WORKING PAPERS

N° 1649

June 2025

Identification in Models for Matched Worker-Firm Data with Two-sided Random Effects

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IDENTIFICATION IN MODELS FOR MATCHED WORKER-FIRM DATA WITH TWO-SIDED RANDOM EFFECTS

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This version: June 18, 2025

Abstract

This paper is concerned with models for matched worker-firm data in the presence of both worker and firm heterogeneity. We show that models with complementarity and sorting can be nonparametrically identified from short panel data while treating both worker and firm heterogeneity as discrete random effects. This paradigm is different from the framework of Bonhomme, Lamadon and Manresa (2019), where identification results are derived under the assumption that worker effects are random but firm heterogeneity is observed. The latter assumption requires the ability to consistently assign firms to latent clusters, which may be challenging; at a minimum, it demands minimal firm size to grow without bound. Our setup is compatible with many theoretical specifications and our approach is constructive. Our identification results appear to be the first of its kind in the context of matched panel data problems.

JEL Classification: C23, J31, J62

Keywords: bipartite graph, nonlinearity, panel data, sorting, unobserved heterogeneity

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Funded by the European Union (ERC, NETWORK, 101044319) and by the French Government and the French National Research Agency under the Investissements d'Avenir program (ANR-17-EURE-0010). Views and opinions expressed are however those of the author only and do not necessarily reflect those of the European Union or the European Research Council. Neither the European Union nor the granting authority can be held responsible for them.

Introduction

Matched panel data are often used to study the interaction between two types of units over a period of time. The importance of unobserved heterogeneity across the units in such data is well recognized and understanding its implications has received considerable attention. The seminal work of Abowd, Kramarz and Margolis (1999), for example, was concerned with matched worker-firm data. They regressed wages on worker and firm fixed effects to quantify the degree of heterogeneity in wages coming from, respectively, worker and firm heterogeneity and used the fixed-effect decomposition to investigate sorting patterns between workers and firms.

The regression approach of Abowd, Kramarz and Margolis (1999) has come under increased scrutiny. The linearity of the model does not permit any form of complementarity between workers and firms, which is at odds with theoretical models (see, e.g., Shimer and Smith 2000 or Eeckhout and Kircher 2011). Furthermore, their fixed-effect decompositions produce highly unreliable results in the type of data to which they are usually applied (Andrews, Gill, Schank and Upward 2008, Jochmans and Weidner 2019, and Kline, Saggio and Sølvsten 2020).

In influential work Bonhomme, Lamadon and Manresa (2019) proposed an alternative framework that permits both complementarity and sorting. Their approach is based on the assumption that worker and firm heterogeneity is discrete and hinges on the presumption that firms can be consistently clustered by type from the cross-sectional distribution of wages in an initial step. Given such a consistent classification the firm types can be treated as observed in the data, so that the model effectively features only one-way heterogeneity. An identification argument reminiscent of those used in the literature on multivariate finite mixtures (see Hu 2017 or Schennach 2020 for overviews) can then be applied to establish identification from short panel data.

The theory underlying the consistent clustering of firms requires minimal firm size to diverge with the sample size. A framework that allows for small firms to exist in large samples would be one where the number of workers and firms in the data grow at the same rate. In such a case average firm size is bounded, and neither worker nor firm effects can be estimated consistently. Such a setting would thus require treating both the worker and firm heterogeneity as random effects. This is challenging, however, and it is not clear to what extent such a model is identified.

In this paper we give a first set of positive results for this setting. Moreover, we establish identification of all primitive parameters in two models from three-wave panel data under mild assumptions. The primitives are the distributions of wages and mobility decisions conditional on the worker and firm effects, which are informative about heterogeneity and complementarity, and the joint distribution of worker and firm effects, which is informative about sorting. The first part of the paper focusses on a model that allows for Markovian dependence in wages within employment spells conditional on the worker and firm effect but requires exogenous mobility. We then give a result for a model that assumes away wage dynamics within employment spells but allows for endogenous mobility (Abowd, McKinney and Schmutte 2019) by permitting mobility decisions to depend on wages conditional on worker and firm heterogeneity.

1 The model

We consider stationary panel data on workers followed over time. For each worker i and each time period t we observe the worker's wage, w_{it}, together with a binary indicator of job mobility, x_{it}, which captures whether the worker is switching employer between periods t and $t+1$ or not. We also known the identity of the firm where worker i was employed at time t, say $f(i,t)$.

Worker i and firm f are characterized by unobserved heterogeneity ϕ_i and ψ_f. We follow Bonhomme, Lamadon and Manresa (2019) and Lentz, Piyapromdee and Robin (2023) and presume that both types of heterogeneity are discrete, with a known number of support points. Let ψ_{it} be shorthand notation for $\psi_{f(i,t)}$, that is, the effect of the firm where worker i is employed at time t. The joint distribution of the worker and firm heterogeneity then is

$$p(\phi,\psi) \coloneqq \mathbb{P}(\phi_i = \phi, \psi_{it} = \psi).$$

The wage and mobility processes are initialized in the following manner. First, workers independently draw their type with probability $p(\phi) := \mathbb{P}(\phi_i = \phi) = \int p(\phi, \psi)\, d\psi$. Firms, in turn, draw their type independently according to $p(\psi) := \mathbb{P}(\psi_f = \psi) = \int p(\phi, \psi)\, d\phi$. An initial allocation then follows from assigning a worker of type ϕ to a firm of type ψ with probability

$$p_\phi(\psi) := \frac{p(\phi, \psi)}{p(\phi)}.$$

First period wages w_{i1} are drawn from the conditional distribution $Q_{\phi_i,\psi_{i1}}$, where we write

$$Q_{\phi,\psi}(w) := \mathbb{P}(w_{it} \leq w | \phi_i = \phi, \psi_{it} = \psi),$$

independently for each worker. Next, the match quality between the worker and his current firm is evaluated. With probability $r_{\phi_i,\psi_{i1}}$, where

$$r_{\phi,\psi} := \mathbb{P}(x_{it} = 1 | \phi_i = \phi, \psi_{it} = \psi),$$

$x_{i1} = 1$ and employment is terminated. In any subsequent period t there are then two possibilities, depending on the realization of x_{it-1}. If $x_{it-1} = 1$ the worker draws a new firm type ψ_{it} from the conditional distribution p_{ϕ_i}, followed by a new wage draw from the implied $Q_{\phi_i,\psi_{it}}$. If $x_{it-1} = 0$ the worker remains in the same firm, so that $f(i,t) = f(i,t-1)$ and, therefore, $\psi_{it} = \psi_{it-1}$. Within job spells wages are allowed to exhibit Markovian dependence, with transition kernel

$$Q_{\phi,\psi,w}(w') := \mathbb{P}(w_{it} \leq w' | w_{it-1} = w, x_{it-1} = 0, \phi_i = \phi, \psi_{it} = \psi),$$

whose steady-state distribution is $Q_{\phi,\psi}$. When $x_{it-1} = 0$, w_{it} is thus drawn from $Q_{\phi_i,\psi_{it},w_{it-1}}$. In either case, before moving on to the next period, the match quality between the worker and his current employer is again evaluated and they decide to separate with probability $r_{\phi_i,\psi_{it}}$.

Our model is a stationary version of Bonhomme, Lamadon and Manresa (2019, Section 2.1), with one exception. Whereas we impose that, when a worker switches firm, the new firm type is independent of the former firm type conditional on the worker effect, they allow for dependence in (x_{it}, ψ_{it}) over time. On the other hand, unlike theirs, our identification result in Theorem 1 below covers all primitive parameters of the model. In any event, like theirs, our specification is compatible with classic wage-posting models such as those of Burdett and Mortensen (1998) or Shimer (2005), as well as with certain models that feature wage bargaining, such as Shimer and Smith (2000), for example. The manner in which wages and mobility decisions vary with worker and firm heterogeneity is not specified and, hence, could be nonlinear, accommodating general forms of complementarity. The assignment of workers to firms, in turn, is allowed to depend on their latent types. Hence, sorting is permitted.

2 Assumptions and identification

Our aim is to nonparametrically identify the steady-state distributions $Q_{\phi,\psi}$, the transition kernels $Q_{\phi,\psi,w}$, and the separation probabilities $r_{\phi,\psi}$, as well as the joint distribution of worker and firm types $p(\phi,\psi)$. Of course, because the types are latent, it is understood that identification here will be up to an arbitrary relabelling of the types. If desired, types could be ordered by a functional of the wage distributions conditional on only worker or firm type, that is,

$$Q_{\phi}(w) \coloneqq \int Q_{\phi,\psi}(w)\, p_{\phi}(\psi)\, d\psi, \qquad \text{and} \qquad Q_{\psi}(w) \coloneqq \int Q_{\phi,\psi}(w)\, p_{\psi}(\phi)\, d\phi,$$

where we let $p_{\psi}(\phi) \coloneqq p(\phi,\psi)/p(\psi)$ in analogy to $p_{\phi}(\psi)$. One could for example work under the presumption that the mean of Q_{ϕ} is strictly increasing in ϕ, as would be reasonable when ϕ is given an interpretation of innate ability. For our purposes any such ordering is not needed and, hence, is irrelevant.

The first of two assumptions we impose is a rank condition.

Assumption 1. *The distributions $Q_{\phi,\psi}$ are linearly independent in (ϕ,ψ).*

Assumption 1 demands that changes in ϕ and ψ affect wages and is intuitive. Inspection of the proof below reveals that the assumption as stated is somewhat stronger than what is needed, but it is a simple and interpretable sufficient condition, explaining why it carries our preference.

The second assumption is a support condition.

Assumption 2. *For all* (ϕ, ψ) *it holds that (i)* $0 < p(\phi, \psi) < 1$ *and that (ii)* $0 < r_{\phi,\psi} < 1$.

Assumption 2 has two parts. Part (i) is a full-support condition on the distribution of the latent types. It states that any worker type can match with any firm type with positive probability. Part (ii), in turn, states that any match between a worker and firm can terminate.

The following theorem states our main result.

Theorem 1. *Let Assumptions 1 and 2 hold. Then the functions* $Q_{\phi,\psi}$ *and* $Q_{\phi,\psi,w}$ *and the probabilities* $r_{\phi,\psi}$ *and* $p(\phi, \psi)$ *are all nonparametrically identified up to relabelling of* (ϕ, ψ) *from the cross-sectional distribution of wages trajectories and job transitions spanning three time periods.*

Higher-order Markovian dependence in wages within employment spells can be allowed for, and can be recovered, if additional time periods are available. The proof, given below, extends naturally.

Bonhomme, Lamadon and Manresa (2019) considered a version of our model where distributions are allowed to change over time and (x_{it}, ψ_{it}) is allowed to feature Markovian dependence. Under the assumption that firm types are observed, their Theorem 1 gives conditions under which, from a two-wave panel, one may identify (i) the initial distribution of wages given worker and firm types, (ii) the same distribution in the subsequent period for workers that have changed employment between the two periods, and (iii) the joint distribution of worker and firm types in the initial period. Their result does not cover the mobility process or the dynamics of wages within employment spells. When translated into our stationary setting, this thus corresponds to identification of $Q_{\phi,\psi}$ and $p(\phi, \psi)$, but not of $r_{\phi,\psi}$ and $Q_{\phi,\psi,w}$.

3 Proof of Theorem 1

To prove our main result we proceed in four steps. The first two of these serve to identify auxiliary parameters that will be used to identify the model parameters in the third and fourth step.

The first step is concerned with identifying the distribution of wages conditional on the worker type alone, that is, the functions Q_ϕ, up to an arbitrary ordering of the ϕ. To do so we use the panel dimension of our setup. More precisely, we exploit the observation that in our model wages and mobility decisions are independent across job spells conditional on the worker effect. To see how this is helpful for our purposes consider the joint probability

$$\mathbb{P}(w_{i1} \leq w_1, x_{i1} = 1, w_{i2} \leq w_2, x_{i2} = 1, w_{i3} \leq w_3) \tag{3.1}$$

for chosen values (w_1, w_2, w_3). Here, workers switch employer between the first and second period, and again between the second and third period. The probability of this happening is non-zero under Assumption 2. Let

$$A_\phi(w) := \mathbb{P}(w_{it} \leq w, x_{it} = 1 | \phi_i = \phi) = \int r_{\phi,\psi}\, Q_{\phi,\psi}(w)\, p_\phi(\psi)\, d\psi.$$

Then the joint probability in (3.1) factors as

$$\int A_\phi(w_1)\, A_\phi(w_2)\, Q_\phi(w_3)\, p(\phi)\, d\phi,$$

which is a tri-variate finite mixture. By Assumption 1 the distributions Q_ϕ and A_ϕ, seen as a function of ϕ, are linearly independent. By Assumption 2, $0 < p(\phi) < 1$ for all ϕ. From Allman, Matias and Rhodes (2009, Theorem 8) or Bonhomme, Jochmans and Robin (2016, Theorem 2) it then follows that the functions Q_ϕ are nonparametrically identified up to label swapping.

The second step of our proof, in turn, identifies the distribution of wages conditional on the firm type alone, that is, the functions Q_ψ, again up to an arbitrary ordering of the ψ. To do this we exploit the cross-sectional dimension of our problem and the fact that firm identities are known. Consider the cross-sectional distribution of wages of distinct workers (i_1, i_2, i_3) employed by the same firm f in time period t. It is helpful to make the dependence of wages on the firm explicit, by writing w_{ift} for the wage of worker i earned in firm f at time t. Then we can write the probability distribution in question, evaluated at (w_1, w_2, w_3), as

$$\mathbb{P}(w_{i_1ft} \leq w_1, w_{i_2ft} \leq w_2, w_{i_3ft} \leq w_3). \tag{3.2}$$

Wages of different workers employed at the same firm are independent conditional on the firm effect. Therefore, their joint probability in (3.2) factors as

$$\int Q_\psi(w_1)\, Q_\psi(w_2)\, Q_\psi(w_3)\, p(\psi)\, d\psi,$$

which is again a tri-variate finite mixture. In the same way as before, this representation implies that the Q_ψ are nonparametrically identified up to a relabelling of the firm types ψ.

In the third step of our proof we use the results obtained so far to recover the conditional wage distributions $Q_{\phi,\psi}$ for the labelling of worker and firm types from the previous two steps. This is done by looking at the joint distribution of wages for two distinct workers initially employed at the same firm, together with the next period's wage of one of them that switches employer at the end of the period. The distribution in question, as a function of (w_1, w, w_2) is

$$\mathbb{P}(w_{i_1f1} \leq w_1, w_{i_2f1} \leq w, x_{i_21} = 1, w_{i_22} \leq w_2).$$

Under the dynamics of our model this probability can be written in terms of the model primitives as

$$\iint Q_\phi(w_2)\, H(w, \phi, \psi)\, Q_\psi(w_1)\, d\phi\, d\psi, \tag{3.3}$$

where

$$H(w, \phi, \psi) \coloneqq \mathbb{P}(w_{it} \leq w, x_{it} = 1, \phi_i = \phi, \psi_{it} = \psi) = Q_{\phi,\psi}(w)\, r_{\phi,\psi}\, p(\phi, \psi).$$

The latter joint probability is identified because the Q_ϕ and Q_ψ are identified and are linearly independent. To see this take a collection of values for the wage, $w_1, \ldots, w_m$ for some finite integer m so that the matrices $(A)_{v,\phi} \coloneqq Q_\phi(w_v)$ and $(B)_{v,\psi} \coloneqq Q_\psi(w_v)$ have maximal column rank. By Assumption 1 such a set of values exists. Further, for any w, let $(C_w)_{v_1,v_2} \coloneqq \mathbb{P}(w_{i_1f1} \leq w_{v_1}, w_{i_2f1} \leq w, x_{i_21} = 1, w_{i_22} \leq w_{v_2})$ and $(D_w)_{\phi,\psi} \coloneqq H(w,\phi,\psi)$. Then, from (3.3), $C_w = A\,D_w B^\top$ so that $D_w = (A'A)^{-1}A'C_wB(B'B)^{-1}$, which contains the $H(w,\phi,\psi)$ for any w, is identified. A value w of particular interest is $w = +\infty$, for which

$$h(\phi,\psi) \coloneqq H(+\infty,\phi,\psi) = \mathbb{P}(x_{it} = 1, \phi_i = \phi, \psi_{it} = \psi) = r_{\phi,\psi}\, p(\phi,\psi).$$

Under Assumption 2 $h(\phi,\psi)$ is strictly positive. Therefore, for any chosen value w we have that

$$Q_{\phi,\psi}(w) = \frac{H(w,\phi,\psi)}{h(\phi,\psi)}$$

is nonparametrically identified up to the same labelling of worker and firm types as before.

In the fourth and final step of our proof we follow a similar approach as in the previous step to identify the remaining parameters, $Q_{\phi,\psi,w}$, $r_{\phi,\psi}$, and $p(\phi,\psi)$. Rather than looking at workers who switch employer after the first period we look at workers that switch in the second period. The relevant probability distribution, seen as a function of (w_1, w, w', w_2) is

$$\mathbb{P}(w_{i_1f1} \leq w_1, w_{i_2f1} \leq w, x_{i_21} = 0, w_{i_22} \leq w', x_{i_22} = 1, w_{i_23} \leq w_2).$$

This joint probability factors as

$$\iint Q_\phi(w_2)\, G(w,w',\phi,\psi)\, Q_\psi(w_1)\, d\phi\, d\psi, \tag{3.4}$$

where

$$G(w,w',\phi,\psi) \coloneqq \mathbb{P}(w_{it-1} \leq w, w_{it} \leq w', x_{it-1} = 0, x_{it} = 1, \phi_i = \phi, \psi_{it} = \psi).$$

Observe that $G(w,w',\phi,\psi) = Q_{\phi,\psi}(w,w')\, r_{\phi,\psi}\,(1-r_{\phi,\psi})\, p(\phi,\psi)$, where we use the shorthand

$$Q_{\phi,\psi}(w,w') \coloneqq \mathbb{P}(w_{it} \leq w, w_{it+1} \leq w' | x_{it} = 0, \phi_i = \phi, \psi_{it} = \psi)$$

for the joint distribution of two wage observations within a given employment spell. From this decomposition, by the same argument as used for the function H before, the function G is identified up to the same labelling of worker and firm types. From this we may then recover

$$g(\phi,\psi) \coloneqq G(+\infty,+\infty,\phi,\psi) = \mathbb{P}(x_{it-1} = 0, x_{it} = 1, \phi_i = \phi, \psi_{it} = \psi) = r_{\phi,\psi}(1-r_{\phi,\psi})p(\phi,\psi),$$

given which we find

$$Q_{\phi,\psi}(w,w') = \frac{G(w,w',\phi,\psi)}{g(\phi,\psi)}$$

for any pair (w,w'). From this we then equally obtain the conditional distribution $Q_{\phi,\psi,w}(w')$. Furthermore, we also have

$$r_{\phi,\psi} = 1 - \frac{g(\phi,\psi)}{h(\phi,\psi)},$$

and with it,

$$p(\phi,\psi) = \frac{h(\phi,\psi)}{r_{\phi,\psi}} = \frac{h(\phi,\psi)^2}{h(\phi,\psi) - g(\phi,\psi)},$$

all again up to the same ordering of worker and firm types. All parameters of the model have thus been shown to be identified. □

4 Endogenous mobility

Extensions and variations of our model can be entertained. One alternative specification of interest allows for mobility decisions to depend on current wage, in addition to worker and firm effects. That is

$$r_{\phi,\psi,w} := \mathbb{P}(x_{it} = 1 | w_{it} = w, \phi_i = \phi, \psi_{it} = \psi) \neq \mathbb{P}(x_{it} = 1 | \phi_i = \phi, \psi_{it} = \psi) = r_{\phi,\psi}.$$

Such dependence translates into what is usually referred to as endogenous mobility (see, for example, Abowd, McKinney and Schmutte 2019). Our identification approach can be modified to deal with this at the expense of ruling out Markovian dependence in wages within employment spells, i.e. $Q_{\phi,\psi,w} = Q_{\phi,\psi}$. Dealing with both at the same time appears to be more complicated.

The model is thus the same as before with the exception that, now, in every period, workers wages w_{it} and mobility decisions x_{it} are determined jointly according to distribution

$$Q^x_{\phi,\psi}(w) := \mathbb{P}(w_{it} \leq w, x_{it} = x | \phi_i = \phi, \psi_{it} = \psi) = r_{\phi,\psi,w}\, Q_{\phi,\psi}(w).$$

To deal with this Assumption 1 needs to be modified. To state the new assumption we let

$$A^x_{\phi}(w) := \mathbb{P}(w_{it} \leq w, x_{it} = x | \phi_i = \phi)$$

for $x \in \{0, 1\}$.

Assumption 1′. The distributions A^1_ϕ and Q_ϕ, and Q_ψ are linearly independent in ϕ and ψ, respectively.

The following theorem concerns identification in the model with endogenous mobility.

Theorem 1′. Let Assumptions 1′ and 2 hold. Then the joint distributions $Q^x_{\phi,\psi}$, all implied marginal and conditional distributions, and $p(\phi, \psi)$ are nonparametrically identified up to relabelling of (ϕ, ψ) from the cross-sectional distribution of wages trajectories and job transitions spanning three time periods.

The proof of Theorem 1′ is similar in spirit to the proof of Theorem 1. The first step of that proof changes in the sense that, now, (3.1) factors as

$$\int A^1_\phi(w_1)\, A^1_\phi(w_2)\, Q_\phi(w_3)\, p(\phi)\, d\phi.$$

This decomposition is still a tri-variate mixture which, under Assumption 1′, identifies Q_ϕ up to re-arrangement of the worker types. The second step of the proof requires no modification as the factorization in (3.2) continues to go through. Therefore, the Q_ψ are identified up to relabelling of the firm types. The third and fourth step of the proof change. While the decompositions in (3.3) and (3.4) still hold, the terms that can be recovered from them,

$$H(w, \phi, \psi) = \mathbb{P}(w_{it} \leq w, x_{it} = 1, \phi_i = \phi, \psi_{it} = \psi)$$

and

$$G(w, w', \phi, \psi) = \mathbb{P}(w_{it-1} \leq w, w_{it} \leq w', x_{it-1} = 0, x_{it} = 1, \phi_i = \phi, \psi_{it} = \psi),$$

now factor differently. First, by conditional independence of the (w_{it}, x_{it}) we observe that

$$H(w, \phi, \psi) = Q^1_{\phi,\psi}(w)\, p(\phi, \psi), \qquad G(w, w', \phi, \psi) = Q^1(w')\, Q^0(w)\, p(\phi, \psi),$$

from which we identify

$$Q^0_{\phi,\psi}(w) = \frac{G(w, w', \phi, \psi)}{H(w', \phi, \psi)}.$$

Next, because we still have that $h(\phi, \psi) = H(+\infty, \phi, \psi) = r_{\phi,\psi}\, p(\phi, \psi)$ and also that $g(\phi, \psi) = G(+\infty, +\infty, \phi, \psi) = (1 - r_{\phi,\psi})\, r_{\phi,\psi}\, p(\phi, \psi)$ we recover, in the same way as before,

$$r_{\phi,\psi} = 1 - \frac{g(\phi, \psi)}{h(\phi, \psi)},$$

from which we can then identify

$$Q^1_{\phi,\psi}(w) = \frac{H(w, \phi, \psi)}{h(\phi, \psi)}\, r_{\phi,\psi} = \frac{H(w, \phi, \psi)\,(h(\phi, \psi) - g(\phi, \psi))}{h(\phi, \psi)^2}.$$

The functions $Q^x_{\phi,\psi}$ are thus identified up to a given ordering of worker and firm types for both $x = 0$ and $x = 1$, and so are the various implied marginal and conditional distributions. The type distribution, for the same ordering, then again follows as $p(\phi, \psi) = h(\phi, \psi)/r_{\phi,\psi}$. This completes the proof. □

Conclusion

In this paper we have given identification results for models for matched panel data with discrete two-sided unobserved heterogeneity. Our approach differs from the one followed in Bonhomme, Lamadon and Manresa (2019) and Lentz, Piyapromdee and Robin (2023) in that we treat the heterogeneity on both sides as random effects. This by-passes the need to consistently estimate the heterogeneity on (at least) one side. The latter is fundamental to the identification results available to date but may be difficult to do in many situations of interest. Our approach is nonparametric and constructive, permitting the construction of an estimator by replacing population quantities by sample counterparts. Our derivations reveal that the models we consider are overidentified. Hence, there appears to be scope for further generalization.

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