Productivity and Employment Dynamics of U.S. Manufacturing Plants*

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August 2015

Abstract

This study estimates the plant-level dynamics of productivity and employment in the United States. We use the Annual Survey of Manufactures from the U.S. Census Bureau for the period 1972 to 1997. Applying the system generalized method-of-moments estimation developed by Blundell and Bond (1998), we find that productivity and employment processes are both strongly persistent.

Keywords: plant-level productivity, plant-level employment, dynamic panel estimation
JEL Classifications: E23, E24, L11, L60

*We thank Pierre Sarte, Nezih Guner, Seung Chan Ahn, Tim Dunne, and Yoonseok Lee for their comments and suggestions. Part of this paper's content was circulated under the title "Entry, Exit, and Plant-level Dynamics over the Business Cycle." The research in this paper was conducted while the authors were Special Sworn Status researchers of the U.S. Census Bureau at the Michigan Census Research Data Center. Research results and conclusions expressed are those of the authors and do not necessarily reflect the views of the Census Bureau. This paper has been screened to ensure that no confidential data are revealed.

1 Introduction

Over the past several decades, it has been widely documented that establishment- and firm-level productivity and employment exhibit far more volatile dynamics than do aggregate-level productivity and employment.[1] Based on this insight, recent models of firm dynamics have analyzed the effects of various market frictions and policies on firm-level behavior and macroeconomic outcomes.[2] Typically, this literature utilizes an estimated simple stochastic process, such as an AR(1) process, to calibrate the idiosyncratic productivity dynamics of establishments and firms. Although the persistence of idiosyncratic shocks is considered an important parameter,[3] there is no consensus on the estimated persistence from the data. While some estimates (e.g., Cooper and Haltiwanger (2006), Foster, Haltiwanger, and Syverson (2008), and Midrigan and Xu (2014)) suggest that the productivity process is persistent, others find the persistence to be quite low (e.g., Ábrahám and White (2006)). A low persistence is somewhat puzzling in light of the estimated employment process, which is considered typically as very persistent (e.g., see Hopenhayn and Rogerson (1993)).

In this study, we estimate the productivity and employment processes of U.S. manufacturing plants, using the Annual Survey of Manufactures (ASM) dataset from the U.S. Census Bureau for the period 1972 to 1997. We argue that the above disagreement in the literature is largely due to the econometric method used. We show that with our preferred econometric method, based on the work of Blundell and Bond (1998), the idiosyncratic productivity and employment processes in U.S. manufacturing exhibit strong persistence.

[1] See, for example, Dunne, Roberts, and Samuelson (1989), Davis, Haltiwanger, and Schuh (1996), and Bartelsman and Doms (2000).

[2] See, for example, Hopenhayn and Rogerson (1993) for firing costs, Restuccia and Rogerson (2008) for taxes, Guner, Ventura, and Xu (2008) for size regulations, Moscoso Boedo and Mukoyama (2012) for entry costs and firing costs, and Buera, Kaboski, and Shin (2011) and Midrigan and Xu (2014) for financial frictions.

[3] For example, Moll (2014) argues that the persistence of productivity crucially affects the impact of financial frictions on the aggregate outcome.

2 Data

We use the Annual Survey of Manufactures for the period 1972 to 1997, collected by the U.S. Census Bureau. This dataset has been utilized by a number of researchers to analyze patterns of job creation and destruction, as well as the productivity dynamics of plants (e.g., Davis, Haltiwanger, and Schuh (1996), Baily, Bartelsman, and Haltiwanger (2001), Ábrahám and White (2006), and Lee (2007)).[4]

We estimate the productivity process at the plant level. Our measure of productivity is revenue total factor productivity (TFP, often called TFPR), which is constructed following Baily, Hulten, and Campbell (1992).[5] Assuming that the production function is $y_t = s_t {k_t}^{\theta_k} {n_t}^{\theta_n} {m_t}^{\theta_m}$, where y_t is real gross output, s_t is TFP, k_t is real capital stock, n_t is labor input, and m_t is real material inputs, the TFP (s_t) can be measured from the growth accounting equation:

$$\ln(s_t) = \ln(y_t) - \theta_k \ln(k_t) - \theta_n \ln(n_t) - \theta_m \ln(m_t).$$

As the output measure, we use the total value of shipments, deflated by the shipments deflator from the National Bureau of Economic Research (NBER) manufacturing productivity database.[6] Real capital stock is obtained by summing the real value of structures and the real value of equipment, constructed using the perpetual inventory method.[7] Labor input is measured as total hours for production and nonproduction workers. Note that hours for nonproduction workers are not collected. Thus, we estimate the value for total hours following the method in Baily, Hulten, and Campbell (1992), which multiplies the total hours

[4] See Davis, Haltiwanger, and Schuh (1996) for details about the data.

[5] Without a proper measurement of prices for individual plants, it is not possible to calculate TFP at the plant level properly. While we call our measure of productivity "TFP," it is actually real revenue per unit input and reflects within-industry price variation. See Foster, Haltiwanger, and Syverson (2008) for possible issues involved in using revenue-based productivity measures.

[6] Although it is possible to adjust output for the change in inventories, inventories for some plants are imputed (Baily, Bartelsman, and Haltiwanger (2001)). We choose to use gross shipments to avoid a possible measurement issue.

[7] We follow Dunne, Haltiwanger, and Troske (1997) closely in constructing the capital stock value. See Lee and Mukoyama (2008) for details on constructing real capital stock and TFP.

	Productivity	Employment
ρ	0.754	0.972
	(0.003)	(0.001)
σ	0.298	0.379

Table 1: OLS estimation

of production workers by the ratio of the total payroll for all workers to the payroll for production workers. Material inputs are obtained by deflating the costs of materials using material deflators from the NBER manufacturing productivity database. We use four-digit industry-level revenue shares as factor elasticities.[8]

3 Estimation and Implications

First, we estimate the AR(1) processes

$$\ln(s_{it}) = \alpha + \rho \ln(s_{i,t-1}) + \mathbf{x}'_{it}\boldsymbol{\beta} + \varepsilon_{it},$$

where $\varepsilon_{it} \sim N(0, \sigma^2)$, for productivity, and

$$\ln(n_{it}) = \alpha + \rho \ln(n_{i,t-1}) + \mathbf{x}'_{it}\boldsymbol{\beta} + \varepsilon_{it},$$

where $\varepsilon_{it} \sim N(0, \sigma^2)$, for employment. The subscript i indicates plant i and t indicates time t. The controls $\mathbf{x}_{it}$ include year, plant age, and industry dummies. In addition, for productivity, we include size dummies.

Table 1 describes the estimates of ρ and σ for productivity and employment. Consistent with earlier literature, the employment process is very persistent. The productivity process is fairly persistent, but not as much as the employment process.[9] In a competitive model

[8] We use the average of revenue shares between adjacent time periods (i.e., the Tornqvist index). In calculating labor's share, we follow Bils and Chang (2000) and use information from the National Income and Product Accounts. We adjust each industry's wage and salary payments to reflect other labor payments, such as fringe payments and employer FICA payments. The Appendix presents summary statistics of θ_k, θ_n, and θ_m (Table A1).

[9] Using a different dataset, Foster, Haltiwanger, and Syverson (2008) obtain an annual autocorrelation in the range of 0.75 to 0.8.

	Productivity	Employment
ρ	0.272	0.493
	(0.006)	(0.005)
σ	0.209	0.267

Table 2: Fixed-effect estimation

without frictions and adjustment costs, the productivity and employment at each plant should move one-to-one. The discrepancy suggests the existence of adjustment costs at the plant level, although it can also reflect some measurement issues. It is well known that measurement errors may bias the regression coefficient toward zero (see, e.g., Griliches and Hausman (1986)). The calculation of our productivity measure is based on capital and material inputs as well as labor. If plant-level productivity is more likely to suffer from measurement errors than employment because of the measurement errors in other inputs, an attenuation bias may result in lower estimates of persistence.

One concern with the ordinary least squares (OLS) regression is that there may be unobserved heterogeneity across plants, which can make the OLS estimator inconsistent. A usual econometric remedy for this problem is to perform a fixed-effect regression. This path is taken by Ábrahám and White (2006). Table 2 describes the fixed-effect results in our regressions. As in Ábrahám and White (2006), the persistence is significantly lower in both productivity and employment.[10] The problem here is that the fixed-effect estimator in this type of dynamic panel regression is inconsistent unless the time dimension goes to infinity.[11] In fact, the fixed-effect estimator is also downward biased. This bias is often called the "Nickell bias," and it can be quite large when the time dimension of the panel is short.[12]

One solution for this problem is to use an instrumental variable (IV) estimator, as suggested by Anderson and Hsiao (1981), Arellano and Bond (1991), and Blundell and Bond (1998). In particular, Blundell and Bond (1998) argue that their system GMM method

[10] Ábrahám and White's (2006) method of obtaining the productivity series is different from ours, and their estimates of the annual persistence range from 0.37 to 0.41.

[11] See, for example, Baltagi (2013, Chapter 8) and Cameron and Trivedi (2005, p.764).

[12] See Nickell (1981) and Lee (2012).

	Productivity	Employment
ρ	0.843	0.993
	(0.028)	(0.008)
σ	0.301	0.380
$m1$	-25.01	-41.40
$m2$	2.75	3.01

Table 3: System GMM estimation

leads to a substantially more efficient estimation compared to earlier IV methods when the persistence is high and the time dimension is short. These conditions apply to our situation.

Table 3 presents our results using the system GMM estimation of Blundell and Bond (1998). Here, the IVs are $s_{i,t-4}$ and $s_{i,t-5}$ for productivity, and $n_{i,t-4}$ and $n_{i,t-5}$ for employment.[13] The estimated value of ρ is even larger than in the OLS case. Therefore, within the AR(1) framework, it is reasonable to conclude that both productivity and employment processes are persistent. Note that the difference in the value of ρ between productivity and employment is smaller than that observed in the OLS case.[14]

In Table 3, the null hypothesis of no first-order serial correlation (i.e., the $m1$ test proposed by Arellano and Bond (1991)) is rejected. When the model is AR(1) and there is no autocorrelation in the error term, the differenced error term may have first-order autocorrelation, and the $m1$ test is usually rejected. However, the issue here is that the $m2$ test also rejects the null hypothesis of no second-order serial correlation in the residuals from the first-difference equation. This suggests that the instruments may not be valid because of serial correlation in the residuals, the AR(1) model may be misspecified, or both problems may be

[13] The Appendix Section B reports additional estimation results using shorter lags as instruments, starting with $n_{i,t-2}$ and $n_{i,t-3}$ (Tables A2 and A3). Note that Arellano and Bond's (1991) $m2$ tests are rejected in all cases with AR(1) specifications, indicating the possible existence of misspecification regardless of the lag length, as discussed below. In the AR(2) specifications, which are also reported in the Appendix (Tables A4 and A5), $m2$ tests are again rejected when shorter lags are used. In Table 3, we report the results based on the instruments with the same lag length as those used in Table 4. In Table 4, we choose to present the AR(2) results with these instruments because the $m2$ tests are not rejected when these instruments are used.

[14] In addition, we estimated using the standard first-differenced GMM estimator and found a much lower persistence. However, the poor performance of the first-differenced GMM estimator at high values of ρ is well documented in Blundell and Bond (1998).

	Productivity	Employment
ρ_1	0.956 (0.093)	0.901 (0.063)
ρ_2	0.014 (0.080)	0.080 (0.063)
$\tilde{\sigma}$	0.282	0.358
$m1$	-6.97	-7.72
$m2$	-0.91	-0.63

Table 4: System GMM estimation, AR(2)

present.[15] To address the concern that the system GMM estimator may be inconsistent, we estimate AR(2) processes of the form

$$\ln(s_{it}) = \alpha + \rho_1 \ln(s_{i,t-1}) + \rho_2 \ln(s_{i,t-2}) + \mathbf{x}_{it}'\boldsymbol{\beta} + \varepsilon_{it},$$

where $\varepsilon_{it} \sim N(0, \tilde{\sigma}^2)$, for productivity, and

$$\ln(n_{it}) = \alpha + \rho_1 \ln(n_{i,t-1}) + \rho_2 \ln(n_{i,t-2}) + \mathbf{x}_{it}'\boldsymbol{\beta} + \varepsilon_{it},$$

where $\varepsilon_{it} \sim N(0, \tilde{\sigma}^2)$, for employment. Once again, the controls $\mathbf{x}_{it}$ include year, plant age, size, and industry dummies for productivity, and year, plant age, and industry dummies for employment.

Table 4 presents the result of the system GMM estimation for the AR(2) model. The IVs are $s_{i,t-5}$ and $s_{i,t-6}$ for productivity and $n_{i,t-5}$ and $n_{i,t-6}$ for employment. The results on ρ_1 and ρ_2 indicate that both series exhibit strong persistence. In particular, the productivity persistence, even with the ρ_1 term only, is much stronger than in the AR(1) case. The $m1$ and $m2$ tests of serial correlation in the first-difference residuals are consistent with the key assumption of no serial correlation in the residuals. Therefore, here, there is less concern of misspecification than in the AR(1) model.[16]

[15] Sargan tests of overidentification restriction are rejected. However, according to Arellano and Bond (1991), simulation results suggest that those identification tests reject the null hypothesis too often in the presence of heteroskedasticity. This is very likely the case in an establishment-level dataset like ours.

[16] There have been recent developments on the topic of the lag-order selection in dynamic panel models, although they are beyond the scope of this study. See, for example, Han, Phillips, and Sul (2013) and Lee and Phillips (2014).

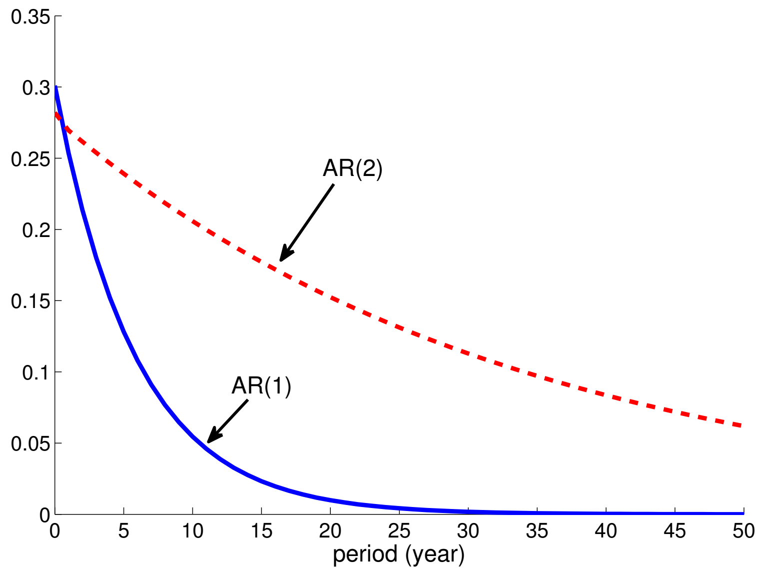

Figure 1: Comparison of impulse-response functions for AR(1) estimates (Table 3) and AR(2) estimates (Table 4) for the productivity process.

Note that our estimates are based on plants that survived at least 4 or 5 years, because the estimation uses lagged variables as instruments. It must always be kept in mind the bias that might be caused by the sample selection, although the direction of the bias is not obvious.[17]

Given this result, one question that might be asked is what would be the problem of using the AR(1) specification for the productivity process in a quantitative model analysis instead of the AR(2) specification? This is a relevant question since there is substantial literature in macroeconomics and industrial organization that uses AR(1) productivity processes as a main building block. One way of answering this question is to compare the impulse-response functions for the AR(1) specification and the AR(2) specification.

Figure 1 makes this comparison. The solid line plots the impulse-response function to a 1 standard deviation shock for productivity process, using the estimates from Table 3. The dashed line instead uses the estimates from Table 4. There is a marked difference in terms of

[17]Owing to the panel rotation of the ASM, more of the "certainty" plants, which tend to be large, are included in the sample, when longer lags are used in the estimation.

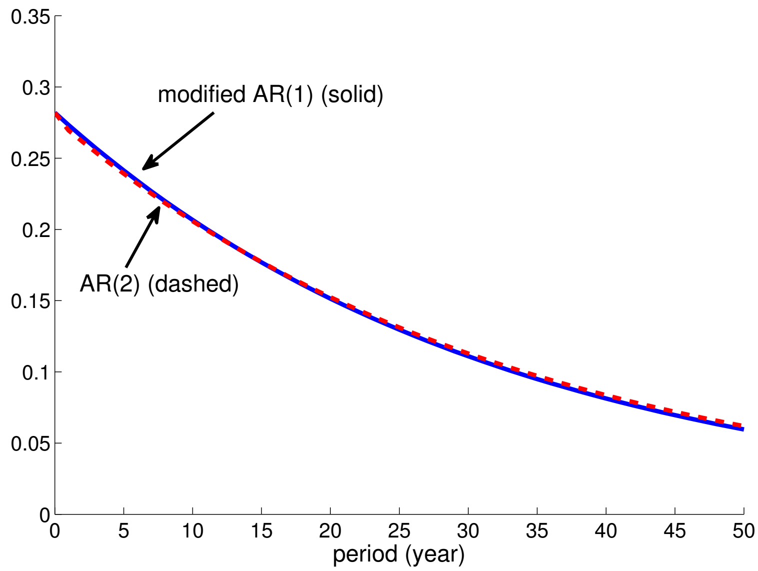

Figure 2: Comparison of impulse-response functions for AR(1) process with $\rho = \rho_1 + \rho_1\rho_2$ and $\sigma = \tilde{\sigma}$ in Table 4 and AR(2) estimates (Table 4) for the productivity process.

the persistence of productivity shock. Thus, using the AR(1) results from Table 3 may lead to misleading results.

Now, in order to search for an AR(1) specification that can reasonably be used in a quantitative model, we instead use $\rho = \rho_1 + \rho_1\rho_2 = 0.969$ and $\sigma = \tilde{\sigma}$ obtained in Table 4 as the parameter values for the AR(1) process. The impulse-response functions are presented in Figure 2.[18] This modified AR(1) impulse-response function (solid line) is almost indistinguishable from the AR(2) impulse-response function (dashed line). This is mainly due to the fact that the estimated value of ρ_2 is very small. Therefore, if this modified AR(1) process is used, the quantitative properties of the model would be quite close to the case in which the (correct) AR(2) process is used. Thus, our recommended calibration strategy when an AR(1) process is used in a quantitative model is to use this modified ρ and σ. If, instead, the estimates in Table 3 (or the estimates from Table 1 or Table 2) are used, it would likely lead to misleading quantitative results.

[18]The results are similar if we use $\rho = \rho_1 + \rho_2$ instead.

	ρ
Cooper and Haltiwanger (2006)	0.981
Ábrahám and White (2006)	0.373–0.406
Foster, Haltiwanger, and Syverson (2008)	0.757–0.814
Castro, Clementi, and Lee (2015)	0.439

Table 5: Values of ρ estimated in the literature

	ρ (adjusted to annual value)
Hopenhayn and Rogerson (1993)	0.982
Restuccia and Rogerson (2008)	1.0 (constant)
Guner, Ventura, and Xu (2008)	1.0 (constant)
Moscoso Boedo and Mukoyama (2012)	0.970

Table 6: Values of ρ used in quantitative models

How does our result compare to the literature? Table 5 lists some of the representative annual estimates of ρ in the literature when an AR(1) specification is used.[19] Interestingly, our modified AR(1) estimate is very similar to that of Cooper and Haltiwanger (2006), who structurally estimate a dynamic model of investment. Table 6 lists the values of ρ used in quantitative models. These are largely in line with our modified AR(1) number in terms of persistence.

4 Conclusion

We estimated the time-series properties of plant-level productivity and employment for the U.S. manufacturing sector. With our preferred econometric method, based on Blundell and Bond (1998), both productivity and employment exhibit strong persistence. In the case of the

[19] For Cooper and Haltiwanger (2006), we report only the number that achieves the highest likelihood. For Castro, Clementi, and Lee (2015), we report simple means of AR(1) coefficients across 3-digit industries. Some other studies, such as Midrigan and Xu (2014), use specifications that are different from AR(1).

system GMM, we found that the AR(2) specification is preferable to the AR(1) specification. In a theoretical model, an AR(1) specification for the productivity process often has to be used to minimize the number of state variables. This situation can be accommodated by using an AR(1) process with a persistence parameter suitably calculated from the persistence parameters from the AR(2) process and the standard deviation estimate from the AR(2) estimation.

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Appendix

A Summary Statistics of Factor Elasticities

Table A1 presents summary statistics of estimated factor elasticities θ_k, θ_n, and θ_m. It reports the summary statistics for the averages of estimated factor elasticities across four-digit industries between 1972 and 1997. We set the elasticities equal to the averages of four-digit industry level revenue shares between adjacent time periods (i.e., the Tornqvist index).

	Sample Size	Mean	Std. Dev.
θ_k	11307	0.204	0.090
θ_n	11307	0.254	0.100
θ_m	11307	0.505	0.127

Table A1: Summary statistics of factor elasticities

B Additional Tables for Estimation Results

This section presents additional results on the estimations we performed in Section 3. Tables A2 and A3 supplement Table 3 (the third column of each table corresponds to Table 3 results). They present the system GMM estimation of productivity and employment processes with AR(1) specification, using different instruments. As noted in footnote 13, both $m1$ and $m2$ tests are rejected in all of the specifications in Tables A2 and A3. This indicates the possible existence of misspecification.

Similarly, Tables A4 and A5 supplement Table 4. In both tables, the third column corresponds to the results in Table 4. In each table, the $m1$ and $m2$ tests are rejected in both the first and the second column. In the third column, the $m2$ test is not rejected.

Productivity, AR(1)				
ρ	0.601	0.746	0.843	0.884
	(0.010)	(0.019)	(0.028)	(0.019)
σ	0.307	0.298	0.301	0.304
$m1$	−39.09	−25.54	−25.01	−31.43
$m2$	2.08	2.33	2.75	2.56
Instruments	s_{t-2}	s_{t-3}	s_{t-4}	s_{t-5}
	s_{t-3}	s_{t-4}	s_{t-5}	s_{t-6}

Table A2: System GMM estimation of productivity process, AR(1)

Employment, AR(1)				
ρ	0.881	0.992	0.993	0.998
	(0.007)	(0.009)	(0.008)	(0.007)
σ	0.397	0.380	0.380	0.380
$m1$	−49.55	−38.82	−41.40	−41.95
$m2$	3.40	3.00	3.01	2.99
Instruments	n_{t-2}	n_{t-3}	n_{t-4}	n_{t-5}
	n_{t-3}	n_{t-4}	n_{t-5}	n_{t-6}

Table A3: System GMM estimation of employment process, AR(1)

Productivity, AR(2)			
ρ_1	1.086	0.996	0.956
	(0.059)	(0.077)	(0.093)
ρ_2	−0.167	−0.049	0.014
	(0.036)	(0.061)	(0.080)
$\tilde{\sigma}$	0.290	0.283	0.282
$m1$	−14.53	−8.90	−6.97
$m2$	6.28	2.11	0.91
Instruments	s_{t-3}	s_{t-4}	s_{t-5}
	s_{t-4}	s_{t-5}	s_{t-6}

Table A4: System GMM estimation of productivity process, AR(2)

Employment, AR(2)			
ρ_1	1.087 (0.050)	1.247 (0.087)	0.901 (0.063)
ρ_2	-0.266 (0.049)	-0.049 (0.086)	0.080 (0.063)
$\tilde{\sigma}$	0.365	0.380	0.358
$m1$	-12.48	-8.51	-7.72
$m2$	2.73	3.23	-0.63
Instruments	n_{t-3} n_{t-4}	n_{t-4} n_{t-5}	n_{t-5} n_{t-6}

Table A5: System GMM estimation of employment process, AR(2)