}$	The cumulative hours of services received by establishment i between years X and Y on service type Z	NIST-MEP	Aggregated from NIST MEP data based on number of hours (center/affiliate) devoted to services of specified type over the period of interest
Control variables			
L_{it}	Number of employees and production workers at establishment i in period t	LBD/CMF	Total number of employees; total number of production workers
$\dfrac{K_{it}}{L_{it}}$	Capital-to-labor ratio for establishment i in period t	CMF	• K: Total capital expenditures expressed in 2007 dollars
			• L: Number of production workers
$NAICS_i$	The 5-digit NAICS code for establishment i, coded into dummies for durables and nondurables	CMF	Directly from database; also computed 2-digit sector identifier and 3-digit subsector identifier
$MinDist_{ij}$	A continuous variable that measures the distance of establishment i to nearest MEP center j	SSEL/NIST MEP	Use address from SSEL and center data from NIST MEP to identify the closest center to each establishment in the data set
$InitProd_i$	Productivity of establishment i in 1997	CMF	Value added in 1997 for establishment i
$PrevSales_i$	Previous (1992-1997) sales growth of establishment i	CMF	Use CMF data from 1992 to 1997 to calculate previous sales growth
$InitCapInt_i$	Capital intensity level of establishment i in 1997	CMF	Capital-to-labor ratio for establishment i in 1997
Emp_group_i	Dummy variables for different plant sizes (number of employees) of establishment i in 2007	LBD	Number of employees in 2007 in categories
Instrumental variables			
$Rurality_i$	Rural-Urban Continuum Codes, 2003 (1 = counties with 1+ million population, . . . , 9 = completely rural counties with less than 2,500 population, etc.)	U.S. Department of Agriculture, Economic Research Service	Calculated based on county in address data in SSEL
$Estab\_age_{it}$	Age of plant i in period t	LBD	Calculated as 2011 minus commencement date of establishment

Note. CMF = Census of Manufactures; LBD = Longitudinal Business Database; NIST = National Institute of Standards and Technology; MEP = Manufacturing Extension Partnership; SSEL = Standard Statistical Establishment Listing.
[a]Analysis by different time periods conducted to gauge how results change over time. Variables X and Y cover different periods (1997-2002, 2002-2007, and 1997-2007).

Table 3. Matched Establishments, by MEP Clients and Nonclients, Across the 2003 USDA-ERS Rural–Urban Continuum Codes.

Continuum code	Description	Did not receive MEP services	Did receive MEP services
1	Counties in metro areas of 1 million population or more	53%	39%
2	Counties in metro areas of 250,000 to 1 million population	18%	24%
3	Counties in metro areas of fewer than 250,000 population	9%	12%
4	Urban population of 20,000 or more, adjacent to a metro area	5%	8%
5	Urban population of 20,000 or more, not adjacent to a metro area	2%	3%
6	Urban population of 2,500 to 19,999, adjacent to a metro area	6%	8%
7	Urban population of 2,500 to 19,999, not adjacent to a metro area	3%	5%
8	Completely rural or less than 2,500 urban population, adjacent to a metro area	1%	1%
9	Completely rural or less than 2,500 urban population, not adjacent to a metro area	1%	1%

Note. MEP = Manufacturing Extension Partnership. Cells are rounded, therefore columns may not sum to 100%. Although 2013 codes are available, we used 2003 codes because they fell within the timeframe of our analysis.

2002 and 2007, the Heckman correction did not produce more efficient estimates. In other words, the instruments we used in the Heckman selection model (to handle the possible selection bias) did not make a statistically significant difference in the impact of MEP services on productivity differences. Therefore, we present the results of the OLS regression model below. However, for the DiD regression model estimated for the 1997 to 2002 period, the Heckman correction did produce more efficient estimates, but the coefficient on extension services was negative and significant, which is consistent with the Ordowich et al. (2012) study's finding.

We anticipated finding and applying instruments that would control for selection bias. The age of the establishment and rural/urban location are correlated with client status but not correlated with productivity growth, so presumably they would be good instruments. However, we had mixed success in applying them. Drawing on prior instruments used to control for selection bias, as well as using other instruments in this study, we were unable to find a single instrument that controlled for selection bias across all years in the study. Table 5 in the next section will show that MEP-assisted clients had higher productivity (as measured by value-added per employee) and employment than nonclients, suggesting that the selection bias is a positive one. Future research could make progress on this part of the analysis by trying additional instruments, including instruments built on served and unserved establishments in the same firm or enterprise group. Nonetheless, we proceed with this study by estimating the impact of the variable of interest, receipt of MEP assistance, on productivity growth measures in an OLS framework.

DiD Model. First, we replicated the DiD model in the Ordowich et al. (2012) study by reestimating Equation 4. This model controls for time-invariant characteristics of each establishment. This includes both observable factors such as industry and location as well as unobservable factors such as management ability (Mundlak, 1961). This model is estimated for two changes in productivity (1997-2002,

2002-2007) for the set of continuing establishments as well as subsets of the data, including five different employment groups as well as different NAICS sectors. For establishments that survive through all three periods, this analysis tells us the differential impact of being served by the MEP in one of these two 5-year periods. We also consider productivity differences by employment size, industry, and substance of assistance, and report on the use of instruments to address selection bias.

Lagged Dependent Variable (LDV) Model. Second, we replicated the lagged dependent variable model that was also used in the Ordowich et al. (2012) study by reestimating Equation 5. With this model, variation in labor productivity in a given period is expressed as a function of contemporaneous capital-to-labor ratios, contemporaneous employment, and labor productivity in a previous period. This model is estimated to show the degree to which estimates of the impact of MEP assistance on establishment productivity are validated by a different modeling approach. While the DiD model controls for the aforementioned time-invariant attributes of establishments, the LDV model accounts for baseline differences in productivity between served and unserved manufacturers, and controls for the likelihood that the outcome variable is correlated over time (Angrist & Pischke, 2009; Ordowich et al., 2012).

Survival Analysis Models. Survival analysis seeks to provide information on the factors that influence whether establishments survive from one period to the next. Survival analysis was used to study a range of effects, from student attrition rates in universities to firm attrition rates, from year to year. The basic goal is to estimate the shape of the hazard function for the underlying survival process of, in this research, manufacturing firms. We used two different models (Cox proportional hazards model and logit model) to test whether the receipt of MEP services increases the likelihood of survival from one period to another.

We tested very specific hypotheses about the characteristics of establishments that survive from period to period using the Cox proportional hazards model, with one of those characteristics being whether an establishment received MEP services. The Cox proportional hazards model requires the creation of two special variables: (a) a duration variable denoting the length of time a firm used MEP services (in years) and (b) a dichotomous variable denoting whether the endpoint is censored. CENSORED = 0 if the firm continued to use MEP services by 2007 or CENSORED = 1 if the firm stopped using MEP services by 2007. One limitation of using data in this format is that we cannot analyze "time-varying covariates" as a researcher might do using panel data.

The Cox model estimates a hazard function $h_i(t) = h_0(t)\exp(\beta_1 x_1 + \cdots + \beta_k x_k)$, where i references each firm observation and $h_0(t)$ is the baseline hazard (that measures the value of the hazard function common to each firm before the other risk factors x are considered). The hazard function can be rewritten in its familiar log form:

$$\log h_i(t) = \log h_0(t) + \beta_1 x_1 + \cdots + \beta_k x_k \qquad (6)$$

This function tells us the aspects of firms that make an exit from the sample more or less likely in a given time interval. Using the method of maximum likelihood, the Cox model maximizes the Hosemer and Lemeshow (1989) partial log-likelihood function:

$$L = \sum_{j=1}^{D}\left[\sum_{k\in D_j} x_k\beta - d_j \ln\left\{\sum_{i\in R_j}\exp(x_i\beta)\right\}\right] \qquad (7)$$

The second model we used to test the likelihood of survival is the logit model, which estimates the probability of survival from one period to the next conditioned on a set of predictor variables. Mathematically, the logit model is written in its most familiar form as $= \dfrac{e^{\alpha+\beta X}}{1+e^{\alpha+\beta X}}$. For both the Cox model and the logit model, the dependent variable is coded (0, 1), where 0 indicates establishment survival between the two periods and 1 indicates an establishment's death. This operationalization, while counterintuitive compared with traditional OLS structures, is typical of survival analyses and facilitates the interpretation of odds ratios less than 1 in the Cox model as establishments having a lower probability of death, ceteris paribus. In the logit model, this operationalization facilitates the interpretation of an establishment's probability of death as increasing (positive coefficient) or decreasing (negative coefficient).

Results

Our results begin with descriptive statistics of the primary variables used in the analysis. These are presented in Table 4.

Table 4. Descriptive Statistics.

	Number of observations	Mean	Standard deviation
Value-added per employee in dollars, 2002	360,000	98	645
Value-added per employee in dollars, 2007	339,000	110	506
Sales per production worker in dollars, 2002	356,000	306	2,718
Sales per production worker in dollars, 2007	335,000	354	1,905
MEP client (yes/no)	654,000	0.01	0.1
Distance to nearest MEP center in miles	542,000	51	65
Establishment age in years	452,000	19	11
Number of production workers, 2002	371,000	29	209
Number of production workers, 2007	345,000	30	904
Capital-to-labor ratio, 2002	356,000	19	4,865
Capital-to-labor ratio, 2007	335,000	12	214
Rural–urban continuum code	651,000	2.26	1.91

Note. MEP = Manufacturing Extension Partnership.

The number of observations is rounded to the nearest thousand to satisfy Census Bureau disclosure requirements.[10]

Next, we conducted difference-of-means tests (using the student's t statistics) of the differences in value added, employment, and productivity between MEP clients and nonclients. MEP-assisted manufacturing establishments had higher levels of value added and employment than nonclients (Table 5). These differences were significant at $p < .05$, with the exception of value added per employee in 2002 and 2007.

DiD Model

We replicated the DiD model used by Jarmin (1999) and Ordowich et al. (2012) over the 1997 to 2002 and 2002 to 2007 periods. The specific model we used included more covariates than Equation 6. Specifically, we included controls for the age of the establishment—relating back to the focus of the program on established as opposed to start-up manufacturers (Shapira et al., 2015)—and two industry-class dummy variables to represent durables and nondurables based on these establishments' NAICS codes. This industry specification takes advantage of prior work into the greater productivity of durable as opposed to nondurable manufacturers in certain business cycles (Kehrig, 2011). The results show a positive but statistically insignificant coefficient for the extension variable from the 2002 to 2007 period (Table 6).[11] Even though the result is not statistically significant, receipt of MEP services between 2002 and 2007 is associated with 1.0% higher productivity growth (in terms of value added per

Table 5. Difference of Means Test Results.

MEP client status	Value added			Employment			Value added per employee		
Year	1997	2002	2007	1997	2002	2007	1997	2002	2007
Non-MEP client	$4,759	$5,375	$8,120	43	43	43	$88	$101	$125
MEP client	$13,087	$14,645	$21,185	121	112	111	$106	$114	$133
t Statistic	−11.83	−11.41	−9.74	−27.07	−6.82	−3.32	−7.06	−1.48	−1.04
Prob. (two-tailed test)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.29
N(mepcust = 0) − rounded	392,000	349,000	294,000	395,000	365,000	339,000	392,000	348,000	293,000
N(mepcust = 1) − rounded	5,000	5,600	4,900	5,100	5,800	5,000	5,100	5,600	4,900

Note. MEP = Manufacturing Extension Partnership. MEP clients, $N > 7,000$; non-MEP clients, $N > 300,000$.

Table 6. DiD Regression Results, 2002 to 2007.

	DV = Change in ln(Value Added Per Employee)		DV = Change in ln(Sales Per Production Worker)	
Variable name	Coefficient estimate	*t* Statistic (prob.)	Coefficient estimate	*t* Statistic (prob.)
Constant	0.07	14.77 (.00)	0.23	53.94 (.00)
Change in ln(Capital-to-Labor Ratio)	0.09	68.92 (.00)	0.13	105.09 (.00)
Change in ln(Number of Production Workers)	−0.13	−46.59 (.00)	−0.34	−111.73 (.00)
Establishment age	−0.002	−14.19 (.00)	−0.006	−43.92 (.00)
Rural–urban continuum code	0.003	3.84 (.00)	0.004	6.54 (.00)
MEP customer (yes/no)	0.01	1.07 (.28)	0.026	3.00 (.00)
No. of observations (rounded)	173,000		175,000	
R Squared	0.07		0.28	
F statistic	1,759		6,295	

Note. MEP = Manufacturing Extension Partnership; DiD = difference-in-differences; DV = dependent variable.

Table 7. DiD Regression Results, by Employment Category, 2002 to 2007. DV = Change in ln(Value Added Per Employee).

No. of employees	All groups	1-19	20-99	100-249	250-499	500 or more
No. of observations (rounded)	173,000	99,000	50,000	16,000	5,000	3,000
MEP coefficient estimate	0.011	0.030	0.003	−0.063	−0.072	0.002
t Statistic	1.07	1.20	0.26	−2.85	−1.89	0.05

Note. DiD = difference-in-differences; MEP = Manufacturing Extension Partnership; DV = dependent variable.

employee) compared with nonclients (in the DiD model). Other significant predictors of the change in logged value added per employee are the capital-to-labor ratio, the number of production workers, establishment age, and whether an establishment is in a more urban or rural county.

We validated these results by using the same independent variables to explain variation in two different dependent variables: changes in the logged sales per production worker and changes in employment. We found a significant and positive impact of the extension variable on the natural log of sales per production worker, ceteris paribus (Table 6). Receipt of MEP services in the 2002 to 2007 period is associated with 2.6% higher sales per employee compared with nonclients. Also, we found a statistically significant and positive impact of MEP assistance on the natural log of

employment (results not released). When we estimated the same model for the 1997 to 2002 period, we observed similar results as reported in the Ordowich et al. (2012) paper (that productivity was statistically significant and lower for MEP customers). In sum, these findings suggest a level of consistency that enhances the reliability of their DiD results.

We tested the hypothesis of whether the sign and significance of the extension variable vary by the size or subsector of the manufacturing establishment. We estimated the same model specification across various subsets of our data. First, we divided establishments into the following size classes: Group 1 = 1 to 19 employees; Group 2 = 20 to 99 employees; Group 3 = 100 to 249 employees; Group 4 = 250 to 499 employees; and Group 5 = 500 or more employees. Table 7 shows the impact of the extension variable on change in

Table 8. DiD Regression Results, 2002 to 2007, by NAICS Industries. DV = Change in ln(Value Added Per Employee).

Variable name	Nondurable (NAICS 31 and 32)		Durable (NAICS 33)	
	Coefficient estimate	*t* Statistic (prob.)	Coefficient estimate	*t* Statistic (prob.)
Constant	0.08	11.10 (0.00)	0.06	9.69 (0.00)
Change in ln(K/L)	0.10	48.15 (0.00)	0.09	49.02 (0.00)
Change in ln(PW)	−0.16	−34.83 (0.00)	−0.11	−30.94 (0.00)
EstabAge	−0.003	−11.42 (0.00)	−0.001	−8.48 (0.00)
Continuum code	0.004	3.42 (0.00)	0.002	1.93 (0.00)
MEP customer	−0.029	−1.65 (0.10)	0.03	2.42 (0.02)
No. of observations (rounded)	78,000		95,000	
R Squared	0.08		0.06	
F statistic	924		850	

Note. NAICS = North American Industrial Classification System; MEP = Manufacturing Extension Partnership; DV = dependent variable.

value added per employee from 2002 to 2007 across the various groups based on total number of employees. The extension variable shows mixed results at this level of disaggregation: 3.0% growth for Group 1 and 0.3% growth for Group 2 versus −6.3% for Group 3, −7.2% for Group 4, and 0.2% for Group 5, although only the Groups 3 and 4 coefficients are significant at the 95% level of confidence. These results can be loosely interpreted as MEP services having the greatest effect on productivity for smaller establishments, which, presumably, have fewer other alternative activities (e.g., other consulting activities, other activities aimed at increasing productivity) that affect outcomes. By contrast, larger manufacturers likely have other influences on manufacturing performance that could crowd out the effects of MEP services. As pointed out by a reviewer, one caveat of these results is that in 2012, establishments with 1 to 19 employees accounted for approximately 78% of manufacturing establishments, but only 9% of manufacturing employment and 4% of manufacturing value added. Even if MEP assistance doubled the productivity of client establishments, the impact on overall productivity would be minor.

To examine differences by industry group, we divided establishments into a durables subgroup (NAICS 33 sector) and a nondurables subgroup (NAICS 31 and 32 sectors). Based on the durable/nondurable bifurcation, we found significant differences in the impact of MEP assistance on productivity. Specifically, the coefficient on the extension variable (MEP assistance) was positive and significant at the 95% level of confidence for durables manufacturers, and negative and insignificant at the same confidence level for nondurables (Table 8). Durables manufacturers receiving MEP services had 3% higher growth in value added per employee compared with nonclients in these industries over the 2002 to 2007 period. These results are consistent with the positive productivity typically associated with durable, as compared with nondurable, manufacturing establishments in certain business cycles and suggest that MEP assistance may serve to enhance these advantages (Kehrig, 2011).

We also examined differences in manufacturing productivity based on the type of manufacturing assistance provided. We grouped MEP substance codes into two categories to reflect a "top-line" (sales increasing) orientation versus a "bottom-line" (cost savings) orientation. The top-line substance group comprises business services and engineering/technical services; the bottom-line substance group comprises quality systems, manufacturing systems, information technology, and human resources and organizational development. We acknowledge that some bottom-line activities may spill over into the top-line activities and vice versa. However, because of the breadth of the substance codes used in the PIF, we judged that these groupings best proxy the differences in the two orientations. We subsequently weighted these two categories by the number of hours of effort associated with engagements in these categories and normalized the results by dividing by the total number of hours (because of variation in the number of hours of assistance across clients). We use this method to account for the common situation where MEP clients receive multiple types of services over the course of the period under study. Thus, the variable reflects the *emphasis* of the service in one substance category (vs. another substance category) rather than a binary condition of selecting into (or not selecting into) a single substance code.

We then incorporated these variables into the DiD regression model covering the 2002 to 2007 period in lieu of the extension variable. The top-line substance variable had a positive and statistically significant impact on the change in value-added per employee; the bottom-line variable had a negative and statistically insignificant impact on the change in value-added per employee. These results are consistent with what might be expected. These results do not imply that bottom-line assistance should be eschewed; some firms may have a great need for it, including as an entry-level service (National Research Council, 2013). Although bottom-line assistance contributes to reducing the cost of goods and services, which is a component of value added, top-line assistance may augment the sales component of value added more directly.

Table 9. LDV Regression Results, by Employment Category, 1997 to 2002 and 2002 to 2007.DV = Change in ln(Value Added Per Employee).

	All groups	1-19	20-99	100-249	250-499	500 or more
1997-2002						
No. of observations (rounded)	186,000	120,000	48,000	13,000	4,000	3,000
MEP coefficient estimate	0.019	0.053	0.012	−0.012	0.004	−0.002
t Statistic	2.330	3.290	1.080	−0.670	0.130	−0.060
2002-2007						
No. of observations (rounded)	186,000	107,000	55,000	16,000	5,000	3,000
MEP coefficient estimate	−0.014	0.034	−0.006	−0.077	−0.072	0.010
t Statistic	−1.650	1.930	−0.530	−3.840	−1.980	0.180

Note. MEP = Manufacturing Extension Partnership; DV = dependent variable.

LDV Model

To validate the results of the DiD model, we also estimated the LDV model as was done in the Ordowich et al. (2012) study. The same covariates used in the DiD model were used in the LDV model, with the lagged version of the dependent variable being the only additional independent variable used in the model. For example, when the dependent variable is the natural log of labor productivity for 2002, the lagged variable is the natural log of labor productivity for 1997. In the other model for the 2002 to 2007 period, the dependent variable is the natural log of labor productivity for 2007 and the lagged variable is the natural log of labor productivity for 2002.

The results of the LDV model are fairly consistent with those of the DiD model and are displayed in Table 9. Generally, in the LDV model spanning 1997 to 2002, MEP clients have statistically significant and positive productivity levels compared with nonclients overall (across all employment groups) and for the smallest employment levels (1-19 employees). Receipt of MEP services is associated with a 1.9% growth in value added per employee (in the LDV model) during this period across all manufacturing categories, with a 5.3% growth for clients in the 1 to 19 employment range. This result is consistent with the Ordowich et al. (2012) evaluation done across the same period. The independent variables used in these models are Ext, ln(K/L) in period t, ln(Y/L) in period $t − 1$, *Estab_age*, *Rurality*, and *MinDist*, which are defined in Table 2.

For the period spanning 2002 to 2007, the LDV model suggests that MEP clients have statistically significant and positive productivity levels compared with nonclients for the 1 to 19 employee establishments; having received MEP services in this size class is associated with a 3.4% growth in value added per employee in the 2002 to 2007 period. However, the sign for the MEP assistance variable changes to negative (while remaining statistically significant) for employment groups with 100 to 249 and 250 to 499 employees. These results are quite consistent with the results of the DiD model results displayed in Table 7.

Survival Analysis

The Cox model is constrained to follow the proportional hazards assumption (which means that the hazard ratio is constant across time, not across observations). We confirmed in our preliminary testing that the data do not violate this assumption, which means there was no significant difference in the rate of change in the survival probabilities over time between establishments, as a whole. The evidence, however, suggests that there were significant differences in the survival probabilities for establishments that did and did not receive MEP services in the 1997 to 2007 period. Both models that were estimated come to the same conclusion about establishment survival being positively influenced by receipt of MEP assistance.

The results of the Cox model showed that establishments receiving MEP services had a significantly higher likelihood of surviving (i.e., MEP extension services had a significant and negative impact on establishment death rates). Put another way, MEP assistance increased the survival probabilities of establishments from 1997 to 2007. As for subsets of the data, extension services did not improve survival probabilities in the 1997 to 2002 period, which is consistent with what we observed in the productivity equation. But, extension services did improve survival probabilities in the 2002 to 2007 period. Using the results of the Cox model in Table 9 (assuming a Weibull distribution), the hazard ratio of 0.82 suggests that MEP client establishments are 18% less likely to die compared with nonclients and controlling for other factors. Also, the logit model results reinforce the Cox model results. The logit coefficient of −0.54 suggests that MEP client establishments have a lower probability of death relative to nonclients. Therefore, the increased survival of establishments receiving MEP services survives different econometric specifications, summarized in Table 10, across the 1997 to 2007 period.[12]

Conclusions

Overall, the results portray a nuanced picture of the ways in which MEP services affect productivity, sales, employment,

Table 10. Weibull and Logit Regression Estimates.

Variable	Weibull model			Logit model		
	Hazard ratio	z Statistic	Prob.	Coefficient estimate	z Statistic	Prob.
Constant	3.55E-010	−178.13	.00	−0.01	−2.16	.03
Estab age	0.67	−166.70	.00	−0.02	−70.00	.00
VA97	1.00	1.41	.15	—	—	—
VA02	1.00	−0.70	.48	—	—	—
VA07	1.00	1.66	.09	—	—	—
TE97	1.00	23.63	.00	—	—	—
TE02	1.00	8.78	.00	—	—	—
TE07	0.99	−37.78	.00	—	—	—
MEP customer	0.82	−3.92	.00	−0.54	−18.56	.00
Min distance	1.00	2.83	.01			
p	9.47			Pseudo R^2	0.01	
$1/p$	0.10			N (rounded)	452,000	
N (rounded)	161,000			LogL	−301,235	
LogL	−36,803					

Note. MEP = Manufacturing Extension Partnership; VA = value added; TE = employment.

and establishment survival when compared with a matched nonclient control group. This study considers the program as a whole and does not examine differences among centers. Potentially, the methodology could be applied to center-level comparisons, although the results would be less robust, as was shown in Ordowich et al. (2012), in part because of the smaller number of observations and client matches at the center level.

We find, regardless of econometric model specification, that MEP clients with 1 to 19 employees have statistically significant and higher levels of labor productivity growth than nonclients in this employee size range. In contrast, the extension variable is not positively associated with higher productivity growth for MEP clients with 20 or more employees, and the coefficients on the extension variable are negative and significant for the largest MEP clients. Establishments in the medium-size employment category are often targeted as the most appropriate for MEP services, whereas the findings from this study—as well as the earlier Ordowich et al. (2012) study—underscore the MEP's greater propensity to affect positive change in smaller establishments.

We observed significant productivity differences associated with MEP services by broad sector, with higher impacts for 2002 to 2007 in the durable manufacturing sector than in the nondurable manufacturing sector. One interpretation of this result is that MEP services may be particularly oriented to durable goods establishments such as machine shops, component suppliers, and other durable products manufacturers. Under this interpretation, it might not be surprising that these types of firms would be most apt to have positive growth in value added per employee as a result of MEP services because MEP services are most suitable for their needs. It might also be plausible to suggest that the broader durable goods industry

group fared better than the nondurable goods industry group over this period (2002-2007), and this higher performance spilled over into better MEP client performance for this group. However, this interpretation is not supported by data from the U.S. Bureau of Economic Analysis (2014). Durables had slower growth in current value added per employee than nondurables during these two periods. Change in value-added per employee for durables for 1997 to -2002 was −0.3% versus 0.4% for nondurables, while for 2002 to 2007, it was 1.0% for durables versus 1.2% for nondurables.[13] Therefore, it is particularly noteworthy that MEP clients in the durables sector saw significant positive growth in value-added per employee, given these overall industry group trends. Another possible explanation is that durables manufacturers are best able to absorb MEP services, many of which are particularly oriented to these types of manufacturers.

We caution that while quantitative changes in value added or sales are important program impact measures, many small firms cannot readily provide this information (Shapira et al., 2004). Additionally, MEP clients' productivity improvements may not raise overall manufacturing productivity, as indicated by BEA data for this period, if less productive firms crowd out more productive ones, as a general equilibrium approach might imply.

The results also show that establishments receiving MEP assistance have a statistically significant and higher probability of survival than those that do not receive MEP assistance. The longer-term survival of a manufacturing enterprise can also be an outcome of program intervention. Survival is not always unequivocally positive, however, especially if a federal program supports inefficient firms. The analyses presented here suggest that this outcome is generally unlikely in that MEP clients had higher productivity and employment. In

an era of downward or slow economic growth, the ability to enable an establishment to be sufficiently competitive to survive as a result of MEP services may be an additional measure of program effect.

The program theory of the MEP, as discussed earlier, posits that intervention through supplying manufacturing assistance services will improve business performance. This study broadly confirms this program theory, in particular finding that MEP client establishments have higher value added per employee, greater growth in sales per employee, and greater probability of survival. The qualification is that these results are most strongly positive for smaller firms than for medium-sized firms and for firms in durables industries. In addition, the study presented two models (the DiD and the LDV models), which show broadly similar results, especially for smaller manufacturers. However, for the 2002 to 2007 period, neither model shows a positive and statistically significant coefficient for growth in value added per employee. The reasons for this could be changes in the economic cycle, a possible shift in the services provided by the program, and the conceivable accumulation of repeat customers and other customers looking for services other than productivity improvement. Examples of the latter include services to address power and energy consumption, environmental issues, new product development, and strategic management; the results of these services may not readily appear in gross productivity valuations (Youtie, Shapira, Li, & Dodonova, 2016). Further study to update the results of these models and to examine MEP impacts on other business outcomes would help to provide a fuller understanding of the MEP's results over a longer timeframe.

Authors' Note

Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed.

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Declaration of Conflicting Interests

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Notes

1. For a review of the development and operations of the MEP, see National Research Council (2013).
2. This percentage is based on 58 centers (excluding nonoperational centers in Alaska and Florida).
3. National Research Council (2013). According to this study, MEP services peaked most recently in financial year 2007, with 9,000 clients served through some 14,500 projects.
4. 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.
5. See Angrist and Pischke (2009, p. 245).
6. 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.
7. See Angrist and Pischke (2009, pp. 246-247).
8. Using some of these variables, we created variables to use in our analyses that quantified the total number of engagements for each establishment, as well as the total number of cumulative hours of service provided by the MEP center.
9. This low match rate calls for future collaboration between the Census Bureau, NIST MEP, and outside researchers to address recordkeeping and other data elements that facilitate accurate matches across time.
10. Some tabular and model details in subsequent parts of this section were not able to be released through the Census Bureau disclosure process. These are summarized in more general models or in text only.
11. In interpreting this statistically insignificant result, keep in mind the possibility that some treated firms may erroneously be included in the control group, leading to a downward bias in the absolute value of the coefficients.
12. The variable that measures the minimum distance to an MEP office was operationalized using an SAS routine that computes latitude and longitude coordinates. We then generated the minimum distance between an establishment and the nearest MEP office using the standard Haversine formula, which accounts for the circular nature of geographic distance.
13. Value-Added by Industry. Available from http://www.bea.gov.

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