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Econometric analysis of productivity with measurement error: Empirical application to the US Railroad industry

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DISCUSSION PAPER

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Econometric Analysis of Productivity with Measurement Error: Empirical Application to the US Railroad Industry[1]

Daniel Coublucq[2]

Düsseldorf Institute for Competition Economics

June 2013

ABSTRACT

This paper analyzes the productivity in the US rail industry for the period 1980–2006. I propose a value-added production framework to circumvent the problem of measurement error in one input. I find evidence showing that aggregate productivity gains can be attributed to returns to scale and the reshuffling of resources to more efficient firms. However, productivity slows down for the period 1995–2000 after important concentrations. I also look at the correlations between firm-level productivity and the operating environment. My results

[1] I am thankful to the participants of the workshop on "Structural Approaches to Productivity and Industry Dynamics" (EIEF, Roma, April 2012) and the Kuhmo Nectar Conference on Transportation Economics (Berlin, June 2012). I also thank Pierre Dubois, Tomaso Duso, Kenneth Small, and my PhD committeee for useful comments. All errors are my own.

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show that failing to control for the omitted price variable bias leads to an overestimation of productivity gains.

Keywords: industry dynamics, measurement error, productivity, selection, simultaneity, railroad industry.

JEL Codes: C24, L11, L50, L92, L98

1 Introduction

Production function estimation is a powerful tool for economic analysis. First, it allows the recovery of the technology parameters. Second, it allows the assessment of policies on the evolution of firms' productivity. A major econometric issue in the estimation of production function is endogeneity due to the presence of unobserved firm-specific productivity shocks which are determinants of production not observed by the econometrician but observed by the firm. This leads to an endogeneity problem as the choice of inputs will be correlated with the unobserved component. Since the influential work of Olley and Pakes (1996) a significant part of the literature has been devoted to solving this endogeneity issue.

In this paper, I discuss another important econometric issue concerning measurement error in some inputs. Indeed, information on inputs is often imprecise. This measurement error in the explanatory variables is a serious problem in econometrics and often prevents the estimation. Instrumental variables (IV) estimation can deal with this issue in theory. However, IV estimation has not been very successful in production function estimation.[3] One solution to this problem is to subtract out the input(s) with measurement errors from the sales in the dependent variable, which would lead to a value-added production function framework where the value added is used as a measure of output.[4] The measurement error would then be in the

[3] In theory, input prices should be good instruments as they should not be correlated with productivity shocks and correlated with the input choices. However, in practice, input prices are difficult to obtain. Moreover, even if input prices are observed, they do not vary enough across firms to provide identification.

[4] Another reason to use sales is that researchers cannot observe the physical output.

dependent variable, which is a much less important problem than measurement error in the explanatory variables.[5,6]

Ideally, the value added would be deflated using a producer price index at the firm level. However, this type of index is not available in practice and so the value added is deflated using a producer price index at the industry level. This price error creates two major complications (De Loecker, 2011). First, it creates a bias in the estimated coefficients of the production function if inputs are correlated with the price error, i.e., the omitted price variable bias discussed in Klette and Griliches (1996). Moreover, relying on deflated sales generates productivity estimates containing price and demand variation. In this paper, I use insights from De Loecker (2011) to deal with these issues by introducing a demand system in a production function framework. The approach relies on exogenous variables to control for demand and price effects.

This paper analyzes productivity for the US rail freight industry for the period 1980–2006, where the data are characterized by measurement errors in one input. This leads to a value-added production framework. Moreover, this industry presents several characteristics which are interesting for productivity analysis.

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[5] Measurement error in the dependent variable results in a larger error variance than when the dependent variable is not measured with error. This translates into larger asymptotic variances for the estimates.

[6] The problem of measurement error in inputs is also mentioned in Brynjolfssen and Hitt (2003) where it prevents a direct estimation of the output elasticities.

First, the industry is characterized by a complete deregulation following the Staggers Act in 1980. In particular, this institutional change reduced constraints on pricing, exit, and operations with the hope that the industry would become more productive. As deregulation gave the railroads substantial freedom in rate-setting, track abandonments, and exits, it also provided them with a number of possibilities through which productivity could be enhanced. However, the productivity of the industry has not yet been investigated in detail.[7] I recover productivity at the firm-level and industry-level by estimating a production function. Since one input (i.e., the equipment) suffers from measurement error, I subtract out this input from the sales. The measurement error is in the dependent variable, namely real value added (deflated sales minus deflated cost of equipment), which mitigates this issue. I adopt insights from De Loecker (2011) to estimate the production function by using aggregate demand shifters to control for the omitted price variable bias. I extend the methodology by allowing the demand shifters to be correlated over time with a first-order Markov process. My results show evidence of increasing returns to scale which can justify the concentration that happened in this industry. Then, I compare my measure of productivity with an index measure provided by the Association of American Railroads (AAR). I show that these standard measures of productivity are biased upward since they cannot isolate the productivity responses to the Staggers Rail Act from the price and demand responses. I find an increase in productivity of 80%, which is still important, but more moderate than the increase of 170% with index measures.

[7] Several studies looked at the impact of the Staggers Act on rail rates (Ellig, 2002; Wilson, 1994) and costs (Ellig, 2002; Bitzan and Wilson, 2007). They find that rail rates have fallen in real terms and that deregulation has led to cost reductions.

Second, I also consider the selection issue due to the important attrition in the data. The deregulation, by allowing bankruptcies, exit, concentrations, and reallocation of resources across firms, transformed the network and the structure of the industry considerably. Indeed, there were 26 firms in 1978, while there are seven firms today. I find evidence showing that the reallocation of market shares and resources from the less efficient to the more efficient firms is a source of productivity improvement.

Third, I look at the evolution of productivity over time and I find that concentrations in the Western area in the mid-1990s led to a slowdown in productivity growth until 1997–98. This suggests that it took time to integrate the networks and operations successfully, and thus for the long-run effects on productivity to appear. My productivity estimates capture this long-term effect which is missing in index measures.

Finally, I relate changes in productivity to the operating environment of the industry. This highlights the impact of different operating practices and public policies on the performance of the railroad firms. Two methodologies have been used in the productivity literature to identify the causal effects of some variables on productivity growth (i.e., the determinants of productivity growth): either with a first-order controlled Markov process for the evolution of productivity (De Loecker, 2011, Doraszelski and Jamandreu, 2009) or a difference-in-differences approach (Pavcnik, 2002). However, these approaches are difficult to use in the case of the railroad industry due to the high dimensionality of the potential determinants of productivity growth. Indeed, productivity variation can arise from many different sources (see Martland, 2006, Oum, Waters, and Yu, 1999, Tretheway et al., 1997, Hensher et al., 1995): economies of traffic density, differences in network characteristics (e.g., average length of haul, communication and signaling systems), and other factors that

affect the performance (composition of traffic, the percentage of loaded freight cars, better car design, investment in the rail network). Thus I follow a two-step approach where productivity is regressed on a set of variables representing the operating environment. Though I cannot fully rule out the possibility of endogeneity, I follow the general practice by using firm fixed-effects to mitigate this issue. This approach is also used in Topalova and Khandelwal (2011) for the assessment of trade liberalization in India where fixed-effects absorb unobserved time-invariant heterogeneity and deal with potential endogeneity. I find a positive relation between productivity growth and the rationalization of the rail network through the abandonment of unprofitable lines, the shift to particular strategies (unit car and intermodal technologies, communication expenditures), and investment in the network.

The plan of the paper is as follows; the next section introduces the model and the empirical implementation. Section 3 looks at the data and descriptive statistics. Section 4 discusses the estimation results of the production function parameters. Section 5 relates productivity growth to several characteristics of the networks and firms. Section 6 gives concluding remarks.

2 Empirical model

2.1 Empirical issues

A productivity measure such as total factor productivity (TFP) reports how well a firm performs at turning inputs into outputs. I consider a standard Cobb-Douglas production function where a firm j produces an output $Y_{j,t}$ at time t using labor, $L_{j,t}$, energy, $E_{j,t}$, materials, $M_{j,t}$, and capital, $K_{j,t}$:

$$Y_{j,t} = L_{j,t}^{\alpha_l} E_{j,t}^{\alpha_e} M_{j,t}^{\alpha_m} K_{j,t}^{\alpha_k} \exp(\omega_{j,t} + u_{j,t}), \quad (1)$$

where production depends on a firm-specific productivity shock, $\omega_{j,t}$, that is known by the firm but not by the econometrician and an unexpected productivity shock that is not known either by the firm or by the econometrician, $u_{j,t}$. In this framework, it is crucial to obtain consistent estimates of the parameters in the production function to get correct productivity measures. The firm's private knowledge of its productivity, $\omega_{j,t}$, affects its decision whether to exit or stay in the industry, its choice of inputs, and investments into new capital. As Olley and Pakes (1996) and Pavcnik (2002) show, this introduces two biases in the estimation, namely the simultaneity and the selection biases.

In most applications, physical output is replaced by a measure of value added. I also follow this approach for two reasons. First, I have an imprecise measure of the equipment input. Indeed, there is no clear consensus in the literature about the measurement of this input. Several measures have been used. The literature on cost function (Berndt et al., 1993, Wilson, 1997) measured the cost of equipment as the rental price of equipment times an estimate of the replacement value of rolling stock. However, building the rental price of equipment is difficult as it requires information on the opportunity cost of holding equipment. Moreover, the estimate of the replacement value of rolling stock is obtained with a perpetual inventory method, which is conflicting with the treatment of equipment as variable inputs. I use a different measure of the equipment cost from data of the Association of American Railroads (see section on data description).[8] Since there are different ways to measure the equipment cost, measurement errors seem very likely for this input. Moreover, it is also necessary to

[8] Ivaldi and McCullough (2012) use a similar measure of the equipment cost.

deflate the equipment cost since the real cost of the equipment should be included as an input of the production function. This requires having a price index for the equipment input, which is not available in the data (see the data section; price indexes are available for the other variables inputs, labor, material, and energy using the Railroad Cost Recovery cost indexes, but not for the equipment). Thus I use a producer price index to deflate the equipment cost. Since the producer price index is likely to be different from the equipment price index, this adds a new source of measurement error in the equipment input. Since this measure of the equipment input (in current and in real terms) is imprecise due to measurement error, I use a value-added framework where the dependent variable is the deflated sales minus the deflated cost of equipment.[9] Therefore, the measurement error is now moved to the dependent variable (value added) which does not create a serious issue during the estimation. This may also justify why applied researchers often use a deflated measure of the value added when estimating the production function.

The second reason for using a value-added production framework is to allow a clear comparison between my estimates of productivity and previous studies which used an index measure of productivity (see the index in Figure 1, and Oum, Waters, and Yu, 1999, for further details, where output is measured with deflated sales). This allows me to assess the impact of the omitted price variable bias of Klette and Griliches (1996) on standard measures of productivity (index measure). I also compare my estimates with the Olley and Pakes (1996) approach where the issue of the omitted price variable bias is also not taken into account.

[insert Figure 1 here]

[9] I use the producer price index to deflate the sales as well.

The recent literature highlights two major complications in a value-added production framework. First, as discussed in Klette and Griliches (1996), using the deflated value added as the dependent variable will potentially bias the coefficients of the production function if inputs are correlated with prices, i.e., the omitted price variable bias. Second, De Loecker (2011) shows that it will generate productivity estimates containing price and demand variation. This introduces a relationship between measured productivity and deregulation through the deregulation's impact on prices and demand.

Therefore, I face the challenge of isolating the productivity response to deregulation. To this end, I follow De Loecker (2011) and I consider a horizontal product differentiation CES-type demand system:

$$Y_{j,t} = Q_t \left(\frac{P_{j,t}}{P_t}\right)^{\eta} \exp(\xi_{j,t}), \tag{2}$$

where the demand for the firm depends on its own price, $P_{j,t}$, an average price of the industry, P_t, an aggregate demand shifter, Q_t, and an unobserved demand shock, $\xi_{j,t}$. The revenue of the firm, denoted $R_{j,t} = P_{j,t}Y_{j,t}$, can be written as:

$$R_{j,t} = Y_{j,t}^{\frac{\eta+1}{\eta}} Q_t^{-\frac{1}{\eta}} P_t \big(\exp(\xi_{j,t})\big)^{-\frac{1}{\eta}}. \tag{3}$$

Then, I plug (1) into (3), and I consider the log deflated revenue ($\tilde{r}_{j,t} = r_{j,t} - p_t$). This implies the following estimating equation for the value-added generating production function:

$$\tilde{r}_{j,t} = \beta_l l_{j,t} + \beta_m m_{j,t} + \beta_e e_{j,t} + \beta_k k_{j,t} + \beta_q q_t + \omega^*_{j,t} + \xi^*_{j,t} + u_{j,t,} \tag{4}$$

where $\beta_l = \frac{\eta+1}{\eta}\alpha_l$, $\beta_m = \frac{\eta+1}{\eta}\alpha_m$, $\beta_e = \frac{\eta+1}{\eta}\alpha_e$, $\beta_k = \frac{\eta+1}{\eta}\alpha_k$, $\beta_q = -\frac{1}{\eta} = \frac{1}{|\eta|}$, $\xi^*_{j,t} = -\frac{1}{\eta}\xi_{j,t}$, and $\omega^*_{j,t} = \frac{\eta+1}{\eta}\omega_{j,t}$. The error term $u_{j,t}$ represents the measurement error in the dependent variable, the real value added $\tilde{r}_{j,t}$.

The parameters $\{\beta_l, \beta_m, \beta_e, \beta_k\}$ of the production function are reduced form parameters including production and demand parameters, as opposed to the true technology parameters $\{\alpha_l, \alpha_m, \alpha_e, \alpha_k\}$. Once I have estimates of the demand elasticity parameter, η, and the reduced form parameters, $\{\beta_l, \beta_m, \beta_e, \beta_k\}$, I can recover the technology parameters $\{\alpha_l, \alpha_m, \alpha_e, \alpha_k\}$. Then, the returns to scale in production are obtained as $\gamma = \alpha_l + \alpha_m + \alpha_e + \alpha_k$. When the omitted variable bias is not taken into account, the productivity estimates must be interpreted as sales per input measures, and this does not allow recovery of the returns to scale (this is also a drawback of index procedures). This is the case for an imperfectly competitive industry. Under perfect competition (high enough demand elasticity η), then the parameter β_q converges to zero, and the parameters $\{\beta_k, \beta_l, \beta_m, \beta_e\}$ converge to the true technology parameters $\{\alpha_k, \alpha_l, \alpha_m, \alpha_e\}$. In other words, standard productivity estimates (e.g., the approach of Olley and Pakes, 1996, and index measures) give a correct idea of the technology only under perfect competition. Otherwise, the omitted price variable bias prevents identification of the technology parameters. Moreover, note that unobserved prices are controlled through the demand shifter q_t.

Two technical issues remain to obtain consistent estimates of productivity: I need to control for the unobserved demand shocks, $\xi^*_{j,t}$, and the unobserved productivity shocks, $\omega^*_{j,t}$. For this, I rely on firm-specific demand shifters to control for the unobserved demand shock. I decompose demand shocks into demand shifters, $\boldsymbol{z}_{j,t}$, and a residual demand shock, $\tilde{\xi}_{j,t}$, which is assumed to be *i.i.d* across firms and time:

$$\xi_{j,t} = \boldsymbol{z}_{j,t}\beta_z + \tilde{\xi}_{j,t}. \tag{5}$$

This leads to the following estimating equation:

$$\tilde{r}_{j,t} = \beta_l l_{j,t} + \beta_m m_{j,t} + \beta_e e_{j,t} + \beta_k k_{j,t} + \beta_q q_t + \boldsymbol{z}_{j,t}\boldsymbol{\beta}_z + \omega^*_{j,t} + \epsilon_{j,t}, \tag{6}$$

where $\epsilon_{j,t}$ captures the idiosyncratic shock/measurement error to production, $u_{j,t}$, and demand, $\tilde{\xi}_{j,t}$.

Lastly, to consistently estimate the productivity, I need to control for the simultaneity and selection bias due to unobserved productivity shocks. The simultaneity bias comes from the correlation between inputs choices with the unobserved productivity. The selection bias comes from the liquidation of firms. To deal with these issues, I build on Olley and Pakes (1996) and Pavcnik (2002) to proxy for unobserved productivity using a dynamic control, the investment choice.[10] I use a dynamic model of firm behavior to show how the investment is used as a proxy for productivity shocks (which allows me to deal with the simultaneity bias in the estimation), and how productivity shocks play a role in the decision of exiting the market (which allows me to deal with the selection bias in the estimation). The next section reviews the approach of Olley and Pakes (1996).

2.2 Theoretical background

I base my econometric analysis upon the theoretical and empirical frameworks of firm profit-maximizing behavior in a dynamic context. I build on Ericson and Pakes (1995), Olley and Pakes (1996), Pavcnik (2002), and Doraszelski and Satterthwaite (2010).

A firm's goal is to maximize the expected value of its current and future profits. A firm is described by a vector of state variables consisting of productivity, $\omega_{j,t} \in \Omega$, capital stock,

[10] Moreover, using a dynamic control is less sensitive to colinearity issues with respect to the Levinsohn and Petrin (2003) approach, see Ackerberg et al. (2006) for further details.

$K_{j,t} \in R_+$, and demand characteristics $\boldsymbol{z}_{j,t} \in Z$. The aggregate demand shifter q_t is also considered as a state variable. At the beginning of each period, the firm decides whether to exit the market or to continue to operate. A firm continues to operate if its expected future cash flows exceed its liquidation value, denoted $\phi_{j,t}$. If the firm stays in the market, it chooses its investment and labor. Capital is a dynamic output that accumulates according to $K_{j,t+1} = K_{j,t}(1-d) + I_{j,t}$, where d is the depreciation rate. It is common to assume that all the state variables evolve as a first-order Markov process. The expected discounted value of all future cash flows for firm j is denoted $V_{j,t}(\omega_{j,t}, K_{j,t}, \boldsymbol{z}_{j,t}, q_t)$. Note that I consider the demand shifters $(\boldsymbol{z}_{j,t}, q_t)$ as state variables since they are likely to be correlated over time.

The firm's problem can be described by the dynamic program:

$$\begin{aligned} V(\omega_{j,t}, K_{j,t}, \boldsymbol{z}_{j,t}, q_t) \\ = Max\{\phi_{j,t}, \pi_{j,t}(\omega_{j,t}, K_{j,t}, \boldsymbol{z}_{j,t}, q_t) - c(i_{j,t}) \\ + \delta E[V(\omega_{j,t+1}, K_{j,t+1}, z_{j,t+1}, q_{t+1}) | \omega_{j,t}, K_{j,t}, \boldsymbol{z}_{j,t}, q_t]\}, \end{aligned} \tag{7}$$

where δ is the discount rate. The dynamic program yields a Markov perfect equilibrium for the firm's choice of exit and investment. The decision whether to stay/exit is represented by:

$$\chi_{j,t}(\omega_{j,t}, K_{j,t}, \boldsymbol{z}_{j,t}, q_t) = \begin{cases} 1 \; if \; \omega_{j,t} > \underline{\omega}_{j,t}(K_{j,t}, \boldsymbol{z}_{j,t}, q_t) \\ 0 \; otherwise, \end{cases} \tag{8}$$

where $\chi_{j,t} = 1$ represents the firm's decision to stay in the market, $\chi_{j,t} = 0$ represents the decision to exit the market, and $\underline{\omega}_{j,t}(.)$ is an unknown function of the state variables. The investment policy function is given by:

$$I_{j,t} = i_{j,t}(\omega_{j,t}, K_{j,t}, \boldsymbol{z}_{j,t}, q_t) = i_{j,t}(\omega_{j,t}, k_{j,t}, \boldsymbol{z}_{j,t}, q_t). \tag{9}$$

In the estimation, the investment rule will be used to control for unobserved productivity shock, while the exit/stay rule will be used to control for selection due to the exit

of the least productive firms. The next section discusses the estimation procedure to control for the unobserved productivity shocks.

2.3 Empirical implementation

To control for the productivity and exit of firms, I use a semi-parametric procedure similar to Olley and Pakes (1996) and Pavcnik (2002) in a value-added generating production function. This includes three steps.

In the first step, I focus on the coefficient of labor in (6). By inverting the investment rule in (9), unobserved productivity can be expressed as a function of observable variables:

$$\omega_{j,t} = i^{-1}\left(I_{j,t}, k_{j,t}, \boldsymbol{z}_{j,t}, q_t\right) = h(I_{j,t}, k_{j,t}, \boldsymbol{z}_{j,t}, q_t) \tag{10}$$

Substituting the above expression in (6) yields:

$$\tilde{r}_{j,t} = \beta_l l_{j,t} + \beta_m m_{j,t} + \beta_e e_{j,t} + \lambda\left(k_{j,t}, I_{j,t}, \boldsymbol{z}_{j,t}, q_t\right) + \epsilon_{j,t}, \tag{11}$$

where: [11]

$$\lambda\left(k_{j,t}, I_{j,t}, \boldsymbol{z}_{j,t}, q_t\right) = \beta_k k_{j,t} + \beta_q q_t + \boldsymbol{z}_{j,t}\boldsymbol{\beta}_z + h(.). \tag{12}$$

Since λ controls for unobserved productivity $\omega_{j,t}$, the error term is no longer correlated with the flexible inputs, labor, material, and energy, and I get a consistent estimate of the coefficients $(\beta_l, \beta_m, \beta_e)$. I specify a polynomial in $(k_{j,t}, I_{j,t}, \boldsymbol{z}_{j,t}, q_t)$ with interactions with period dummies to allow for different policy functions over time. The invertibility of the

[11] The control function $\lambda(.)$ also contains the demand parameters and reflects the difference between the structural error $\omega_{j,t}$ and how it enters the main estimating equation with $\omega^*_{j,t}$.

function $i(.)$ in (9) requires the investment to be positive (see Olley and Pakes, 1996, and Pavcnik, 2002). Thus, I consider only those observations with a positive investment.

After estimating the parameters $(\beta_l, \beta_m, \beta_e)$, I need to separate the effect of capital on output from its effect on a firm's decision to invest. The selection issue due to liquidation must also be taken into account. In order to estimate the parameters $(\beta_k, \beta_q, \beta_z)$, I use a GMM approach (see Ackerberg et al., 2006).

Using the first stage, for the given value of parameters $(\beta_k, \beta_q, \beta_z)$, I recover the productivity from

$$\omega_{j,t}(\beta_k, \beta_q, \beta_k) = \hat{\lambda}_{j,t} - \beta_k k_{j,t} - \beta_q q_t - \boldsymbol{z}_{j,t}\boldsymbol{\beta}_z. \tag{13}$$

I recover the innovation in productivity, denoted $\nu_{j,t}$, using the equation

$$\begin{aligned} \omega_{j,t} &= E(\omega_{j,t}|\omega_{j,t-1}, \chi_{j,t} = 1) + \nu_{j,t} \\ &= g(\omega_{j,t-1}, \chi_{j,t}(\underline{\omega}_{j,t}) = 1) + \nu_{j,t} \\ &= g(\omega_{j,t-1}, \underline{\omega}_{j,t}) + \nu_{j,t}. \end{aligned} \tag{14}$$

Indeed, due to the exit decisions, I have to take into account the selection issue since it is likely that the less efficient firms will exit the market. The exit/stay decision is given by equation (8). The decision to stay in the market depends on the threshold $\underline{\omega}_{j,t}(K_t, q_t, z_t)$. The evolution of the capital is deterministic as it depends only on the capital stock in the previous year, $K_{j,t-1}$, and the previous investment, $I_{j,t-1}$. However, the state variables $(q_t, \boldsymbol{z}_t)$ evolve as a first-order Markov process. Thus we cannot rewrite the threshold ratio as a function of $(q_{t-1}, \boldsymbol{z}_{t-1})$ due to the uncertainty in the evolution of these state variables. Overall, this prevents rewriting the threshold as a function of variables which are only in the information set at date $(t-1)$. In that case, we cannot use the non-linear least-squares framework of

Olley and Pakes (1996) since the parameters (β_q, β_z) would not be identified (the correction term, through the probability of staying, would depend on the contemporaneous state variables that appear in the right-hand side as well). Assuming these variables $(q_t, \boldsymbol{z}_{j,t})$ to be state variables is quite general since it allows for serial correlation over time. This is an extension of De Loecker (2011) where the demand shifters are not considered as state variables. With respect to the literature on production function estimation, the main improvement is that the probability of staying at date t cannot be regressed anymore only on variables in the information set at date $(t-1)$, but must be regressed on $\left(I_{j,t-1}, K_{j,t-1}, q_t, \boldsymbol{z}_{j,t}\right)$. I denote this probability $p_{j,t-1,t}$. This probability is estimated using a probit model with a fourth-order polynomial approximation in $\left(I_{j,t-1}, K_{j,t-1}, q_t, \boldsymbol{z}_{j,t}\right)$, and denoted $\hat{p}_{j,t-1,t}$.

The probability of staying at date t can be written as

$$\begin{aligned} P(\chi_{j,t}=1) &= P\left(\omega_{j,t} > \underline{\omega}_{j,t}(K_{j,t}, q_t, \boldsymbol{z}_{j,t}) \middle| \omega_{j,t-1}\right) \\ &= p\left(\underline{\omega}_{j,t}(K_{j,t}, q_t, \boldsymbol{z}_{j,t}), \omega_{j,t-1}\right) \\ &= p(i_{j,t-1}, k_{j,t-1}, q_t, \boldsymbol{z}_{j,t}) = p_{j,t-1,t}. \end{aligned} \tag{15}$$

The first and second equalities follow from the decision rule in (8), the third equality uses the investment to control for the unobserved quality $\omega_{j,t-1}$, and we must use $(q_t, \boldsymbol{z}_{j,t})$ as mentioned above to include all the information on the uncertainty inherited from the Markov processes. I can inverse the equation (15) to obtain a proxy for the threshold $\underline{\omega}_{j,t}$ as:

$$\underline{\omega}_{j,t} = f\left(\hat{p}_{j,t,t+1}, \omega_{j,t-1}\right), \tag{16}$$

where $\hat{p}_{j,t,t+1}$ is the estimated probability of the indicator at date t against $(i_{j,t-1}, k_{j,t-1}, q_t, \boldsymbol{z}_{j,t})$.

Using (16) and (14), we can rewrite the productivity process as

$$\omega_{j,t} = g\left(\omega_{j,t-1}, \hat{p}_{j,t-1,t}\right) + \nu_{j,t}. \tag{17}$$

Using the first-stage estimates for $\hat{\lambda}_{j,t}$, for a given value of parameters $(\beta_k, \beta_q, \boldsymbol{\beta}_z)$, I recover the productivity using equation (13). I obtain $\nu_{j,t}(\beta_k, \beta_q, \boldsymbol{\beta}_z)$ as the residual by non-parametrically regressing $\omega_{j,t}(\beta_k, \beta_q, \boldsymbol{\beta}_z)$ on $\omega_{j,t-1}(\beta_k, \beta_q, \boldsymbol{\beta}_z)$ and $\hat{p}_{j,t-1,t}$. The parameters are obtained by GMM using the moment conditions:

$$E\left\{\nu_{j,t}(\beta_k, \beta_q, \boldsymbol{\beta}_z)\begin{pmatrix} k_{j,t} \\ q_{t-1} \\ \boldsymbol{z}'_{j,t-1} \end{pmatrix}\right\} = 0. \tag{18}$$

The moment conditions rely on the principle that the innovation $\nu_{j,t}$ belongs to the information set at date t, and it is orthogonal to variables belonging to the information set at date $(t-1)$. The capital parameter is identified using the condition $E\left(\nu_{j,t}k_{j,t}\right) = 0$. Indeed, the capital stock at date t is a deterministic function of the previous capital stock and investment, which belongs to the information set at date $(t-1)$. The parameters $(\beta_q, \boldsymbol{\beta}_z)$ are identified under the assumption that the innovation in productivity is not correlated with the lag industry-demand shifter and the lag-firm-specific demand shifters.

3 Data: the US railroad industry

The US railroad industry is composed of several types of railroads: Regional and Class 1 railroads. The dataset covers only the Class 1 railroads (operating revenue in excess of US$346.8 million in 2006), which account for 90% of its employees and 93% of its freight revenue. The main sources of data are the "Analysis of Class 1 Railroads" (hereafter *Analysis*) published annually by the Association of American Railroads (AAR). The *Analysis* is based

on regulatory reports that railroads submit to the Surface Transportation Board (STB). The descriptive statistics are presented in Table 1.

[insert Table 1 here]

The US rail industry is characterized by a rather "light" regulation. This regulatory freedom came from the Staggers Act, which deregulated US railroads in 1980. The Staggers Act gave the railroads substantial freedom in rate-setting, capital adjustment, track abandonments, and exit. This deregulation process led to several exit and takeover waves which led to a concentrated industry today. Namely, there were 26 firms in 1980, while there are only seven firms today (see Appendix on data construction).

Output measurement. Railroad firms provide freight services. The data on freight traffic consist of freight revenue (item 599 of the *Analysis*). As a measure of output, I consider value added, that is freight revenue minus the cost of equipment (measured by the items 254–259 minus item 172 of the *Analysis*).[12] Then, these monetary variables are converted in current dollars (real $1982) using the producer price index from the Statistical Abstract of the US (see also the US Bureau of Labor Statistics).

Input measurement. The labor variable is constructed by taking the total numbers of hours worked (item 326 of the *Analysis*). The material expenditures are measured by item 252 of the *Analysis* and they are deflated using the AAR railroad cost index for materials. The fuel expenditures are measured using item 253 and they are deflated using the AAR railroad cost

[12] I follow Ivaldi and McCullough (2012) to measure the cost of equipment (the depreciation, item 172, must be removed from the cost of the equipment).

index for fuel. Note that these two cost indexes differ depending on whether the railroad firm is active on the Western or on the Eastern area of the US. Capital is the input that is the most difficult to measure correctly. It is measured in currency units rather than physical quantities. The most common procedure is the perpetual inventory method:

$$K_{j,t} = K_{j,t-1}(1-d) + I_{j,t-1} \tag{19}$$

where $I_{j,t-1}$ is measured for each year and converted in real \$1982 using a producer price index, and d is the depreciation rate.

The construction of the capital stock follows the methodology of Berndt, Friedlaender, and McCullough (1992). Accordingly, I start with an authoritative estimate of the reproduction cost of capital in 1973 using Nelson (1975), and I update the stock of capital of firm j using the perpetual inventory relation (19). The depreciation rate d is derived by solving an equation that allows railroad capital to depreciate exponentially over 25 years to a salvage value of 10 per cent.[13] This perpetual inventory process is iterated to bring the series of way and structure capital until 2006.[14] The "Analysis of Class 1 Railroads (1980–2006)"

[13] The 25-year assumption is based on Berndt et al. (1992).

[14] It is important to mention the treatment of exit and takeovers in the construction of the capital stock. For example, consider the takeover between "UP" and "MKT" in 1987 (see the Appendix on data construction). The *Analysis* gives us the data on the capital stock at the end of 1987 for "MKT" and "UP" and the data for the capital stock at the end of 1988 for the merged firm "UP_MKT". To measure the investment of the merged firm "UP_MKT" in 1988, it is necessary to know its capital stock at the beginning of 1988. However, this data is not available in the *Analysis.* This data exists in the initial R1 reports filled by the railroad

allows the measurement of the nominal investment which is then converted into real value ($1982). The main difficulty lies in measuring this nominal investment component for way and structures capital. Prior to 1982, railroads used "betterment" accounting in which the work on railroad way and structures is listed as an expense and is thus excluded from the undepreciated book value of road (item 67 in the *Analysis*). Thus a first difference of the undepreciated book value of road allows measuring the nominal investment at an annual point. After 1982, the railroad industry adopted a depreciation accounting system, where the work on way and structures is added to the book value of road. It is thus necessary to remove the expenditures linked to the maintenance of the network (item 174 minus item 172 in the *Analysis*) from the undepreciated book value of road and then take a first difference to obtain the nominal investment.

Aggregate demand shifter. I apply insights from Klette and Griliches (1996) and De Loecker (2011) to construct the aggregate demand shifter, q_t, as the market share average of the deflated log-revenue: $q_t = \sum_{j=1}^{N_t} s_{j,t}\tilde{r}_{j,t}$, where N_t is the number of active firms at date t, and $s_{j,t}$ is the market share of firm j at date t.

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firms in 1988, but the R1 reports for the period 1978–1995 are no longer available except on microfiche in the library of the Surface Transportation Board in Washington, DC. Only the R1 reports for the period 1996–2006 are available on the STB website. Thus, I make the assumption that the capital stock of the merged firm "UP_MKT" at the beginning of 1988 is equal to the sum of the capital stocks of the merging parties "UP" and "MKT" at the end of 1987.

Demand shifters. These two variables are used to control for unobserved demand shocks in the estimation of the production function (6). I follow Vellturo (1989) and Berndt et al. (1993a, 1993b) in using a set of exogenous demand related variables that can be constructed on a firm-specific basis (see Coublucq, 2012, for additional details). These variables —*coal consumption (CCON), coal production (CPRO)*— are measured on a state-by-state basis and are then aggregated across states to be railroad-specific and to conform to each railroads' operating territory.[15] These aggregations vary from year to year as some railroad firms exited the industry while others extended their networks by buying their assets. These variables are based on the annual data from the Association of American Railroads, the Department of Transport Statistics, and the Statistical Abstract of the US.

4 Estimation results and aggregate productivity analysis

Table 2 presents the estimates of the input coefficients from the production function. I use two different approaches which both control for the issue of unobserved productivity shocks. The first one is the approach of Olley and Pakes (1996) denoted OP, which is standard in the literature on productivity. I compare the results with the new approach of De Loecker (2011), denoted DL, which takes into account the omitted price variable bias and the unobserved demand shocks. Indeed, under imperfect competition, equation (4) shows that the omitted price variable bias prevents the identification of the true technology parameters.

[15] The use of the variables *CCON* and *CPRO* is justified since coal is the main commodity carried by the US railroad firms. In 2007, coal accounted for 44% of rail tonnage and 21% of rail revenue.

Moreover, standard methodologies fail to distinguish between the pure productivity shocks and the demand shocks.

Several estimation issues should be pointed out. This paper uses series approximations in all stages of estimation: the estimation of the variables inputs' coefficients, the estimation of the survival probability, and the estimation of the capital stock and the demand shifters' coefficients. Since the limiting distribution has not been worked out, I report bootstrap estimates of the standard errors. First, when I estimate the partially linear regression model in (11), I use a fifth-order polynomial expansion in *capital*, *investment*, *CCON*, and q_t for model 2; a fifth-order polynomial expansion in *capital*, *investment*, *CPRO*, and q_t for model 3; a fourth-order polynomial expansion in *capital*, *investment*, *CPRO*, *CCON*, and q_t for model 4; and a fourth-order polynomial in *capital*, *investment*, and q_t for model 5. I allow the polynomial to vary over time since the investment policy function may be different over time.[16,17] Second, I estimate the survival probability (15) using a probit with a polynomial approximation of degree 4 in *capital* and *investment*, and pairwise interactions between the

[16] I distinguish between the periods 1980–1990, 1991–1998, 1999–2002, and 2003–2006 by including time indicators corresponding to these periods. The results are robust if I include a time trend instead of period dummies. I also interact time indicators with the variables *capital*, *investment*, *CPRO* and/or *CCON*, and q_t. I also checked the robustness of the estimates when I use a higher-order polynomial.

[17] For the approach of Olley and Pakes (1996), I use a fourth-order polynomial expansion in capital and investment. I also checked the robustness of the estimates when I use a higher-order polynomial.

demand shifters (*CPRO* and/or *CCON*, and q_t) and the *capital* and *investment*. I also include period dummies. Third, I use a third-order polynomial expansion in $\hat{\lambda}_{j,t-1} - \hat{\beta}_k k_{j,t} - \boldsymbol{z}_{j,t}\widehat{\boldsymbol{\beta}}_z - \hat{\beta}_q q_t$ and $\hat{p}_{j,t,t-1}$ to approximate the function $g(.)$ in (17).

With the OP approach, the sum of the coefficients is equal to one, $\hat{\beta}_l + \hat{\beta}_f + \hat{\beta}_m + \hat{\beta}_k = 1.03$. However, it cannot be interpreted as a constant returns to scale since there is no perfect competition.[18] When I take into account the omitted price variable bias, I find increasing returns to scale between 1.18 and 1.39 (see Table 2). This suggests that part of the productivity gains is explained by the exploitation of returns to scale. This finding of increasing returns to scale is robust to several specifications regarding the firm-specific demand shifters; in the model 2, the variable *CCON* is used as a demand shifter; in the model 3, the variable *CPRO* is used; in model 4, the variables *CCON* and *CPRO* are used together as demand shifters; and in model (5), I do not use firm-specific demand shifters. The implied demand elasticities are in the range [-3;-4]. This is coherent with previous work on the US railroad industry (see Coublucq, 2012, where the average demand elasticity over time is around -4). These results confirm that the omitted price variable bias matters under imperfect competition, and it prevents a correct measure of technology from being obtained using standard measures of productivity (for example, the index approach in Figure 1 or the OP approach). This supports the results of Klette and Griliches (1996) who discussed the downward bias of the production function coefficients due to the omitted price variable bias.

[18] In equation (4), for a high enough demand elasticity η (i.e., perfect competition), the estimates of the OP approach converge to the true technology parameters and the omitted price variable bias of Klette and Griliches (1996) does not matter.

[insert Table 2 here]

To obtain a measure of firm productivity, I use the input coefficients based on semi-parametric estimation from model 5 in Table 2, which gives returns to scale of 1.30, between the lower bound of 1.18 and the upper bound of 1.39. The firm's productivity is measured as:

$$prod_{j,t} = \exp(\widehat{\omega}_{j,t}) = \exp\left[\left(\tilde{r}_{j,t} - \hat{\beta}_l l_{j,t} - \hat{\beta}_k k_{j,t} - \hat{\beta}_q q_t\right)\left(\frac{\hat{\eta}}{\hat{\eta}+1}\right)\right] \quad (20)$$

Then I construct an index for the productivity in the industry, which is a market share average of each firm's productivity:

$$prod_t = \sum_{j=1}^{N_t} s_{j,t} prod_{j,t}. \quad (21)$$

The same procedure is done with the productivity estimates from the approach of Olley and Pakes, 1996, (see model 1 in Table 2):

$$\widetilde{prod}_{j,t} = \exp\left[\left(\tilde{r}_{j,t} - \hat{\beta}_l l_{j,t} - \hat{\beta}_k k_{j,t}\right)\right], \text{ and}$$
$$\widetilde{prod}_t = \sum_{j=1}^{N_t} s_{j,t} prod_{j,t}. \quad (22)$$

Figure 2 and Figure 3 present the evolution for these productivity indices. The OP approach implies an increase in productivity of 130% for the period 1980–2006 (see Figure 2). This is lower than the index measure of productivity published by the Association of American Railroads (see Figure 1, +170%). However, once I take into account the omitted price variable bias and unobserved demand shocks, Figure 3 shows that productivity increased by 80%. This finding is consistent with De Loecker (2011), which shows that standard

measures overestimate productivity due to the omitted price variable bias and due to their failure to distinguish between pure productivity shocks and demand/price shocks.

[insert Figure 2 and Figure 3 here]

Next, Figure 3 also shows three distinct periods regarding the evolution of productivity. An interesting feature is the very weak increase of productivity gain for the period 1994–2000. This corresponds to two important concentrations in the Western area of the US: *Southern Pacific* was acquired by *Union Pacific* (denoted UPSP), and *Atchinson Topeka and Sante Fe* was acquired by *Burlington Northern* (denoted BNSF). Important disruptions emerged after the UPSP concentration (see Winston, Maheshri, and Dennis, 2011). This resulted in extended periods of congestion and service complaints concerning rail performance. The complexity of networks suggests that it can take time to successfully integrate networks and operations and thus for the long-run effects on productivity to appear. Indeed, after these changes in the structure of the industry, congestion and delays increased on the UPSP network. Some shippers switched to BNSF, which then created congestion problems on the BNSF network as well. The Surface Transportation Board reported that service problems in the Western area due to the acquisition of "Southern Pacific" by "Union Pacific" were over by January 2000. My productivity estimates in Figure 3 capture this characteristic and illustrate that it took time for the firms to integrate the operations successfully (weak increase in productivity for the period 1995–2000). This feature is absent from standard productivity measures (see the AAR index in Figure 1 and the OP index in Figure 2) since these measures of productivity capture demand shocks as well during the period 1995–2000.

Lastly, the productivity literature shows the presence of firm heterogeneity and suggests that liberalization (or deregulation) may yield productivity improvement by reshuffling resources among firms and that firm dynamics such as exit may contribute significantly to this process (Olley and Pakes, 1996, Pavcnik, 2002). Indeed, deregulation might lower prices, forcing the high-cost firms to exit the market; and this would lead to a reallocation of output from less efficient to more efficient firms. To check for the importance of productivity gains stemming from the reshuffling of resources from the less to more efficient firms, I compute the covariance between the firm's market share and its productivity:

$$\text{cov} = \sum_j (s_{j,t} - \overline{s}_t)(prod_{j,t} - \overline{prod}_t),$$

where the bar over a variable denotes the mean over all active firms in a given year. This covariance represents the contribution to the aggregate productivity index resulting from the reallocation of market shares and resources across plants of different productivity levels. Since this covariance is positive, it indicates that more output is produced by the more efficient firms. Figure 4 suggests that, over time, for the whole period 1980–2006, the more productive firms are providing an increasing share of freight services. Thus, evidence from the industry-level aggregate productivity index suggests that the reallocation of market shares and resources from less to more efficient producers is an important channel of the productivity improvements. Moreover, during the period 1995–2000, Figure 4 shows that this reallocation vanished. This is coherent with the weak increase in productivity for the same period in Figure 3. Again, this suggests that it took time for the firms to integrate networks and operations successfully, and thus for the long-term effects on productivity to appear.

[insert Figure 4 here]

5 Determinants of productivity gains

From a policy perspective, it is important to understand the determinants of productivity in order for governments to design regulatory policies concerning the rail industry and for railroad companies to set appropriate strategies to improve productivity. The aggregate analysis shown above cannot shed light on the sources of productivity gains across firms, but only at the aggregate industry level. More detailed analysis is necessary to estimate the importance of specific technological or institutional factors influencing productivity improvement at the firm level.

This section identifies the sources of variation of productivity across firms. A comparative assessment across time and railroads must take into account the different operating environments. The differences between railroads in total factor productivity (TFP) may be related to network characteristics, economies of density, innovations in technologies and management practices, and the composition of services. To distinguish among the sources of productivity growth, I regress TFP on a number of variables to attribute TFP diferentials to several sources. I consider the effect of the average length of haul and the miles of road operated as network characteristics, technological innovations (for example, the increased importance of unit trains, the investment in double-stack containers for intermodal freight, advances in computers, signaling and communications, better design of freight cars), economies of traffic density, and investment in the network. Table 3 presents the descriptive statistics for the variables used in the productivity analysis.

Two methodologies have been used in the productivity literature to identify the causal effects of some variables on productivity growth: either with a first-order controlled Markov

process for the evolution of productivity (De Loecker, 2011, Doraszelki and Jamandreu, 2009) or a difference-in-differences approach (Pavcnik, 2002). However, this is difficult in the case of the railroad industry due to the high dimensionality of the potential determinants of productivity growth. Thus I follow a two-step approach where productivity is regressed on a set of variables representing the operating environment. Though I cannot fully rule out the possibility of endogeneity due to omitted variables, I use firm fixed-effects to mitigate this issue. Once I identify the links between changes in productivity with operation components, I can evaluate the productivity implications of changes in the operating and institutional environment.

5.1 Description of variables

Larger, lighter cars (technological improvement). As Martland (2006) mentions, larger cars carry more freight, and the capacity increases more than their weight. I build a variable called ***LARGELIGHT***, which represents the ratio of gross tonnage (weight of equipment plus contents) to net tonnage (weight of contents). This variable decreases over time. Technological improvements in rail freight wagons (better car designs, lighter materials) have also reduced this ratio, leading to savings in fuel consumption and labor force. This variable is measured in the *Analysis* as item 704 (total gross tonnage in ton-miles) over item 711 (total ton-miles).

Unit trains. A unit train, carrying one commodity type only, consists of one train of cars which is shipped from a single origin to a single destination, avoiding the need to handle cars at intermediate yards. It is used mainly to transport coal or grain. Fewer switchings are needed, much less time is spent on a trip (it avoids the need for sorting, storing,

loading/unloading railroad cars, for example), and locomotive utilization is higher. Longer and heavier trains allow the railroads to move more freight with fewer resources. The unit train traffic is proxied by measuring **the percentage of car miles operated for unit-trains**, that is the number of car-miles used for unit trains (item 691 of *Analysis*) divided by the total car-miles (item 694 in the *Analysis*). This variable is called ***percentUNITCM*** in Table 3.

Intermodal service: TOFC/COFC cars, Double-Stack cars. Intermodal traffic represents the the movement of trailers or containers on railroad freight cars. The trends concerning cargo transport using trailers on flat cars (TOFC) and containers on flat cars (COFC) illustrate the increasing adoption of intermodal transport. The rail intermodal traffic has been multiplied by 4 over 25 years, rising from 3.1 million trailers and containers in 1980 to nearly 12.28 million units in 2006. In 2006, intermodal accounts for about 20 per cent of rail revenue. In 2003, for the first time, intermodal surpassed coal in terms of revenue for US Class 1 railroads. Since the 1990s, railroads have invested in the double-stack rail technology to develop intermodal freight. A double-stack container carries almost twice as many containers as a standard flat car. Hence, there are dramatic savings in crew costs and benefits in terms of capacity.

In my data, I do not have access to TOFC/COFC loadings in millions of units at firm level; indeed, these data are available only at the industry level (as mentioned above, rail intermodal traffic raises from 3.1 million loaded TOFC/COFC units in 1980 to nearly 12 million in 2006). Nevertheless, I have a proxy for the intermodal freight provided, which is the number of loaded car-miles by TOFC/COFC (item 669 of the *Analysis*), denoted as ***INTERM_LOAD*** in Table 3. At the industry level, the loaded car-miles by TOFC/COFC increased from 1.9 million car-miles in 1980 to 3.8 million car-miles in 2006. This proxy for

rail intermodal traffic has a limitation. Since the 1990s, TOFC services have been decreasing and COFC increasingly dominates due to the investment in double-stack containers. Unfortunately, this is absent from my data since I am not able to distinguish the exact percentage for each category: TOFC, COFC-single-stack, and COFC-double-stack.

Signaling and communications. The impact of technological change comes through developments in signaling, telecommunications, and automation related to track activities. This allows more freight to be carried with fewer resources, by improving the coordination associated with assembling and disassembling trains at a rail yard, for intance. In the data, I measure the expenditures in communications systems (item 375 in the *Analysis*) and in signals and interlockers (item 376 in the *Analysis*). These two variables are added and called ***COMMSIGN*** in Table 3. They are converted into real $1982 using the producer price index.

Miles of road operated. The US railroads rationalized their networks by closing unprofitable lines as well as eliminating several stops. Rail companies abandoned tracks and removed excess terminals and warehousing capacity. This implied significant cost savings with the reduction of train crews. In the data, I captured this network rationalization using the miles of road operated (item 13 in the *Analysis*), and this variable is called ***ROAD*** in Table 3.

Average length of haul. It represents the average distance in miles that one ton is carried. At the industry level, it increased from 616 miles in 1980 to 906 miles in 2006, and one might expect that it allows more freight to be provided with fewer resources, and thus leads to an increase in productivity. This variable is measured with the item 737 in the *Analysis* and it is denoted as ***HAUL*** in Table 3.

Loaded and empty cars miles. When loaded car-miles increase with respect to empty car-miles, more freight services are provided. I expect that the cars are used more productively. I measure the **percentage of loaded car-miles** in the *Analysis* by dividing the loaded freight car-miles (item 655) by the sum of loaded and empty freight car-miles (item 655 for loaded car-miles and item 656 for empty freight car-miles). This variable is called ***percentLOAD*** in Table 3.

Investment in the network. The main difficulty lies in measuring this nominal investment component for way and structures capital (see section 3 for additional details regarding the construction for the investment variable). The investment in network represents land for transportation purposes, tunnels, bridges, ties, rail materials, ballast, and terminals, for instance (see schedule 330 of R1 reports on the Surface Transportation Board website).[19] This investment increases the capacity and the reliability of the rail network and thus the productivity of firms. This variable is denoted as ***invesWS*** in Table 3.

Net ton miles per miles of road operated. There is a consensus to recognize economies of traffic density as an important characteristic of the US rail freight industry. I follow Hensher et al. (1995) and use the net ton-miles per miles of road as a proxy for the density of traffic over the network (item 724 in the *Analysis*, and ***NTMRoad*** in Table 3). Economies of density occur if the unit costs fall when the output inceases within a network. In other words, less resources are necessary to carry a given amount of freight within a higher density network. Thus, it might be an important determinant of productivity.

[19] http://www.stb.dot.gov/stb/index.html

Period dummies. Period dummies are included in the regression analysis to capture disembodied technological change. This represents things such as new scientific results, general knowledge, or new organizational techniques for instance. I define four periods: 1980–1990, 1991–1996, 1997–2001, 2002–2006.[20]

[insert Table 3 here]

5.2 Estimation of variation in firm-level productivity

The regression results are presented in Table 4. I look at two specifications, comparing the pooled OLS regression and the fixed-effect regression for each specification. I add a quadratic time trend to take into account the long-time horizon.

In the first specification, I consider the whole set of variables that might explain productivity growth. In both the pooled OLS and the FE regressions some variables appear to not be significant, such as the percentage of loaded car-miles (*percentLOAD*), the variable *LARGELIGHT* which represents the better design of freight cars, and the average length of haul (*HAUL*). Surprisingly, the economies of traffic density (*NTMRoad*) also appear to not be significant. To check the robustness of the non-significativity of the traffic density, in the second specification I removed the other non-significant variables, and I still find that the economies of traffic density fail to be significant. Thus, economies of traffic density do not appear to be positively correlated with productivity growth. My findings suggest that the

[20] I have checked that the estimation results are robust when I replace period dummies with a time trend.

decrease in traffic density might not significantly threaten the productivity of the rail industry; this might be the case if the economies of traffic density are exhausted.

The communication expenditures (*COMMSIGN*) and the investment (*InvesWS*) are significant and do not appear to change much between the pooled OLS and the FE specification. Three variables appear to be affected by unobserved heterogeneity: the percentage of car-miles operated for unit trains (*percentUNITCM*), the increase in intermodal traffic (*INTERM_LOAD*), and the miles of road operated (*ROAD*). Adding firm fixed-effects allows me to control for unobserved fixed heterogeneity and mitigates the potential endogeneity. Indeed, these variables have the intuitive signs and appear to be significant. In the second specification, when all non-significant variables are removed, I also find that these three coefficients are still underestimated under a pooled OLS specification. Therefore, these variables seem to be the most affected by endogeneity. As an extension, these variables could be made fully endogenous in the production function framework, but this is beyond the scope of this paper. Table 4 leads to several interpretations.

[insert Table 4 here]

Regarding the technological variables, the expenditures in communications and the miles of road operated seems to play a role in productivity growth. A better communication system increases productivity. Track abondonment, i.e., network's rationalization, is also a significant determinant of productivity growth.[21] Thus, the deregulation of the US rail

[21] The negative coefficients, associated with a decrease in the variable *ROAD*, led to an increase in firm productivity.

industry, with a liberal policy toward track abandonment, was beneficial for the performance of the US rail freight industry.

Regarding the composition of the traffic, the shift to unit trains traffic and intermodal traffic are two important determinants of productivity growth. First, unit trains carry only one type of commodity, mainly coal, from a single origin to a single destination without being split up or stored en route. Knowing that the typical coal train is 100 to 120 cars long, this saves time and money, as well as the delays and confusion associated with assembling and disassembling trains at rail yards near the origin and destination. Second, the proxy for the intermodal freight traffic is also an important determinant of the productivity growth. Since the 1990s, railroads have invested heavily in the double-stack rail technology, and a double-stack container carries almost twice as many containers as a standard flat car. This has played an important role in productivity due to savings in crew costs and benefits in terms of capacity.

The last variable that significantly explains the productivity is the investment in the rail network. Its effect is robust across all specifications in Table 4. The investment in the network represents land for transportation purposes, tunnels, bridges, ties, rail materials, ballast, and terminals, for instance (see schedule 330 of R1 reports on the STB website). The investment increases the capacity and the reliability of the rail network. This source of productivity gain is also essential with respect to the current debate on the market structure of the US rail industry. Indeed, a debate has started regarding the market power of the large railroad firms. In this context, an open-access market structure, where the incumbent must provide access to competitors over portions of its network facilities, is put forward to foster competition. However, as Coublucq et al. (2012) show, under an access charge equal to the marginal cost

of providing access, increasing the level of competition might have a negative impact for the incumbent on the incentives to invest in the network. In that specific case, with more competition, the increase in the rail volume is not enough to compensate the lower anticipated margins, which leads to a decrease in the returns from investing in the network. Thus, regulatory agencies should pay particular attention to preserving the investment incentives. This argument becomes stronger since a decrease in the investment in infrastructures is a negative correlate of firm productivity, which might lower the long-run performance of the industry.

6 Conclusion

This paper provides a careful analysis of productivity in the US rail industry. I justify the use of a value-added production framework because of measurement error in one input. Indeed, there is no consensus that emerged from the literature to measure the equipment input and there is no specific price index to deflate the equipment expenditure. Since measurement error in the explanatory variables is a serious issue, I subtract out this input from the deflated sales and this leads to a value-added production framework. The measurement error becomes part of the dependent variable, which does not create any bias in the estimation. I also pay particular attention to the methodological issues that have haunted previous empirical studies: construction of a productivity measure that takes into account the omitted price variable bias and that is based on consistent estimates of the production function coefficients, the role of concentration and the resources reallocations from less to more efficient firms within the US rail industry, and the identification of the determinants/correlates of productivity growth.

These methodological aspects turn out to be important. After I adjust for the omitted price variable bias, I find that productivity increases by 80% whereas standard measures of productivity (like the index measure or the OP approach) show an increase (around 130%; 170%). These results confirm De Loecker's (2011) findings that one cannot ignore the omitted price variable bias and that standard productivity measures fail to distinguish between pure productivity shocks and demand/price shocks.

Then, I study the impact of concentration and exit on productivity gains. Aggregate industry level productivity indices suggest that the exploitation of the returns to scale and the reshuffling of resources from less to more productive firms contribute to the aggregate productivity gains. Given the importance of firm heterogeneity, my findings imply that removing the barriers to firm exit and concentration are important determinants of the success of the deregulation in 1980. In other words, the institutional arrangements that prevent firm liquidation can be harmful for the performance of the industry. However, my analysis also shows a slowdown in productivity due to the important concentrations that happened in the mid-1990s. This suggests that it took time for railroad firms to integrate their networks and operations successfully and for the long-term effects on productivity to appear.

Next, after I obtain measures of the firm productivity, I analyze the determinants of the productivity growth in a regression framework. Altough I cannot rule out the endogeneity of some variables, I find that fixed-effects mitigate this issue. My results suggest that the rationalization of the rail network allowed by the deregulation (Staggers Act, 1980) increased productivity. The communication expenditures also played a role in shaping the productivity gains. Regarding the composition of the traffic, the trend toward unit trains, which allow time and resources to be saved, and intermodal traffic, with heavy investment in COFC and in

particular double-stack containers, also played a significant role in productivity improvements. These two types of equipments (unit trains and double-stack containers) led to an increase in line capacity and savings in crew costs. The signaling and communication expenditures also seems to play a significant role. Other variables, like the per cent of loaded freight cars, the lighter weight of new freight cars, and the average length of haul do not seem to have a significant impact on the productivity. Surprisingly, I do not find any significant correlation between traffic density and productivity growth.

The last determinant of productivity growth is the investment in the rail network. This variable has important policy implications for the US rail freight industry. My results suggest that if a regulatory policy does not preserve the economic incentives to invest in the network, opening the rail network to entrants could have a significant negative impact on the productivity and thus on the performance of the US rail freight industry.

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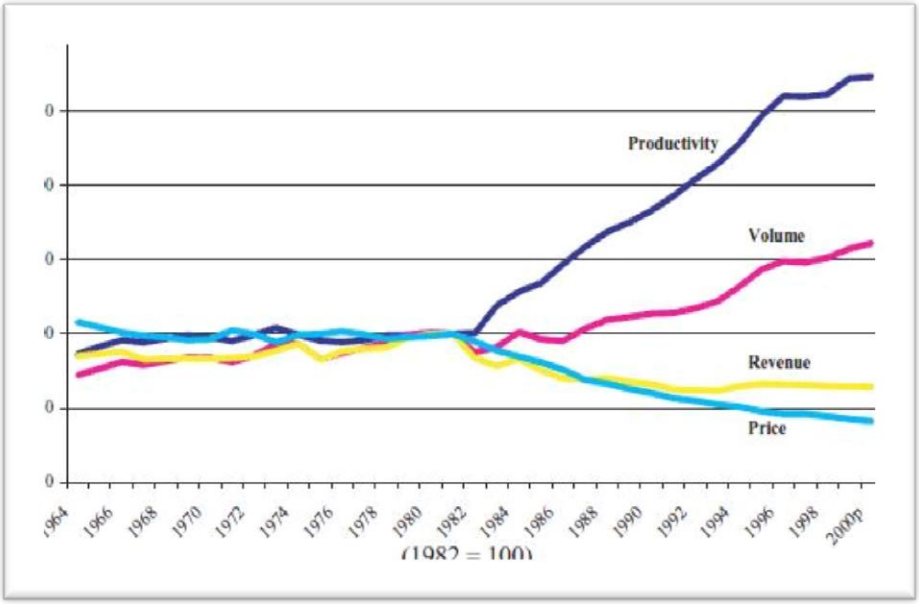
Figure 1. The Impact of the Staggers Act



Sources: Association of American Railroads,

and Hausman ("Will New Regulation Derail the Railroads?" 2001)[22]

[22] This index-measure of productivity considers an index of output, revenue ton-miles, divided by an index of combined inputs, which is the operating expense. The output and input measures are adjusted for the effect of inflation.

Figure 2. Productivity index (OP) at the industry level

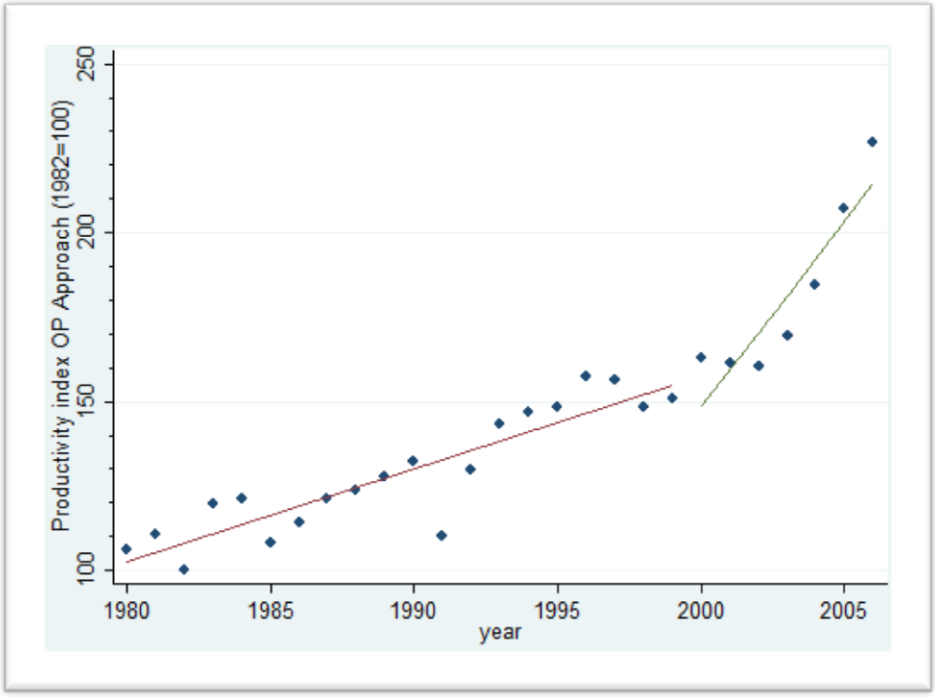


Figure 3. Productivity index (DL) at the industry level

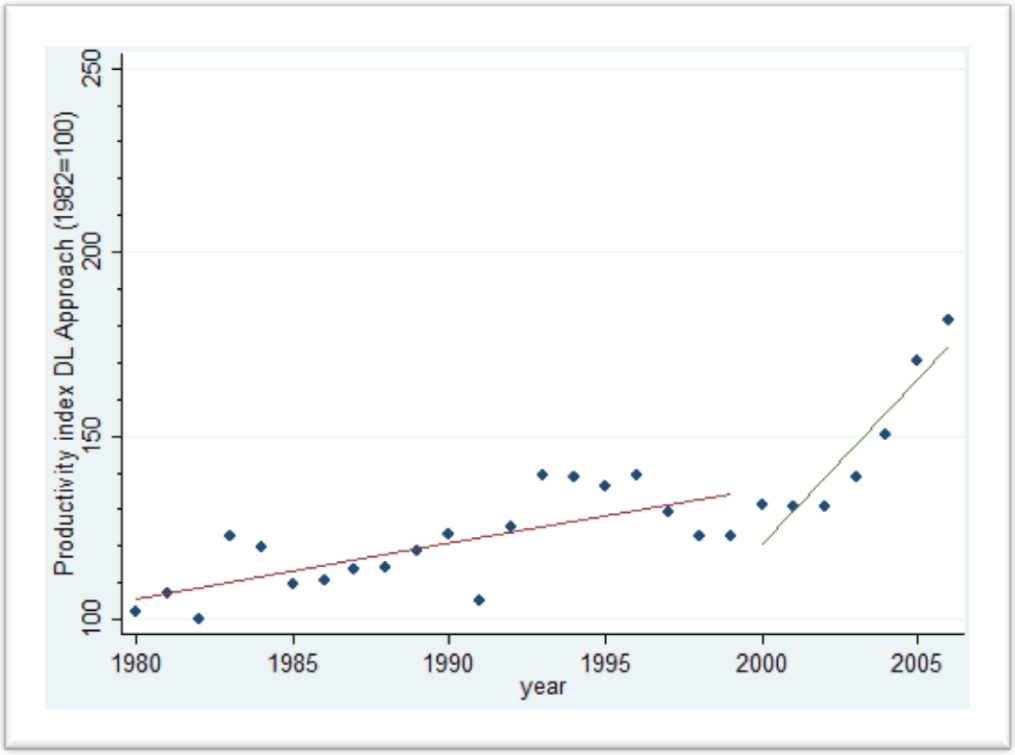


Figure 4. Reshuffling of resources

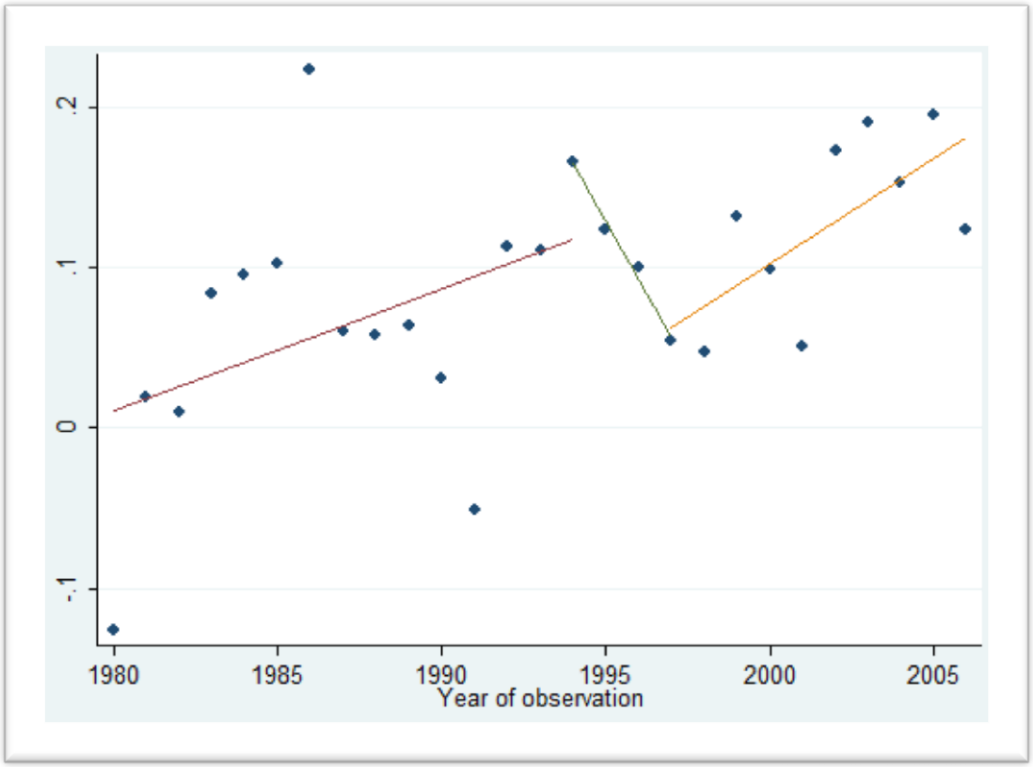


Table 1. Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Deflated value added (in real $1982)	354	1240017	1203370	40146.11	5751965
Total hours worked	349	34022.65	29298.89	1538.323	152051.4
Capital (in real $1982)	349	3289029	2858291	141663.6	1.17e+07
Investment (in real $1982)	349	148556.2	424601.5	-2204974	4223662
Material (in real $1982)	349	1203.425	1087.48	40.69255	5529.128
Fuel (in real $1982)	349	2472.84	2879.483	35.92	13137.27
Aggregate demand shifter q_t	349	14.38937	.3256003	14.04791	15.23257
CCON (Thousand short tons, 000)	349	265.0031	169.3525	11.98112	681.3316
CPRO (Thousand short tons, 000)	349	253.1441	209.7236	0	819.596

Table 2. Production Function Estimates

	OP (model 1)	DL (model 2)		DL (model 3)		DL (model 4)		DL (model 5)	
Coefficient	β	β	α	β	α	β	α	β	α
CCON	NA	Yes		No		Yes		No	
CPRO	NA	No		Yes		Yes		No	
Labor	.3554***	.2606**	.3572***	.2979**	.3969***	.3205*	.4474***	.3877***	.5159***
	(.0787)	(.1004)	(.0166)	(.1168)	(.0321)	(.1733)	(.0273)	(.0875)	(.0098)
Fuel	.3189***	.3591***	.4922***	.3352***	.4466***	.4040***	.5639***	.3166***	.4213***
	(.0630)	(.0628)	(.0229)	(.0682)	(.0361)	(.1003)	(.0345)	(.0621)	(.0080)
Material	.1918***	.2444***	.3350***	.1822**	.2427***	.1885**	.2631***	.1932***	.2571***
	(.0637)	(.0648)	(.0156)	(.0731)	(.0196)	(.0840)	(.0161)	(.0672)	(.0049)
Capital	.1639***	.0996***	.1366***	.0706†	.0940†	.0848**	.1184**	.0864***	.1150***
	(.0434)	(.0310)	(.0427)	(.0448)	(.0669)	(.0429)	(.0591)	(.0219)	(.0290)
Output	NA	.2704***		.2494***		.2835***		.2485***	
		(.0316)		(.0510)		(.0401)		(.0141)	
η	NA	-3.6978		-4.0089		-3.5262		-4.0225	
RTS	NA	1.3211		1.1804		1.3930		1.3094	
CCON	NA	.0009				.0128			
		(.0067)				(.0148)			
CPRO	NA			.0021		-.0209*			
				(.0179)		(.0114)			
Time									
N		288		288		288		288	

Bootstrap standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3. Descriptive statistics for productivity analysis

Variable	Unit	Obs	Mean	Std. Dev.	Min	Max
COMMSIGN	(1000000) $1982	354	18.01038	27.83323	-.1851691	164.3318
percentLOAD	percentage	354	.5777	.0449	.4789	.7475
LARGELIGHT		354	2.1537	.2310	1.4644	2.9357
ROAD	Miles	354	10314.08	9135.11	0	35208
HAUL	Miles	354	456.4971	200.9097	105.4886	992
percentUNITCM	percentage	354	.1887	.1630	0	.7347
INTERM_LOAD	loaded car-miles by TOFC/COFC	354	251061.6	312395.8	0	1521927
NTMRoad	Ton-miles per miles of road	354	7156.907	3793.542	0	29065
invesWS	$1982	354	148586.7	422264	-2204974	4223662

Table 4. Correlates of productivity growth

	First specification		Second specification	
	Pooled OLS	Fixed effect	Pooled OLS	Fixed effect
COMMSIGN	0.005824*	0.009630***	0.007368*	0.007463**
	(0.003260)	(0.003362)	(0.003887)	(0.003039)
percentLOAD	-7.195225	-9.006908		
	(4.874114)	(7.074663)		
percentUNITCM	-0.477084	2.989316*	-0.090303	2.666907*
	(1.198732)	(1.680931)	(1.225416)	(1.304361)
LARGELIGHT	-0.436889	-1.004805		
	(0.686838)	(1.245551)		
NTMRoad	0.000081	0.000110	0.000079	0.000058
	(0.000071)	(0.000106)	(0.000068)	(0.000061)
INTERM_LOAD	0.000001	0.000003***	-0.000000	0.000001*
	(0.000001)	(0.000001)	(0.000001)	(0.000001)
HAUL	0.000126	-0.005188		
	(0.001181)	(0.004537)		
ROAD	-0.000023	-0.000131***	-0.000010	-0.000112***
	(0.000021)	(0.000037)	(0.000025)	(0.000031)
invesWS	0.000348***	0.000290***	0.000366***	0.000345***
	(0.000087)	(0.000089)	(0.000093)	(0.000094)
temps	-0.042727	-0.116224	-0.069207	-0.128494
	(0.071862)	(0.082642)	(0.084888)	(0.095171)
temps2	-0.000779	0.001180	0.000101	0.001593
	(0.002582)	(0.002857)	(0.003023)	(0.003294)
_cons	10.425356***	15.210605***	5.519841***	6.218975***
	(2.788728)	(5.351257)	(0.488934)	(0.480765)
N	349	349	349	349

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

APPENDIX: DATA CONSTRUCTION

This appendix provides some details on the data construction.

I define a takeover between two firms such that one firm buys another firm. There are two elements of ambiguity for the construction of the merged entities, namely the merged firms *CSX* and *NS* in 1986. These two firms appear in 1986 and are the results of a concentration between several firms. The firms *BO* and *CO* were merged into the Chessie System, and that system was then merged into *SBD* in 1986. For *NS*, I assume that the parties sold their assets to the firm with the highest market share before the concentration.[23] Thus, I assume that the firm *NW* sold its assets to *SOU* in 1986. This treatment yields an unbalanced panel data with an attrition characteristic such that (see Wooldridge, 2010, Chapter 17):

$$\chi_{j,t} = 1 \Rightarrow \chi_{j,\tau} = 1, \text{ for all } \tau \leq t - 1.$$

[23] This assumption reflects what I observe in the data for all the railroad firms.

Figure 5. Railroad firms in the Western area

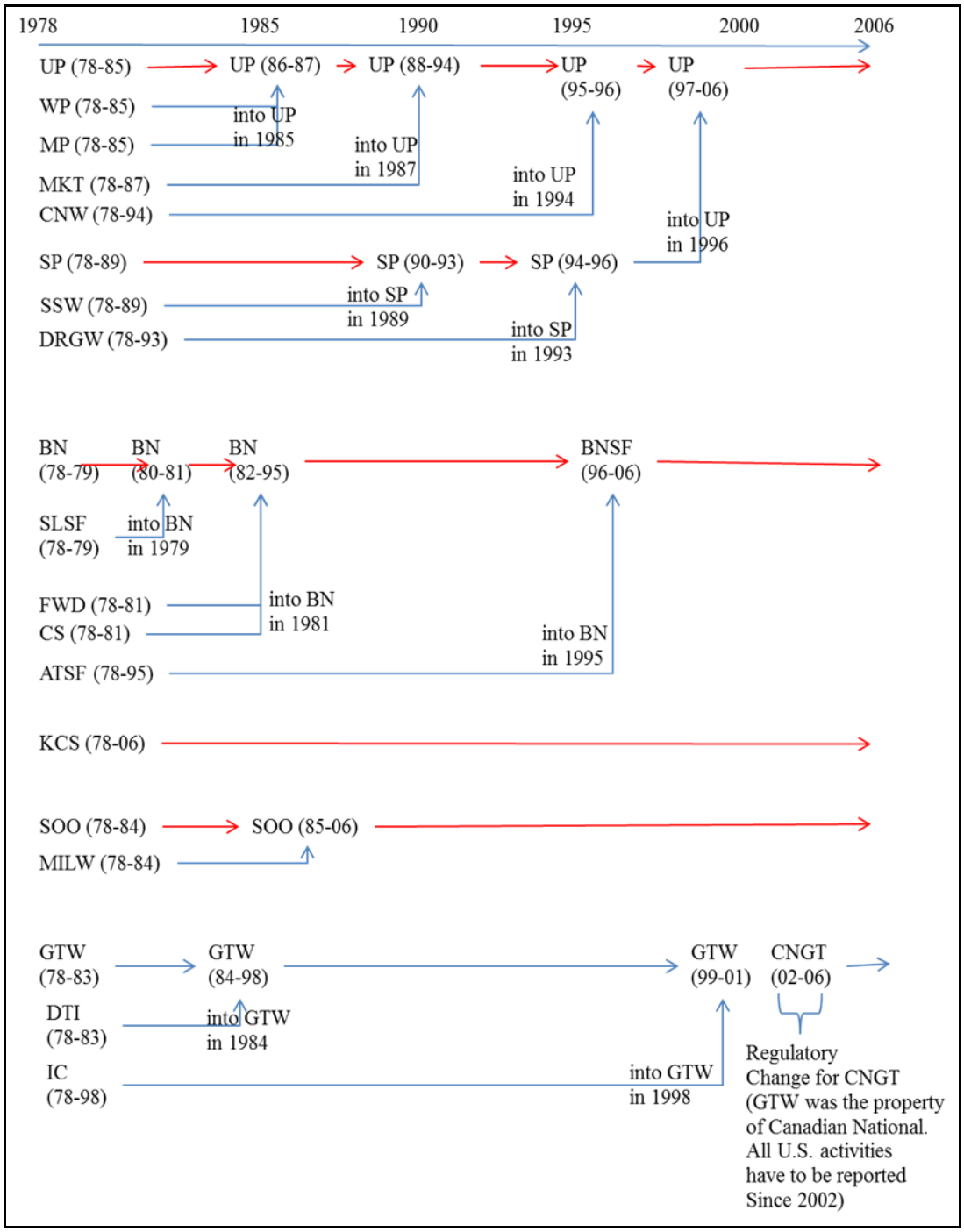


Table 5. Names of railroad firms in the Western area

Railroad	Years in data	Abbreviation (used in Figure 5)
Atchison, Topeka & Santa Fe (ATSF)	1978-1995	ATSF (into with BN in 1995)
Burlington Northern (BN) ; Burlington Northern Sante Fe (BNSF)	1978-2006	BN ; BNSF
Canadian National Grand Trunk Corporation (CNGT)	2002-2006	CNGT (it incorporates all US activities of Canadian National Railroad, which included GTW activities)
Chicago & Northwestern (CNW)	1978-1994	CNW (into UP in 1994)
Colorado and Southern (CS)	1978-1981	CS (into BN in 1981)
Denver, Rio Grande & Western (DRGW)	1978-1993	DRGW (into SP in 1993)
Detroit, Toledo & Ironton (DTI)	1978-1983	DTI (into GTW in 1983)
Forth Worth and Denver (FWD)	1978-1981	FWD (into BN in 1981)
Grand Trunk & Western (GTW)	1978-2001	GTW
Illinois Central (Gulf) (IC)	1978-1998	IC (into GTW in 1998)
Kansas City Southern (KCS)	1978-2006	KCS
Milwaukee Road (MILW)	1978-1984	MILW (into SOO in 1984)
Missouri-Kansas-Texas (MKT)	1978-1987	MKT (into UP in 1987)
Missouri Pacific (MP)	1978-1985	MP (into UP in 1985)
Saint Louis and San Francisco (SLSF)	1978-1979	SLSF (into BN in 1979)
Saint Louis, Southwestern (SSW)	1978-1989	SSW (into SP in 1989)
SOO Line (SOO)	1978-2006	SOO
Southern Pacific (SP)	1978-1996	SP (into UP in 1996)
Union Pacific (UP) ; Union Pacific-Southern Pacific (UPSP)	1978-2006	UP ; UPSP
Western Pacific (WP)	1978-1985	WP (into UP in 1985)

Figure 6. Railroad firms in the Eastern area

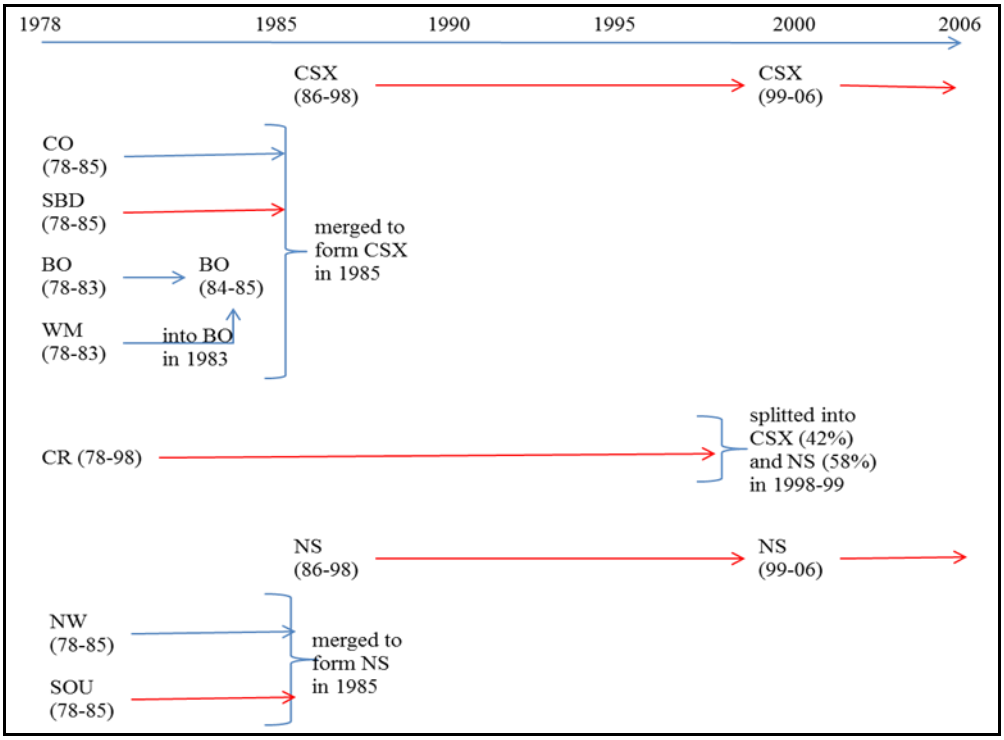


Table 6. Names of railroad firms in the Eastern area

Railroad	Years in data	Abbreviation (used in Figure 6)
Baltimore & Ohio (BO)	1978-1985	BO (into CSX in 1985)
Chesapeake & Ohio (CO)	1978-1985	CO (into CSX in 1985)
Consolidated Rail Corp. (CR)	1978-1998	CR (split between CSX and NS in 1999)
CSX Transportation (CSX)	1986-2006	CSX
Norfolk Southern (NS)	1986-2006	NS
Norfolk & Western (NW)	1978-1985	NW (into NS in 1985)
Seaboard System Railroad (SBD)	1978-1985	SBD (into CSX in 1985)
Southern Railway System (SOU)	1978-1985	SOU (into NS in 1985)
Western Maryland (WM)	1978-1983	WM (into BO in 1983)

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