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International trade and labor reallocation: misclassification errors, mobility, and switching costs*

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Abstract

Over the last few decades, international trade has increased at a rapid pace, altering domestic production and labor demand in different sectors of the economy. A growing literature studies the heterogeneous effects of trade shocks on workers' employment and on welfare when reallocation decisions are costly. The estimated effects critically depend on data on workers' reallocation patterns, which is typically plagued with coding errors. In this paper, I study the consequences of misclassification errors for estimates of the labor market effects of international trade and show that structural parameter values and the estimated employment and welfare effects are biased when the analysis uses uncorrected data. I develop an econometric framework to jointly estimate misclassification probabilities, corrected mobility matrices, and structural parameters in a unified way. Under different model specifications, I compare how the estimated effects of a trade shock differ on whether the analysis uses correct mobility measures and parameters. The results show that estimated employment and welfare effects of a trade shock are substantially different, raising an important warning for quantitative exercises using mobility data with coding errors.

Keywords: International trade, labor markets, classification errors, mobility, worker reallocation, structural estimation

JEL Classification: F16, F66, J24, J62, C25.

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1 Introduction

The rapid expansion of international trade over the last few decades has altered domestic production of a wide range of goods and reshaped labor demand across different sectors of the economy. The economic literature has extensively studied how trade liberalizations affect workers, a question that continues to be a topic of intense debate in policy circles. Central to this question is how costly it is for factors of production, particularly labor, to reallocate from industries or occupations that are adversely affected by international trade to those that benefit from it. If reallocation is costly for workers due to periods of unemployment, earnings losses, or a mismatch in the skill they supply relative to those demanded, then reallocation would take place gradually over time and the effects of international trade would be heterogeneous, leading to winners and losers.

In an influential paper, [Artuç, Chaudhuri, and McLaren \(2010\)](#) show that the costs workers face to reallocate across different labor markets critically shape the dynamics of adjustment after a trade liberalization and affect workers' welfare in ways that are not directly reflected by earnings alone. As they clearly put, “[t]he welfare effects of trade shocks turn on the nature and magnitude of the costs workers face in moving between sectors”. These forces are typically missing in widely-used models studying the welfare effects of international trade, as workers are assumed to be homogeneous and perfectly mobile across sectors. For example, [Arkolakis, Costinot, and Rodríguez-Clare \(2012\)](#) show that trade flows and the trade elasticity are key determinants in the quantification of the gains from trade in many standard models. However, [Caliendo, Dvorkin, and Parro \(2019\)](#) extend their welfare formulas and show that, in addition to the trade flows and the trade elasticity, the matrix of *workers' mobility flows* across industries and the *mobility elasticity* shape the gains from trade in a model where labor reallocation is costly. Thus, to fully understand the effects of international trade on labor markets and workers' welfare, information about how individuals reallocate across industries and occupations becomes critical.

An important limitation in measuring worker mobility across labor markets is the pervasive contamination of workers' industry and occupation information by misclassification errors. In survey data, workers are asked about the characteristics of their job and their employer, and the answers are then mapped into a specific industry or occupation by a professional coder. Small differences in the way individuals answer these questions or differences in the person coding the answers over time for the same individual can lead to errors in the industry and occupation codes assigned. This type of misclassification errors has long been studied in the literature. In particular, [Murphy and Topel \(1987\)](#), study the effects

of industry misclassification on estimates of industry earnings and how these change when workers switch industries. Moreover, [Moscarini and Thomsson \(2007\)](#), and [Kambourov and Manovskii \(2008\)](#), study the effects of misclassification errors in measures of industry and occupation mobility and how mobility has evolved over time. All of these studies find evidence of an artificially large amount of mobility that is the result of misclassification errors.

[Simonovska and Waugh \(2014\)](#) emphasize the importance of adequate estimates of the trade elasticity, as this is “one of only two statistics needed to measure the welfare cost of autarky in a large and important class of structural gravity models of international trade”, an insight from [Arkolakis et al. \(2012\)](#). Following a similar argument, the key message of the study I present here is that when worker mobility is not properly measured, the estimated effects of international trade will be wrong. In this paper, I highlight the importance of unbiased estimates of the mobility elasticity and mobility flows for calculations of the welfare effects from trade and the dynamics of adjustment to trade shocks.

I start by revisiting the evidence of misclassification in the Panel Study of Income Dynamics (PSID), following [Kambourov and Manovskii \(2008\)](#). I find that, for a very broadly defined group of industries, mobility rates computed using uncorrected data are roughly two times larger than alternative data for which misclassification is likely absent. Errors would be even larger for a finer disaggregation of industry or occupation information. I take this fact as the starting point of my analysis and evaluate how misclassification affects the estimates of the labor market effects of international trade.

The paper’s contributions are threefold. First, I use a standard model of costly labor reallocation following [Artuç et al. \(2010\)](#) and introduce a misclassification probability that generates differences between true mobility rates and observed mobility rates. I show that parameters estimated using data with errors are biased and, in the example I use, misclassification biases estimates of the mobility elasticity upwards and the costs of switching industries towards zero. These estimates would imply a more dynamic economy that is able to adjust rapidly to shocks, where changes in workers’ welfare would be more homogeneous. The main conclusion of this simple example is that the presence of misclassification errors in this class of models, which as discussed is a well-known feature of widely used data, severely bias the estimates of structural parameters and the quantification of the labor market effects of trade shocks.

Second, I propose a method to estimate misclassification probabilities, mobility rates, and the model’s structural parameters. This method adapts the algorithm proposed by [Arcidiacono and Miller \(2011\)](#) and uses the Expectation Maximization algorithm, treating workers’ true industry (or occupation) as an unobserved state. While the method exploits

a specific characteristic of the PSID data to identify the misclassification probabilities, the method is more general and it would be straightforward to modify the likelihood function to accommodate different identification assumptions. Moreover, the method not only estimates mobility matrices corrected for misclassification, but also a corrected measure of wages. Misclassification errors not only severely bias measures of occupation and industry mobility, but also measures of wage changes for workers that switch labor markets. In this way, I propose a unified method to obtain measures of mobility and wages corrected for misclassification. In addition, in Appendix E I illustrate how, using the estimated misclassification probabilities, it is possible to correct mobility measures obtained using other survey data, like the CPS.¹

Third, I show that differences in estimated mobility flows and structural parameters due to misclassification matter for the calculations of labor market adjustment and welfare changes due to trade shocks. Using the estimates of mobility flows corrected of misclassification I perform three exercises. In the first case, I take wages as exogenous, assume a simple switching cost structure, and estimate the parameters that affect the mobility elasticity and the switching costs both with corrected and uncorrected data. A shock that lowers manufacturing wages leads to a larger and more rapid drop in manufacturing employment when using uncorrected data. Moreover, the welfare of workers initially attached to manufacturing falls substantially less when using estimates from uncorrected data. Next, I relax some of the assumptions for switching costs, allowing them to vary by origin and destination, and use dynamic hat algebra techniques to evaluate the effects of an exogenous wage change. The results are similar to the previous case, and using uncorrected data leads to a more dynamic economy that adjust faster and where workers' welfare is not as heterogeneous across sectors compared to the economy that uses corrected mobility measures. While in these two cases wage changes are taken as exogenous, to simplify the exposition and make the analysis more transparent, this should not be interpreted as closed-economy results, but rather as how the labor supply block of a richer model is affected by misclassification. In the last case, I specify a general equilibrium model with production and international trade, where wages *endogenously* change due to a trade shock. In the general equilibrium model, additional factors are used in production and consumers are able to substitute across goods in consumption. The quantitative effect on wages of a trade shock that reproduces important aspects of the U.S. economy is smaller than in the previous exercises. Yet, the qualitative and quantitative findings are largely the same, and the estimated effects of a trade shock on employment

¹This way to proceed assumes that misclassification probabilities are similar between the PSID and the CPS. As discussed in the Appendix, given the similarities in the way individuals are asked to report this information and the way the description is then coded, this assumption seems a reasonable.

and welfare are significantly distorted when using uncorrected mobility data. For example, differences in computed employment effects can be as much as 20% between the calibrations that use corrected and uncorrected data. Similarly, using uncorrected data would suggest very modest, but positive, welfare effects for workers initially attached to manufacturing, while in the economy that uses corrected data the size of the welfare *losses* are significant and of a similar order of magnitude, in absolute value, to the gains experienced by workers in other sectors not directly exposed to the trade shock. Thus, this example shows how using incorrect data can lead to the wrong conclusions on welfare effects.

This paper connects with an important recent literature that studies the effects of international trade on workers and their dynamic decisions to work in different labor markets. Recent examples include [Artuç and McLaren \(2015\)](#), [Dix-Carneiro \(2014\)](#), [Caliendo et al. \(2019\)](#), and [Traiberman \(2019\)](#). In all these papers, the adjustment to a trade shock and how welfare changes for different workers depends on estimates of the elasticity of worker mobility across sectors and occupations, and on the estimates of the switching costs or the mobility flow matrix. Some of these works use administrative data from Nordic countries or emerging economies, which in many cases would not be subject to misclassification errors of the type discussed here. However, it is not clear how differences in labor market institutions and employment protection in Europe, or the large levels of informality in emerging economies affect the levels of mobility and how comparable these are with those of the United States, which affect the estimates of the mobility elasticity and welfare effects of a trade shock. For the United States, access to administrative data in the Longitudinal Employer-Household Dynamics is restricted. Moreover, the starting period for this dataset is the year 2000 and there is no information on occupations nor on (most) of worker’s demographic characteristics in this dataset, which may be particularly important as mobility flows vary with worker’s types. In this paper, I show how to estimate corrected measures of industry and occupation flows using publicly available datasets, and how misclassification errors affects estimates of the employment and welfare effects of a trade shock for the United States.

Misclassification errors are not only a feature of industry and occupation mobility. For example, [Poterba and Summers \(1986\)](#) and [Feng and Hu \(2013\)](#) study the effects of misclassification errors on measurements of labor market flows—that is, measures of workers’ transitions between employment, unemployment and not in the labor force. The estimation method I propose in this paper can be used to measure misclassification and obtain corrected labor market flows. More recently, [Carrillo-Tudela and Visschers \(2020\)](#) follow the approach in [Poterba and Summers \(1986\)](#) to estimate occupational mobility matrices corrected for misclassification. [Hausman, Abrevaya, and Scott-Morton \(1998\)](#) propose a semiparametric

estimator to measure misclassification probabilities. My work differs from these papers in that I propose a structural model of workers' industry or occupational choice, where the observed industry or occupation codes of workers can be affected by misclassification. The focus is in the joint estimation of model parameters, true mobility flows, and misclassification probabilities. I show how misclassification biases estimated parameters and flows, and how this affects the dynamics of employment and welfare effects of a trade shock. [Moscarini and Thomsson \(2007\)](#), [Kambourov and Manovskii \(2008\)](#), and more recently [Vom Lehn, Ellsworth, and Kroff \(2020\)](#), propose methods to estimate the probability of occupation or industry switching (a binary decision) using CPS or PSID data, corrected for misclassification. Critically, estimates of the employment and welfare effects of trade depend on the *whole matrix* of industry or occupation flows, rather than on the binary decision of whether to switch the current industry or occupation. The method I propose here delivers corrected estimates of the mobility matrix, as in [Carrillo-Tudela and Visschers \(2020\)](#),² but contrary to them, offers the advantage of generating estimates of individual-level probabilities of industry and occupation mobility, which I used to correct measures of wages for different industries and occupations.³

The paper is organized as follows. Section 2 describes the data and presents evidence of misclassification errors. Section 3 uses a standard model of labor market choice with frictions and shows how, in a simple calibration, misclassification biases measures of mobility and parameter values, providing intuitive explanations for the direction of the bias. Section 4 develops an econometric framework to correct for misclassification. Section 5 uses this method to obtain estimates of mobility flows and structural parameters that are not affected by this error. Section 6 circles back to the model of labor market choice, but uses estimates from the data rather than an simple calibration, and shows how the estimated effects of a trade shock differ when using corrected and uncorrected data. Section 7 concludes.

2 Inter-industry mobility in the PSID data

I build on [Kambourov and Manovskii \(2008\)](#) and analyze worker mobility across industries in the Panel Study of Income Dynamics (PSID). The main difference here relative to [Kam-](#)

²Note that [Kambourov and Manovskii \(2008\)](#) also estimate corrected mobility flows, but their analysis focuses more closely on the switching rate, that is worker's probability of moving out of the current industry or occupation.

³This is particularly valuable for richer models that have occupation or industry-specific human capital and returns to tenure, a feature I abstract of in this paper, where measures of wage changes at the individual level for workers switching labor markets are needed for estimation.

[bourov and Manovskii \(2008\)](#) is my focus on the patterns of industry mobility by origin and destination. In other words, I focus on the *matrix of mobility flows*, while they focused largely on the probability of an industry or occupation switch.

The PSID is a longitudinal survey with a nationally representative sample of over 18,000 individuals in the United States. The survey contains information about these individuals and their descendants, and has been collected continuously since 1968. The PSID contains information about demographic characteristics and socio-economic conditions, including labor earnings and characteristics of individuals' jobs at the time of the interview, such as information about industry and occupation. The data has an annual frequency from 1968 to 1997 and biennially since then. In this paper I use only the annual information and my analysis stops in 1997. The main advantage of the PSID relative to other available data sources, like the Current Population Survey (CPS), is the panel dimension and the many decades of data. An important limitation of the PSID is that the sample size is not very large and, since industry switches are infrequent, estimates of mobility and their statistical significance may be affected by sampling error.

My sample includes individuals between 23 and 64 years of age, most of which have finished schooling and have not yet retired. Moreover, I use the core Survey Research Center (SRC) sample of the PSID, which is nationally representative, and exclude the Survey of Economic Opportunity (SEO) sample from the analysis, which oversamples low-income households.⁴ Unless otherwise noted, all of the moments are computed using individuals that are employed at the time of the survey. Moments on industry mobility are computed over two consecutive years for individuals employed in each of those years.

A well-known problem with self-reported industry (and occupation) information in survey data is the prevalence of misclassification errors. [Murphy and Topel \(1987\)](#), [Kambourov and Manovskii \(2008, 2013\)](#) and [Moscarini and Thomsson \(2007\)](#) study the importance of misclassification in the CPS and the PSID, two of the most important labor market surveys in the United States.⁵ Misclassification errors are typically related to how survey respondents answer the questions on “what kind of business or industry” they work in, or “what sort of

⁴In later years the PSID also added immigrant and Latino samples, which I also exclude from my analysis.

⁵In a recent work, [Carrillo-Tudela and Visschers \(2020\)](#) also study occupational mobility and correct for misclassification using the Survey of Income and Program Participation (SIPP). Their approach to correct mobility measures follows [Poterba and Summers \(1986\)](#). [Vom Lehn et al. \(2020\)](#) also study occupation misclassification errors in the CPS data exploiting retrospective and panel data information about individuals surveyed. They offer corrected estimates of the overall switching rate, that is, the probability that a worker changes his/her occupation, but do not offer corrected measures of the flows by origin or destination. While their online Appendix E presents a corrected mobility flow matrix, this is just the result of a correction of the main diagonal of the matrix (one minus the probability of switching) and a proportional adjustment/imputation of the off-diagonal elements.

work” they do, and how these answers are then interpreted and mapped to a code in the classification system by a coder. If workers perform a variety of tasks and firms produce different types of products and services, the description that respondents provide to answer these questions may vary from time to time, even if the characteristics of their work did not change. A coder would then assign different industry or occupation codes over time for an individual, leading to misclassification.

As discussed in [Kambourov and Manovskii \(2008\)](#), in 1999 the PSID released a new set of occupation and industry codes for most individuals in the sample in years 1968 to 1980 that had industry and occupation information. These are known as retrospective industry and occupation codes.⁶ The retrospective industry and occupation information originated as part of the Working Lives and Mortality in an Aging National Cohort project, funded by the National Institute on Aging and the National Science Foundation, which required industry and occupation information at a level of disaggregation finer than the one available in the original PSID files. To produce this finer level of disaggregation, coders accessed individuals’ responses with the written descriptions of their job characteristics from the PSID archives. “To save time and increase reliability, the coder coded all occupations and industries for each person across all required years before moving on to the next case” ([PSID, 1999](#)). [Kambourov and Manovskii \(2008\)](#) argue that coding the entire time-series responses on industry and occupation of an individual drastically reduces misclassification errors, particularly those that inflate mobility rates.

One way to evaluate the effects of misclassification errors is comparing the original and retrospective industry information of individuals in the sample. Table 1 shows the proportion of individuals for which industry codes are different. In the table, and much of the next analysis, I aggregate industry into broad groups. These groups align closely with those defined in [Artuç et al. \(2010\)](#) and are slightly more aggregate than one-digit SIC codes.⁷ The industries I use are, (1) agriculture, forestry, fisheries and mining; (2) construction; (3) manufacturing; (4) transportation, communications, and other public utilities; (5) wholesale and retail trade; and (6) all other services, including public administration.⁸ The table shows employment shares in columns 2 and 3, and proportions of disagreement for all individuals by industry in columns 4 to 8, which distinguish by gender and age groups. At this level

⁶Some individuals were excluded from the retrospective coding sample. This includes individuals that had died by 1992 or that reported a main job in fewer than three waves of the survey. See [PSID \(1999\)](#) for more information.

⁷The PSID uses the industry codes in the 1970 Census of Population, which follow closely the 1967 Standard Industrial Classification codes.

⁸Appendix B provides more details on the PSID data and the codes I use to construct these broad industry groups.

of aggregation, differences in industry codes assigned to individuals are, on average, 8%, but there is important heterogeneity across different industries and demographic groups.⁹ Wholesale and retail trade and construction are on the higher end of misclassification errors, while all other services are at the lower end. Across age groups, discrepancy levels seem similar, but they tend to be lower for women.

Table 1: Differences in original and retrospective industry and occupation coding
(fraction of cases with differences, PSID 1968-1980)

Industries	Employment shares (%)		Fraction with differences in coding				
	Original	Retrospective	All	Men	Women	24-35 yrs.	36-64 yrs.
Agric./Mining	4.8	4.9	0.098 (0.010)	0.090 (0.010)	- -	0.086 (0.015)	0.109 (0.013)
Construction	7.2	7.7	0.136 (0.010)	0.135 (0.010)	- -	0.145 (0.015)	0.125 (0.012)
Manufacturing	28.4	29.1	0.073 (0.004)	0.076 (0.004)	0.055 (0.009)	0.077 (0.007)	0.072 (0.005)
Transport/Util	8.5	8.1	0.073 (0.007)	0.075 (0.007)	0.054 (0.019)	0.089 (0.012)	0.059 (0.008)
Wholesale/Retail	13.9	14.5	0.153 (0.007)	0.177 (0.009)	0.073 (0.011)	0.148 (0.011)	0.157 (0.010)
Other serv.	37.1	35.7	0.048 (0.003)	0.064 (0.004)	0.019 (0.003)	0.048 (0.004)	0.049 (0.004)
All	100.0	100.0	0.081 (0.002)	0.093 (0.002)	0.039 (0.003)	0.084 (0.003)	0.080 (0.003)

Note: Author's calculation using PSID data between 1971 and 1980 for industries. Sample restricted to SRC individuals between 23 and 64 years old employed at the time of the survey in two consecutive years. Standard errors in parenthesis. Cells with missing values are cases with a small number of observations.

It is important to highlight that the employment shares of industries are almost identical between original and retrospective coding in Table 1. This suggests that, on average, misclassification of individuals into a different industry is offset by the misclassification of other individuals, leaving the *stocks* of people in each group largely unchanged. However, if individuals' industry codes are subject to misclassification errors, the measures of industry *flows* will be noticeably impacted. Table 2 shows matrices of yearly mobility across broad industries using the original and retrospective codes. In both cases, and at this level of disaggregation, industry switching is not very frequent, as can be seen by the high rates along the diagonal of the matrices relative to the mobility rates outside of the diagonal. However, as these matrices show, mobility rates are lower using retrospective codes than the original codes. On average, industry mobility rates are 10.7% using the original codes and

⁹The level of disaggregation in industry classification matters. Differences between original and retrospective codes are even larger for more disaggregated industry groups.

5.5% using the retrospective codes. These numbers align well with those in [Kambourov and Manovskii \(2008\)](#), with the differences stemming mostly from a different level of industry disaggregation and sample selection criteria.¹⁰

In sum, misclassification errors overstate the amount of industry (and occupation) mobility in the data. I now study the effects of these errors on parameter estimates using a dynamic model of industry and occupation switching.

3 A simple model of labor reallocation with coding error

Given the prevalence of misclassification of workers' industry and occupation in the data, a natural question is how much it affects estimates of switching costs and mobility elasticities, which are key ingredients for understanding the labor market effects of international trade.

The starting point is a model of labor reallocation which closely connects to [Artuç et al. \(2010\)](#).¹¹ To simplify the exposition, in this section, I focus only on labor supply and present here the problem of the worker that chooses a labor market in which to supply labor, taking current and future wages as given.¹²

Following [Artuç et al. \(2010\)](#), I define a labor market as an industry. Workers begin the period attached to a labor market, which is a consequence of past labor supply decisions, and inelastically supply all labor in that market, obtaining the market wage. At the end of each period, workers optimally decide the industry to supply labor in the following period. Reallocation is subject to frictions in the form of switching costs, which can vary by origin and destination. These frictions make the problem of the worker dynamic, as workers trade off the sunk costs of switching with benefits that accrue slowly over time.

In addition, I assume that workers decisions are influenced by idiosyncratic shocks that affect the costs or benefits of switching to a different labor market. As commonly assumed in the literature, I let these shocks follow a Type-I Extreme Value distribution. Workers are

¹⁰For occupations, [Kambourov and Manovskii \(2008\)](#) show mobility rates of 22% and 11% using original and retrospective coding, respectively between 1968 and 1980, which indicates that occupational mobility rates are twice as large using the original coding relative to the retrospective coding. Using CPS data, [Murphy and Topel \(1987\)](#) and [Moscarini and Thomsson \(2007\)](#) also find a considerably large occupation and industry mobility driven by misclassification error.

¹¹Several papers have contributed to the literature on dynamic labor reallocation due to international trade, such as [Dix-Carneiro \(2014\)](#), [Caliendo et al. \(2019\)](#), and [Traiberman \(2019\)](#).

¹²The assumption of perfect foresight for workers is just to simplify the exposition. I relax this assumption later in the analysis following [Artuç et al. \(2010\)](#).

Table 2: Matrices of industry mobility
(PSID, 1968-1980)

	Using original coding				
	Agric./Mining	Construction	Manufacturing	Transport/Util	Wholesale/Retail
Agric./Mining	0.877 (0.011)	0.026 (0.005)	0.039 (0.006)	0.012 (0.004)	0.017 (0.004)
Construction	0.014 (0.003)	0.821 (0.011)	0.057 (0.007)	0.030 (0.005)	0.016 (0.004)
Manufacturing	0.006 (0.001)	0.012 (0.002)	0.912 (0.004)	0.009 (0.001)	0.028 (0.002)
Transport/Util	0.006 (0.002)	0.022 (0.004)	0.026 (0.004)	0.873 (0.009)	0.026 (0.004)
Wholesale/Retail	0.004 (0.001)	0.012 (0.002)	0.064 (0.005)	0.015 (0.003)	0.837 (0.008)
Other serv.	0.005 (0.001)	0.011 (0.001)	0.026 (0.002)	0.014 (0.001)	0.023 (0.002)
					0.029 (0.005)
					0.061 (0.007)
					0.032 (0.003)
					0.046 (0.006)
					0.068 (0.005)
					0.921 (0.003)

	Using retrospective coding				
	Agric./Mining	Construction	Manufacturing	Transport/Util	Wholesale/Retail
Agric./Mining	0.927 (0.008)	0.017 (0.004)	0.019 (0.004)	0.007 (0.002)	0.013 (0.003)
Construction	0.013 (0.003)	0.911 (0.007)	0.030 (0.004)	0.014 (0.003)	0.014 (0.003)
Manufacturing	0.003 (0.001)	0.008 (0.001)	0.956 (0.003)	0.005 (0.001)	0.012 (0.001)
Transport/Util	0.006 (0.002)	0.009 (0.002)	0.009 (0.002)	0.939 (0.006)	0.015 (0.003)
Wholesale/Retail	0.005 (0.001)	0.009 (0.002)	0.023 (0.003)	0.007 (0.002)	0.922 (0.005)
Other serv.	0.003 (0.001)	0.005 (0.001)	0.016 (0.001)	0.006 (0.001)	0.015 (0.001)
					0.017 (0.004)
					0.019 (0.003)
					0.016 (0.002)
					0.022 (0.004)
					0.035 (0.003)
					0.956 (0.002)

Note: Author's calculation using PSID data between 1971 and 1980 for the first panel and 1968 and 1980 for the second panel. Fraction of movers in an industry. First year industry by row and second year industry by column. Sample restricted to SRC individuals between 24 and 64 years old employed at the time of the survey in two consecutive years. Standard errors in parenthesis.

also heterogeneous in their permanent characteristics, like demographic factors or educational attainment, which I capture with a vector of characteristics τ , defining a worker's type.¹³

The recursive problem of the worker of characteristics τ that begins the period in labor market j and has a realization of preference shocks ϵ , is defined in the following way,

$$V_t^j(\tau, \epsilon) = w_t^j(\tau) + \max_{\ell} \left\{ \beta E_{\epsilon'} [V_{t+1}^{\ell}(\tau, \epsilon')] - \kappa^{j\ell}(\tau) + \nu \epsilon_t^{\ell} \right\},$$

where $V_t^j(\tau)$ is the value function, or lifetime utility, of the worker, β is the discount factor, $\kappa^{j\ell}(\tau)$ are the origin-destination-specific costs of switching industry, which may differ by workers' characteristics, $w_t^j(\tau)$ is the wage workers with characteristics τ get in labor market j , and ν is a parameter that scales the variance of the preference shocks ϵ and is inversely related to the elasticity of mobility with respect to wage changes.

The first term in the right is the flow utility from consumption. Workers are hand-to-mouth and spend all their labor earnings in the consumption of the numeraire good. The second term describes the worker's choice at the end of the period. The worker chooses the labor market that maximizes future expected lifetime utility, taking into account the costs of switching and preference shocks.

As is well-known, the assumption of i.i.d. Type-I Extreme Value shocks for ϵ leads to a simpler expression for the *ex-ante* value function, $v_t^j(\tau) = E_{\epsilon} [V_t^j(\tau, \epsilon)]$, such that,

$$v_t^j(\tau) = w_t^j(\tau) + \nu \log \left[\sum_{\ell=1}^J \exp \left(\beta v_{t+1}^{\ell}(\tau) - \kappa^{j\ell}(\tau) \right)^{1/\nu} \right]. \quad (1)$$

Moreover, the probability that the worker chooses labor market ℓ at the end of the period also has a tractable expression given by,

$$\mu_t^{j\ell}(\tau) = \frac{\exp \left(\beta v_{t+1}^{\ell}(\tau) - \kappa^{j\ell}(\tau) \right)^{1/\nu}}{\sum_{k=1}^J \exp \left(\beta v_{t+1}^k(\tau) - \kappa^{jk}(\tau) \right)^{1/\nu}}. \quad (2)$$

By the law of large numbers, this also represents the fraction of workers that move from j to ℓ each period, such that if $L_t^j(\tau)$ is the total number of workers in labor market j at time t , then the distribution of workers evolves as, $L_{t+1}^{\ell}(\tau) = \sum_{j=1}^J L_t^j(\tau) \mu_t^{j\ell}(\tau)$.

In the absence of misclassification errors, the matrix $\mu_t(\tau)$ can be mapped directly to the matrix of mobility flows in the data analyzed in the previous section. This is the usual way

¹³ In Section 5.2 and Appendix A, I relax the assumption of time-invariant worker's characteristics τ , allowing, for example, workers' aging.

to proceed in many studies in the literature. However, when there are coding errors in the data, the econometrician does not perfectly observe workers' industry choices. Let s be the true industry of the worker and j the one observed in the data, and define $\alpha_{j|s}(\tau)$ as the probability that the labor market of worker with characteristics τ is recorded as j when the true labor market is s . [Poterba and Summers \(1986\)](#) define the matrix with elements $\alpha_{j|s}(\tau)$ as the matrix of error rates.

Assumption 1: The distribution of misclassification errors depends only on the worker's true industry in the current period and his/her observed characteristics τ .¹⁴

This assumption, which is commonly used in the misclassification literature (i.e. [Feng and Hu \(2013\)](#)), limits the amount of temporal dependence in misclassification. Any past history of occupation choices and coding errors does not affect misclassification in the current period. This assumption seems reasonable if a worker's industry (or occupation) is coded independently from any past information each period, as is the case in many surveys, including the way original codes were assigned in the PSID.

In this way, I can represent the observed number of workers in labor market j at time t as,

$$\tilde{L}_t^j(\tau) = \sum_{s=1}^J L_t^s(\tau) \alpha_{j|s}(\tau),$$

where $\tilde{L}_t^j$ denotes the *observed* number of workers in labor market j . The observed number of workers moving from market j to ℓ is,

$$\tilde{L}_t^j(\tau) \tilde{\mu}_t^{j\ell}(\tau) = \sum_{s=1}^J \sum_{s'=1}^J L_t^s(\tau) \alpha_{j|s}(\tau) \alpha_{\ell|s'}(\tau) \mu_t^{ss'}(\tau), \quad (3)$$

where $\tilde{\mu}_t^{j\ell}(\tau)$ is the mobility matrix of the observed flows between j and ℓ , and s, s' are the true industries of workers in period t and $t + 1$, respectively.

Similarly, observed wages may differ from actual wages according to,

$$\tilde{w}_t^j(\tau) \tilde{L}_t^j(\tau) = \sum_{s=1}^J \alpha_{j|s}(\tau) w_t^s(\tau) L_t^s(\tau), \quad (4)$$

where $\tilde{w}_t^j(\tau)$ are observed wages.

¹⁴Note that it is not necessary for the vector of workers' characteristics τ to be time-invariant. See also footnote [13](#).

3.1 The impact of misclassification errors on parameter estimates

I now evaluate how misclassification errors affect the estimates of structural parameters in the model. Since the goal is to illustrate the effects, I assume a stationary economy in which wages are invariant over time and workers do not differ in observable characteristics τ .¹⁵ As discussed in [Artuç et al. \(2010\)](#), variability in mobility flows and wages over time are needed to separately identify ν and κ , but this variability is absent in a stationary economy. In the example I present here, the value of these parameters is identified by a non-symmetric economy with differences in the level of wages across industries and the functional form assumption of the flow utility. Note that different specifications of the flow utility, like multiplying by a constant, impact the values of ν and κ . Despite this caveat, this example illustrates the impact of misclassification errors on parameter estimates, keeping all else equal.

Here I use the six industries discussed in the previous section. I calibrate wages such that the shares of employment in each sector approximate employment shares listed in the sixth column of Table 2 in [Artuç et al. \(2010\)](#).¹⁶ As is commonly assumed in the literature, the cost of staying in the same industry are normalized to zero, $\kappa^{jj} = 0$, for all j , and for simplicity, here I assume switching costs are homogeneous, such that $\kappa^{j\ell} = \kappa$ for all $j \neq \ell$.¹⁷ I use two set of parameter values in this example. First, I use $\nu = 1.9$, $\beta = 0.97$, which are taken from Panel IV of Table 3 in [Artuç et al. \(2010\)](#), as this is their preferred estimation. Moreover, I make $\kappa = 8$, which is slightly larger than their estimate, but this value delivers mobility matrices and a stationary allocation of labor over sectors that approximate well the ones listed in Tables 1 and 2 in [Artuç et al. \(2010\)](#) and the ones discussed in Section 2. The second set of values I use are $\nu = 3.45$ and $\kappa = 17.03$, also assuming $\beta = 0.97$. These larger values correspond to estimates in Section 5 discussed later on. Finally, I assume that misclassification errors are $\alpha_{j|s} = 1 - (J - 1)\psi$, for $j = s$, and $\alpha_{j|s} = \psi$, for $j \neq s$, where ψ is a small scalar representing the importance of misclassification error.¹⁸

To estimate parameters ν and κ , I use equation (9) in [Artuç et al. \(2010\)](#), which links

¹⁵In the estimation in Section 5, I relax both these assumptions.

¹⁶The model I use abstracts from amenities that may influence worker's flow utility and industry choice. However, calibrated wages do not differ substantially from those listed in the fourth column of Table 2 in [Artuç et al. \(2010\)](#). Qualitatively, using wages from the PSID, or the employment shares in the PSID would not change the main insights. Quantitatively, the results do not change much.

¹⁷Appendix A shows the results for the case of heterogeneous switching costs that vary by origin and destination.

¹⁸These assumptions just simplify the exposition, as the goal here is to illustrate the effects of the errors. The method discussed later in Section 4 is more general and allows for richer heterogeneity in the probability of misclassification and model parameters.

model parameters with mobility probabilities and wages that can be measured in the data. I re-arrange that equation and reproduce it here for convenience,¹⁹

$$[\log(\tilde{\mu}^{ij}) - \log(\tilde{\mu}^{ii})] - \beta [\log(\tilde{\mu}^{ij}) - \log(\tilde{\mu}^{jj})] = \mathbb{C}_1 + \mathbb{C}_2(\tilde{w}^j - \tilde{w}^i). \quad (5)$$

The left-hand side of equation (5) is a function of observed mobility rates between two labor markets, i and j , and the discount factor β , which I take as known by assumption and is not estimated. The regressors in the equation are wage differences across labor markets, which in a non-symmetric economy will be different from zero, and a constant term. In the absence of misclassification, the model relates structural parameters and the estimates in the regression in the following way, $\mathbb{C}_1 = -(1 - \beta)\frac{\kappa}{\nu}$ and $\mathbb{C}_2 = \frac{\beta}{\nu}$. In this example there is no need to simulate data: the calibrated wages and parameters deliver values for v^j and μ^{ij} using (1) and (2). With misclassification, I use the moments implied by (3) and (4) to obtain $\tilde{\mu}^{ij}$ and $\tilde{w}^j$, which are the variables an econometrician that ignores misclassification would use in the regression.

Table 3 shows the estimated value of parameters for an economy with no misclassification error ($\psi = 0$) in column 2, and different levels of misclassification error in columns 3 to 5. Not surprisingly, in an economy with no error, estimated values coincide with the true value of parameters and the regression has an R-squared of one. On average, measured mobility in this economy is 6%, a value that is not far from the data discussed in the previous section.

As the value of ψ increases, there is more misclassification in the model. In this particular example with six industries, the probability of being misclassified is five times the value of ψ . Thus, a value of ψ equal to 0.005 implies a probability of 2.5% that a worker will be classified in an industry different than the one she is working in. For all values of ψ greater than zero reported in table 3, the regression does not take into account that the model may be subject to misclassification error. In this case, the R-squared deviates from its theoretical value of one since equation (5) is not derived from a model with misclassification. Moreover, the measured (average) mobility in the last row of the table increases with larger ψ . Column 4 shows the results for an economy with a moderate amount of error ($\psi = 0.005$). Measured mobility is 11% and 8% in Panels A and B, respectively, roughly two to three times the true mobility rate. This aligns well with the discussion in the previous section on differences in mobility in the data for the original and retrospective coding. In this case, estimated values for κ and ν (related to mobility costs and mobility elasticity) are around half their true value in both panels, with the exception of the estimates of κ in Panel B, which is estimated

¹⁹ Appendix A shows the derivation of this expression using model equations.

Table 3: The effect of misclassification on parameter estimates

Panel A				
True parameters	No error	misclassification		
$\nu = 1.9, \kappa = 8.0$	$(\psi = 0)$	$(\psi = 0.001)$	$(\psi = 0.005)$	$(\psi = 0.01)$
Estimated ν	1.9	1.6	1.0	0.7
Estimated κ	8.0	6.7	3.8	2.3
Estimated ratio κ/ν	4.2	4.1	3.6	3.2
R-squared	1.0	0.999	0.989	0.976
Avg. outflow prob.	0.06	0.07	0.11	0.15
Panel B				
True parameters	No error	misclassification		
$\nu = 3.45, \kappa = 17.03$	$(\psi = 0)$	$(\psi = 0.001)$	$(\psi = 0.005)$	$(\psi = 0.01)$
Estimated ν	3.5	2.8	1.6	1.0
Estimated κ	17.0	13.0	6.1	3.4
Estimated ratio κ/ν	4.9	4.7	4.0	3.4
R-squared	1.0	0.998	0.985	0.972
Avg. outflow prob.	0.03	0.04	0.08	0.13

Note: Parameters estimated by OLS according to equation (5). Each observation is a sector of origin-destination, where origin is different from destination. The example uses 6 sectors, and there are 30 observations in each regression. Panel A shows results for structural parameter values $\nu = 1.9, \kappa = 8.0$ and different levels of misclassification errors. Panel B shows results for $\nu = 3.45, \kappa = 17.03$.

around one third the actual value.²⁰

Why does misclassification bias the parameter values towards zero? This economy exhibits an artificially large amount of mobility due to misclassification, but the impact of on wages for the different labor markets is quantitatively small.²¹ If mobility was uniformly larger across all labor markets such that the left-hand side of equation (5) increases by the same magnitude with misclassification, estimates of the constant term would be closer to zero, which can be rationalized by a lower value of the ratio κ/ν . Table 3 show how the estimated ratio κ/ν falls as the error increases. This agrees with Artuç et al. (2010), page 1017, on the effects of misclassification on this ratio.

The effects of misclassification on the estimate of parameter ν are more nuanced. Artuç et al. (2010) argue that “coding errors [...] will definitely provide an overestimate of ν ” as wage differences would appear less relevant for mobility relative to the preference shocks. At first sight, this intuition seems reasonable as the model implies larger mobility rates for a larger ν keeping wages and mobility costs constant. However, the effect on estimates for ν depends on how misclassification affects some mobility rates *relative* to others, altering the slope of the regression line. Figure 1 shows the datapoints used in the estimation of equation (5) for a moderate amount of misclassification ($\psi = 0.005$) and no misclassification, and shows that the slope of the regression line is steeper with misclassification, leading to a *lower* estimated value for ν . The reason is that a pair of labor markets with large wage differentials also has large outflows from the labor market with low wages into the one with higher wages. Mobility rates under misclassification increase more across labor markets with higher mobility, thus making the slope steeper. In this way, the estimated value for ν using data with misclassification *underestimates* the true value of the parameter. Note that, with a lower estimated value for ν and the ratio κ/ν with misclassification, the bias on estimates of costs κ could go in any direction. In the example here, estimated costs are also biased towards zero.

Clearly, this example assumes a particular type of misclassification that is homogeneous and symmetric across different labor markets. Relaxing this assumption and using a more flexible misclassification error structure may bias parameter estimates in a different way, and is not obvious the bias on parameter estimates will always have the same sign.

²⁰In Appendix A, I show that this conclusion also extends to the case of heterogeneous switching costs that vary by origin and destination.

²¹In this example, the economy with misclassification has similar labor shares across labor markets as the economy with no misclassification. As discussed before, misclassification affects the flows substantially more than the stocks. In this way, equation (4) suggests that the observed wage would be approximately equal to the average of the true wages weighted by $\alpha_{j|s}$. For small values of ψ , the values of $\alpha_{j|s}$ are such that $\tilde{w}^j \approx w^j$.

Figure 1: Effect of misclassification on parameter estimates

Note: Each panel shows the data used for the regression (5) under two levels of misclassification errors: $\psi = 0$ and $\psi > 0$. The left panel shows results for structural parameter values $\nu = 1.9$, $\kappa = 8.0$ and the right panel shows results for $\nu = 3.45$, $\kappa = 17.03$.

In addition, it is worth highlighting that welfare calculations depend on observed wages, mobility and the parameter ν . Thus, misclassification error would also bias model-implied measures of welfare and how welfare changes with, for example, trade shocks.²² In the context of this simple model, welfare or expected lifetime utility for a representative individual in industry i would be equal to $v^i = \frac{1}{1-\beta} (w^i - \nu \log(\mu^{ii}))$. As the expression shows, the effect of trade shocks on welfare depends on how actual wages and mobility change, but also on the estimates of parameter ν .

While this section illustrates to what extent misclassification biases estimates of structural parameters, it does not provide a unified treatment to measure misclassification probabilities and parameters in the data. I discuss a way to estimate misclassification and parameters in the next sections.

4 Main econometric framework

I propose an empirical framework that allows me to estimate the probability of misclassification, measure industry and occupational mobility matrices corrected for misclassification, and obtain estimates of the model's structural parameters.²³

The sample consists of N individuals such that $n = \{1, \dots, N\}$. For simplicity, I assume

²²See Appendix D for a derivation of welfare formulas.

²³While most of the analysis and the application in this paper focuses on industry mobility, the method I develop here applies to misclassification of other variables, like occupations. Thus, in this section I refer to both industry and occupation misclassification and how to correct for it.

that the econometrician observes the worker's industry and/or occupation for two consecutive periods, and the wage for the first period, ω .²⁴ I denote by j the observed labor market in the first period and by j' the one in the second period, where $j, j' = \{1, \dots, J\}$.

As discussed before, $\alpha_{j|s}(\tau)$ is the probability that individual n with observed characteristics τ and a true occupation/industry s has an observed occupation/industry j and thus reflects the probability of misclassification. In addition, let $p_s(\tau, \theta)$ and $p_{s'|s}(\tau, \theta)$ be the probability that a worker is in occupation/industry s initially and switches to occupation/industry s' in the second period, respectively. These are functions of structural parameters listed in the vector θ . In the context of the model discussed in Section 3, $p_{s'|s}(\tau, \theta)$ are the conditional choice probabilities of the structural model, which before I denoted by $\mu^{ss'}(\tau)$ and the vector θ is comprised of ν and κ . Note however that the estimation proposed here is more general and does not have to be linked to a specific structural model, thus the alternative notation.

In addition, I assume that observed log-wages for an individual n are subject to classical measurement error or to transitory income shocks realized at the beginning of the period, such that $\log(\omega^n) = \log(w_s(\theta, \tau)) + \eta^n$.²⁵ w_s is the common component of wages for all individuals with characteristics τ in labor market s . In the context of the structural model of Section 3, these are the wages of the model, which may be assumed exogenous as in the previous section, or in a richer general equilibrium framework, they may depend on structural parameters. η is the measurement error or temporary income shock, which is distributed i.i.d. with density f . Let d_j^n and $d_{jj'}^n$ be dummy variables that are equal to one if the observed occupation/industry of individual n is j and j' , respectively, and zero otherwise. Then I can write the likelihood of observing individual n as,

$$\mathcal{L}^n(\tau^n, d_j^n, d_{jj'}^n, \omega_j^n | \theta, \alpha) = \prod_{j=1}^J \prod_{j'=1}^J \left[\sum_{s=1}^J \sum_{s'=1}^J p_s(\tau, \theta) \alpha_{j|s}(\tau) p_{s'|s}(\tau, \theta) \alpha_{j'|s'}(\tau) f(\log(\omega_j^n / w_s(\theta, \tau))) \right]^{d_j^n d_{jj'}^n}. \quad (6)$$

The first four terms in the likelihood denote the joint probability that an individual with actual industry/occupation over both periods s and s' has observed industry/occupation j and j' , respectively. The last term is just the likelihood of the observed wage.

In my empirical application I assume that for part of the sample there are no coding errors, such that $\alpha_{j|s}(\tau) = 1$ if $j = s$ and zero otherwise. This assumption follows [Kambourov and](#)

²⁴It is straightforward to generalize to panel data spanning several periods of worker's labor market history. The setup I use here would work well with the ASEC supplement of the CPS used in [Artuç et al. \(2010\)](#); [Artuç and McLaren \(2015\)](#).

²⁵An important assumption is that transitory income shocks are not persistent and are not known at the time of selecting labor markets or that they do not affect the labor market choice decision.

Manovskii (2008) and the discussion in Section 2, where retrospective coding substantially reduced (or eliminated) misclassification.²⁶ I can split the sample into those observations without coding error, $n = \{1, \dots, N_0\}$ and those that potentially are affected by coding errors, $n = \{N_0 + 1, \dots, N\}$.

Assumption 2: Structural parameters θ are identical across both samples or have a common (parametric) trend across both samples.

Assumption 2 is key for identification of the coding error probabilities α and the structural parameters θ , since parameters are identical across both samples or have a common trend. Once again, this follows closely Kambourov and Manovskii (2008), as their estimated probit models had common parameters across periods and parameteric trends, affected by a discrete shifter for the sample with no retrospective coding.²⁷ To simplify the exposition, I abstract from changes in the patterns of industry/occupation mobility over time, but the method is able to handle a reasonably flexible, but not completely general, time-variation in the patterns of mobility.²⁸ In the application of the next section, I do allow for time trends.

Then, the log-likelihood of the sample is,

$$\begin{aligned} \mathcal{L}(\mathbf{d}, \boldsymbol{\tau}, \boldsymbol{\omega} | \theta, \alpha) = & \sum_{n=1}^{N_0} \sum_{j=1}^J \sum_{j'=1}^J d_j^n d_{jj'}^n \log [p_j(\tau^n, \theta) p_{j'|j}(\tau^n, \theta) f(\log(\omega^n / w_j(\theta, \tau^n)))] + \\ & \sum_{n=N_0+1}^N \sum_{j=1}^J \sum_{j'=1}^J d_j^n d_{jj'}^n \log \left[\sum_{s=1}^J \sum_{s'=1}^J p_s(\tau^n, \theta) \alpha_{j|s}(\tau^n) p_{s'|s}(\tau^n, \theta) \alpha_{j'|s'}(\tau^n) f(\log(\omega^n / w_s(\theta, \tau^n))) \right], \end{aligned} \quad (7)$$

where $\mathbf{d}$, $\boldsymbol{\tau}$, and $\boldsymbol{\omega}$ are vectors containing the sample observations of individuals' choices, characteristics and wages, respectively. Note that in writing the likelihood of the sample in equation 7 I do not use information on misclassification for the first period, where potentially two measures of industry or occupations for individuals is available. The reason is that this information is only available for very aggregate industry or occupation groups, thus my approach here can be used for a finer level of details. However, in Section 5 I compare the estimates of the misclassification probability α with the discrepancy errors reported in Table 1.

²⁶Misclassification errors have a large impact on mobility flows but only a modest impact on the stocks. Even if retrospective coding reduced the amount of mobility, individuals may still be (persistently) misclassified into a different industry/occupation. I abstract from this, but it can be easily incorporated into the analysis.

²⁷Kambourov and Manovskii (2008) did not estimate a structural model of occupational/industry choice, but a statistical one. The parameters of that model would play a similar role as parameters α and θ used here.

²⁸Given my identification assumptions, I cannot allow for a fully flexible, non-parametric, time-variation in the patterns of mobility as they would not be identified separately from misclassification error (or its changes over time).

A structural model, like the one presented in Section 3, specifies a functional form for the conditional choice probability $p_{s'|s}(\tau, \theta)$. By making additional functional form assumptions for the density f and the initial occupation allocation $p_s(\tau, \theta)$, which could also be modeled structurally, it is possible to find values for parameters θ and α that maximize (7). Note, however, that a direct maximization of all these parameters can be quite demanding as the number of parameters to estimate may grow geometrically with the number of occupations/industries, and it involves maximizing a non-linear, and potentially not well-behaved, function over many dimensions. In particular, the double sum inside the logarithm in (7) does not permit simpler expressions and all parameters must be maximized jointly. In the next subsection I adapt the insights from Arcidiacono and Miller (2011) and use the Expectation-Maximization (EM) algorithm to estimate the parameters of the model in a very tractable manner.

4.1 Expectation-Maximization algorithm

The EM algorithm is a widely used technique in statistics and econometrics to estimate parameters by maximizing the likelihood function of a sample, and is commonly used in models with latent variables.²⁹ In a recent influential paper, Arcidiacono and Miller (2011) propose a two-step approach using the EM algorithm to estimate parameter values of dynamic discrete choice models with unobserved heterogeneity. While my setup does not map directly to their class of models, it is closely related as I treat the true industry/occupation of a worker as a latent state unobserved by the econometrician.

In a similar fashion as Arcidiacono and Miller (2011), in the first stage I treat the functions $p_s(\tau, \theta)$ and $p_{s'|s}(\tau, \theta)$ as primitives to be estimated together with misclassification parameters $\alpha_{j|s}(\tau)$, and parameters linked to wages. In this way, I obtain measures of industry/occupation mobility corrected for misclassification. In a second stage, I use these mobility measures to estimate the model parameters related to switching costs and mobility elasticity.

First stage. The starting point of the EM algorithm is to treat the unobserved –or latent state– as observed, assigning a probability to each individual in the sample of being in each particular state. Denote by $q_{ss'}^n$ the probability that individual n , with observed variables d^n , ω^n , τ^n , has true industry/occupations s , s' over the two periods. In this way,

²⁹In other words, the EM algorithm is a method to obtain the maximum likelihood estimates of the structural parameters θ , and α in (7), but does so in an iterative way.

we can re-write (7) as,³⁰

$$\begin{aligned} \mathcal{L}(\mathbf{d}, \boldsymbol{\tau}, \boldsymbol{\omega} | \hat{p}_j, \hat{p}_{j'|j}, \hat{w}_s, \alpha) &= \sum_{n=1}^{N_0} \sum_{j=1}^J \sum_{j'=1}^J d_j^n d_{jj'}^n \log [\hat{p}_j(\tau^n) \hat{p}_{j'|j}(\tau^n) f(\log(\omega^n / \hat{w}_s(\tau^n)))] + \\ &\quad \sum_{n=N_0+1}^N \sum_{j=1}^J \sum_{j'=1}^J \sum_{s=1}^J \sum_{s'=1}^J d_j^n d_{jj'}^n q_{ss'}^n \log [\hat{p}_s(\tau^n) \alpha_{j|s}(\tau^n) \hat{p}_{s'|s}(\tau^n) \alpha_{j'|s'}(\tau^n) f(\log(\omega^n / \hat{w}_s(\tau^n)))] . \end{aligned} \quad (8)$$

where $\hat{p}_s(\tau)$, $\hat{p}_{s'|s}(\tau)$, and $\hat{w}_s(\tau)$ are treated as parameters in this first step and thus I omit the dependence on the structural parameters θ .³¹

The EM algorithm iteratively updates the probabilities $q_{ss'}^n$ and parameter values, increasing the likelihood at each iteration, attaining, in the limit, a (local) maximum. In the first iteration, the algorithm is initialized with some values for parameters $\hat{p}_s^{(1)}(\tau)$, $\hat{p}_{s'|s}^{(1)}(\tau)$, $\alpha_{j'|s'}^{(1)}(\tau)$, and $\hat{w}_s^{(1)}(\tau)$, where the superindex (1) denotes the iteration number. At iteration $m+1$, a new value for $q_{ss'}^{n,(m+1)}$ is computed according to,

$$q_{ss'}^{n,(m+1)} = \frac{\prod_{j=1}^J \prod_{j'=1}^J \left[\hat{p}_s^{(m)}(\tau, \theta) \alpha_{j|s}^{(m)}(\tau) \hat{p}_{s'|s}^{(m)}(\tau, \theta) \alpha_{j'|s'}^{(m)}(\tau) f(\log(\omega_j^n / \hat{w}_s^{(m)}(\theta, \tau))) \right] d_j^n d_{jj'}^n}{\prod_{j=1}^J \prod_{j'=1}^J \left[\sum_{k=1}^J \sum_{k'=1}^J \hat{p}_k^{(m)}(\tau, \theta) \alpha_{j|k}^{(m)}(\tau) \hat{p}_{k'|k}^{(m)}(\tau, \theta) \alpha_{j'|k'}^{(m)}(\tau) f(\log(\omega_j^n / \hat{w}_k^{(m)}(\theta, \tau))) \right] d_j^n d_{jj'}^n}, \quad (9)$$

which is the ratio of the conditional likelihood of individual n being in state s, s' , to the likelihood of that individual in equation (6), but treating the conditional choice probabilities as parameters.

In the maximization step of the algorithm, updated parameter values $\hat{p}_s^{(m+1)}(\tau)$, $\hat{p}_{s'|s}^{(m+1)}(\tau)$, $\alpha_{j'|s'}^{(m+1)}(\tau)$, and $\hat{w}_s^{(m+1)}(\tau)$ are found by maximizing (8) using the probabilities $q_{ss'}^{n,(m+1)}$, where the maximization is subject to restrictions that ensure $\hat{p}_s^{(m+1)}(\tau)$, $\hat{p}_{s'|s}^{(m+1)}(\tau)$, $\alpha_{j'|s'}^{(m+1)}(\tau)$ are probabilities (i.e. they are positive and add up to one when summing across relevant states). If f is the density of a normal distribution, then the maximization for all these parameters has a closed-form solution and it boils down to computing simple averages of the data over the sample using probabilities $q_{ss'}^{n,(m+1)}$ as weights.³² For example, the (non-parametric)

³⁰Note that for the first part of the sample, for which I assume no misclassification error, there is no need to introduce the probabilities $q_{ss'}^n$ as true industry/occupation is observed for those individuals.

³¹If the density function f has additional parameters, they also need to be estimated at this stage. For example, if we assume the measurement errors for wages follow an i.i.d. normal distribution with mean zero and variance σ , then parameter σ is estimated together with $\hat{p}_s(\tau)$, $\hat{p}_{s'|s}(\tau)$, and $\hat{w}_s(\tau)$. For notational simplicity I omit this dependence here.

³²We can relax the normality assumption on the density f and use a different distribution. However, assuming a (log) normal distribution for measurement errors or transitory income shocks is common in the literature.

estimate for the choice probabilities and misclassification probabilities in equation (8) are,

$$\hat{p}_s^{(m+1)}(\tau) = \frac{\sum_{i=1}^{N_0} d_s^n \mathbb{I}(\tau^n = \tau) + \sum_{i=N_0+1}^N \sum_{j=1}^J \sum_{j'=1}^J \sum_{s'=1}^J d_j^n d_{jj'}^n q_{ss'}^{n,(m+1)} \mathbb{I}(\tau^n = \tau)}{\sum_{i=1}^{N_0} \sum_{s=1}^J d_s^n \mathbb{I}(\tau^n = \tau) + \sum_{i=N_0+1}^N \sum_{j=1}^J \sum_{j'=1}^J \sum_{s=1}^J \sum_{s'=1}^J d_j^n d_{jj'}^n q_{ss'}^{n,(m+1)} \mathbb{I}(\tau^n = \tau)} \quad (10)$$

$$\hat{p}_{s'|s}^{(m+1)}(\tau) = \frac{\sum_{i=1}^{N_0} d_s^n d_{ss'}^n \mathbb{I}(\tau^n = \tau) + \sum_{i=N_0+1}^N \sum_{j=1}^J \sum_{j'=1}^J d_j^n d_{jj'}^n q_{ss'}^{n,(m+1)} \mathbb{I}(\tau^n = \tau)}{\sum_{i=1}^{N_0} \sum_{s=1}^J d_s^n d_{ss'}^n \mathbb{I}(\tau^n = \tau) + \sum_{i=N_0+1}^N \sum_{j=1}^J \sum_{j'=1}^J \sum_{s'=1}^J d_j^n d_{jj'}^n q_{ss'}^{n,(m+1)} \mathbb{I}(\tau^n = \tau)}, \quad (11)$$

$$\alpha_{j|s}^{(m+1)}(\tau) = \frac{\sum_{i=N_0+1}^N \sum_{j'=1}^J \sum_{s'=1}^J d_j^n d_{jj'}^n q_{ss'}^{n,(m+1)} \mathbb{I}(\tau^n = \tau)}{\sum_{i=N_0+1}^N \sum_{j=1}^J \sum_{j'=1}^J \sum_{s'=1}^J d_j^n d_{jj'}^n q_{ss'}^{n,(m+1)} \mathbb{I}(\tau^n = \tau)}, \quad (12)$$

where $\mathbb{I}(\tau^n = \tau)$ is an indicator that is equal to one if $\tau^n = \tau$.³³ Moreover, parameters $\hat{w}_s^{(m+1)}(\tau)$ and the variance of the measurement error can be estimated flexibly using weighted means for different τ , using $q_{ss'}^{n,(m+1)}$ as weights.³⁴

With these new parameter values we can perform one more iteration in the algorithm, finding an update for $q_{ss'}^{n,(m+2)}$ and so on. Each iteration of the algorithm increases the value of the likelihood (7), until a (local) maximum is attained.

Second stage. With optimal values for $\hat{p}_s(\tau)$, $\hat{p}_{s'|s}(\tau)$ and $\hat{w}_s(\tau)$ we can estimate the structural parameters θ . As discussed in Section 6.2. of [Arcidiacono and Miller \(2011\)](#), it is possible to form a likelihood function to estimate these parameters, but alternative estimators would also be consistent. In particular, we can use the estimator in [Artuç et al. \(2010\)](#) discussed in Section 3, with the variables corrected for misclassification, $\hat{w}_s(\tau)$ and $\hat{p}_{s'|s}(\tau)$.³⁵

Four aspects are worth highlighting. First, depending on the data and the identification assumptions, it is possible to modify the likelihood function to accommodate different characteristics of the data available.³⁶ However, most of the method proposed here would be the same. This is particularly useful when working with data from the Current Population Survey, widely used in the literature on labor reallocation and international trade. But even if other datasets do not offer a clean identification strategy, the estimates of α using PSID

³³It is possible to make parametric assumptions for the estimators of the choice probabilities and misclassification probabilities. This may be useful in cases where the sample size is small and many transitions from j to j' have no observations. In this case, the likelihood and the expressions for parameter estimates must be modified to capture these assumptions, but otherwise the analysis follows through in a similar fashion. For example, if choice probabilities are assumed to follow a multinomial logit structure, parameters of the multinomial logit can be estimated using a weighted multinomial logistic regression given the additive separability of the different components in equation (8).

³⁴Alternatively, if w_s is assumed to be a linear function of parameters, these can be estimated via weighted Ordinary Least Squares.

³⁵See [Artuç and McLaren \(2015\)](#) for an alternative estimator of structural parameters.

³⁶In other words, the method can be adapted to data without retrospective coding that allows identification of parameters in a different way.

data can be used, under reasonable assumptions, to correct mobility measures using other data. In Appendix E I show how to obtain corrected mobility measures from CPS data and compared those to the ones I estimate here.³⁷ Second, the method not only estimates mobility matrices corrected for misclassification, but also a corrected measure of wages. Wages are a key ingredient in the analysis and in the estimation of structural parameters. As discussed earlier, misclassification errors bias somewhat the level of occupation/industry wages, and to a much larger extent, observed wage *changes* for those workers that switch labor markets. To the best of my knowledge, this is the first paper that proposes a unified method to obtain measures of occupation/industry mobility and wages corrected for misclassification. Third, even for a small number of industries/occupations, direct estimation via maximum likelihood of model parameters can be computationally very demanding. Nonlinear optimization routines typically require a very large number of evaluations to compute not only levels of the likelihood function but also gradients. On the contrary, the optimization step in the EM algorithm for the model proposed here is quite simple to implement, and under fairly common assumptions, the maximization step has a closed-form solution. Fourth, the first stage of the estimator recovers the matrices of industry/occupation mobility, together with wages and industry/occupation shares, corrected for misclassification. For many questions, these variables are interesting on their own. The second stage shows how to use them to obtain estimates of structural parameters of a particular model. While different models would lead to different estimators used in the second stage, the first stage would be the same. Thus, the method developed here can be used across different models where misclassification affects observed variables.

5 Estimation results: mobility flows and switching costs

I now employ the method discussed in the previous section and estimate the probability of misclassification error and measures of inter-industry mobility corrected for misclassification. For this I use the PSID data analyzed in Section 2, where I employ the same sample selection criteria. In addition I focus on the six broad industry groups presented previously. For simplicity, I assume misclassification errors differ by industry of origin and destination, but not by individuals' demographic characteristics. Moreover, I assume they are constant over

³⁷In other words, the method I propose here is portable to other datasets and, as I discuss in Appendix E, can even be used to accommodate different mobility frequencies, like monthly or quarterly mobility rates, and even accommodate dependent coding post-1994.

time. While this is a testable assumption, the sample size in the PSID is not very large, thus this assumption restricts the number of parameters to be estimated. At the same time, it is an assumption that seems reasonable as it implies that individuals' responses do not vary systematically with, for example, gender, age, race, or education.

Estimating $\hat{p}_s(\tau)$, $\hat{p}_{s'|s}(\tau)$, and $\hat{w}_s(\tau)$ non-parametrically using a bin estimator typically requires a large sample, as some transitions tend to be infrequent for some groups of individuals and may not be captured in small samples. An usual approach in the literature is to impose a flexible parametric model to estimate these objects. As the size of the sample I use here is not very large, I follow [Traiberman \(2019\)](#) and use a linear probability model for $\hat{p}_s(\tau)$ and $\hat{p}_{s'|s}(\tau)$ with a time trend, demographic controls in the form of a dummy variable for males, a dummy variable for older workers (36 to 64 years old) and a dummy for some college education or more. In the case of $\hat{p}_{s'|s}(\tau)$, these linear probability models are estimated independently for each origin s and include dummy variables by destination.³⁸ In addition, I assume a log-linear model for wages with Gaussian errors with the same demographic controls and a time trend.³⁹ As noted before, I use the retrospective industry codes from 1968 to 1980 and the original industry codes from 1980 to 1997, assuming that the retrospective sample is free from misclassification errors.

I begin by estimating a model with no worker heterogeneity, similar to the baseline model in [Artuç et al. \(2010\)](#).⁴⁰ Table 4 shows the estimated probability of being classified in industry j (in columns) when the true industry is s (in rows). This corresponds to the estimates of $\alpha_{j|s}$. Misclassification can be inferred by the elements outside the diagonal of the matrix. On average, the probability of misclassification is 4.1%, but there is substantial heterogeneity across different industries, ranging from 1.5% in transportation and utilities, and other services, to 11% in agriculture and retail and wholesale trade. Moreover, a large number of manufacturing workers are misclassified as working in retail and wholesale trade, and most of the misclassified workers in retail and wholesale trade are coded into other services and manufacturing, according to the estimates for $\alpha_{j|s}$. Thus, estimates suggest that classification errors are heterogeneous and non-symmetric.

³⁸In a few cases, projected probabilities may be below zero. I replace these cases by small constant and adjust the complement probabilities such that all add to one. Alternatively, I could use a multinomial logit model or a Poisson/PPML model to estimate these probabilities at each iteration of the algorithm. I prefer a linear probability model since it substantially reduces the computational burden of the estimation.

³⁹Note that the log-linear model for wages is used for the estimation of structural wage parameters, but does not make any assumptions on the flow utility in the structural model.

⁴⁰I initialize the EM algorithm with a symmetric matrix of misclassification error with a parameter $\psi = 0.005$, that is, I assume a small error. The starting values for the algorithm for $\hat{p}_s(\tau)$, $\hat{p}_{s'|s}(\tau)$, and $\hat{w}_s(\tau)$ are the ones estimated from a model with no misclassification.

It is worth noting that the estimates of $\alpha_{j|s}$ are highly correlated with the discrepancies in coding shown in Table 1, with a correlation coefficient of 0.75. That is, industries with high values of $\alpha_{j|s}$ outside of the diagonal, are also industries with more discrepancies between original and retrospective coding. Note, however, that the estimation of $\alpha_{j|s}$ does not use information about original coding for the first part of the sample, thus this correlation provides some external validation to the estimates for misclassification.

Table 4: Estimated misclassification probability matrix, $\alpha_{j|s}$

		Observed industry					
		Agric./Mining	Construction	Manufacturing	Transport/Util	Wholesale/Retail	Other serv.
actual industry	Agric./Mining	0.888 (0.028)	0.007 (0.007)	0.027 (0.011)	0.020 (0.012)	0.018 (0.011)	0.041 (0.019)
	Construction	0.000 (0.001)	0.936 (0.019)	0.002 (0.007)	0.016 (0.008)	0.005 (0.006)	0.041 (0.013)
	Manufacturing	0.000 (0.001)	0.000 (0.000)	0.956 (0.007)	0.004 (0.002)	0.030 (0.005)	0.010 (0.005)
	Transport/Util	0.000 (0.001)	0.002 (0.002)	0.006 (0.006)	0.985 (0.008)	0.003 (0.003)	0.004 (0.005)
	Wholesale/Retail	0.002 (0.001)	0.009 (0.003)	0.032 (0.013)	0.007 (0.003)	0.893 (0.014)	0.057 (0.007)
	Other serv.	0.000 (0.000)	0.003 (0.001)	0.008 (0.002)	0.003 (0.001)	0.000 (0.001)	0.985 (0.002)

Note: Estimated via EM algorithm. The table shows the probability that a worker with true industry s (in rows) has an observed industry j (in columns). See text for details on the estimation method. Block bootstrap standard errors in parenthesis using 500 random samples of individuals (with replacement).

As discussed earlier, misclassification artificially inflates measures of mobility. Figure 2 shows the (average) switching probability using the original PSID coding and the estimates of mobility corrected for misclassification, $\hat{p}_{s'|s}$. The uncorrected mobility measures are around 80% larger than corrected measures. As highlighted by Kambourov and Manovskii (2008), industry mobility increased between 1968 and 1997. In the case of the industry classification I use here and the sample criteria, (corrected) industry mobility increased from a 5% on average in the early 1970s, to over 8% in the mid-1990s.

Average measures of mobility mask substantial heterogeneity across industries. Moreover, as stressed in Section 3, differences in mobility rates across industry-pairs are critical for the estimation of parameter ν in the structural model. Table 5 shows average industry mobility matrices over three decades in the data, 1970s, 1980s, and 1990s. Interestingly, the increase in the probability of switching is not a common feature of all industries. In fact, only in agriculture, manufacturing, and retail and wholesale trade the probability increased sharply over time. In the other sectors, it remained roughly constant or decreased only slightly. Moreover, the outflows from manufacturing translated in large mobility rates into wholesale and retail trade and other services, where the probability more than doubled. The increase

Figure 2: Probability of broad industry switching corrected measure vs. original data

Note: Original coding refers to yearly industry mobility computed using original PSID codes (smoothed via linear probability model). Corrected measure are model estimates of industry switching probability corrected for misclassification. Averages across industries. Estimated via EM algorithm. See text for details on the estimation method.

in the outflows from wholesale and retail trade were also heterogeneous, with switches mostly into other services, transportation and utility and manufacturing.

The different estimates of $\hat{p}_{s'|s}$ in Table 5, and in particular the first panel, are closely aligned with the mobility matrix computed using retrospective codes in the PSID data in Table 2. This is not surprising as the assumption used in estimation is that those transitions are not affected by misclassification errors.

5.1 Structural parameters

As discussed in Section 3, misclassification biases the estimates of structural parameters. I assume individuals face a common cost of switching $\kappa^{ij} = \kappa$ for $i \neq j$. I use a more general version of (5), that allows for time variation in wages and mobility probabilities, and that individuals form expectations rationally. In particular, I follow [Artuç et al. \(2010\)](#) and use

Table 5: Estimated matrices of industry mobility, $\hat{p}_{s'|s}$
(Averages across decades)

Panel A: 1969-1980						
	Agric./Mining	Construction	Manufacturing	Transport/Util	Wholesale/Retail	Other serv.
Agric./Mining	0.888 (0.023)	0.016 (0.006)	0.028 (0.010)	0.023 (0.010)	0.016 (0.008)	0.030 (0.012)
Construction	0.008 (0.003)	0.908 (0.014)	0.033 (0.006)	0.016 (0.005)	0.018 (0.007)	0.017 (0.006)
Manufacturing	0.002 (0.001)	0.009 (0.001)	0.948 (0.004)	0.007 (0.001)	0.014 (0.002)	0.019 (0.003)
Transport/Util	0.004 (0.002)	0.010 (0.003)	0.010 (0.003)	0.948 (0.007)	0.011 (0.003)	0.017 (0.004)
Wholesale/Retail	0.003 (0.001)	0.012 (0.003)	0.017 (0.004)	0.009 (0.003)	0.918 (0.007)	0.041 (0.005)
Other serv.	0.002 (0.001)	0.006 (0.002)	0.020 (0.003)	0.011 (0.002)	0.010 (0.002)	0.951 (0.004)
Panel B: 1981-1990						
	Agric./Mining	Construction	Manufacturing	Transport/Util	Wholesale/Retail	Other serv.
Agric./Mining	0.824 (0.036)	0.018 (0.006)	0.027 (0.010)	0.023 (0.012)	0.036 (0.018)	0.072 (0.024)
Construction	0.006 (0.003)	0.898 (0.020)	0.036 (0.008)	0.015 (0.007)	0.026 (0.013)	0.019 (0.009)
Manufacturing	0.002 (0.000)	0.009 (0.001)	0.920 (0.008)	0.007 (0.002)	0.033 (0.006)	0.029 (0.004)
Transport/Util	0.003 (0.002)	0.007 (0.003)	0.017 (0.005)	0.941 (0.008)	0.010 (0.003)	0.023 (0.004)
Wholesale/Retail	0.003 (0.001)	0.011 (0.002)	0.034 (0.006)	0.011 (0.002)	0.870 (0.010)	0.070 (0.009)
Other serv.	0.002 (0.001)	0.005 (0.001)	0.017 (0.002)	0.010 (0.001)	0.008 (0.001)	0.958 (0.003)
Panel C: 1991-1997						
	Agric./Mining	Construction	Manufacturing	Transport/Util	Wholesale/Retail	Other serv.
Agric./Mining	0.774 (0.045)	0.023 (0.009)	0.028 (0.013)	0.021 (0.013)	0.052 (0.024)	0.103 (0.033)
Construction	0.006 (0.004)	0.889 (0.024)	0.041 (0.011)	0.014 (0.008)	0.028 (0.016)	0.023 (0.012)
Manufacturing	0.002 (0.001)	0.010 (0.003)	0.897 (0.013)	0.007 (0.003)	0.049 (0.010)	0.035 (0.006)
Transport/Util	0.002 (0.002)	0.006 (0.006)	0.024 (0.008)	0.926 (0.014)	0.010 (0.005)	0.031 (0.007)
Wholesale/Retail	0.003 (0.001)	0.013 (0.003)	0.049 (0.012)	0.016 (0.004)	0.834 (0.017)	0.086 (0.014)
Other serv.	0.002 (0.001)	0.004 (0.002)	0.016 (0.003)	0.011 (0.002)	0.007 (0.002)	0.959 (0.004)

Note: Fraction of movers in an industry that switch to a different industry. First year industry by row and second year industry by column. Estimated by EM algorithm using PSID data, see text for details. Sample restricted to SRC individuals between 24 and 64 years old employed at the time of the survey in two consecutive years. Block bootstrap standard errors in parenthesis.

following equation to estimate parameters κ and ν ,⁴¹

$$(\log [\tilde{\mu}_t^{ij}] - \log [\tilde{\mu}_t^{ii}] - \beta (\log [\tilde{\mu}_{t+1}^{ij}] - \log [\tilde{\mu}_{t+1}^{jj}])) = \frac{\beta}{\nu} (\tilde{w}_{t+1}^j - \tilde{w}_{t+1}^i) - \frac{1 - \beta}{\nu} \kappa^{ij} + e_{t+1}^{ij}, \quad (13)$$

where mobility rates, $\tilde{\mu}_t^{ij}$, and wages, $\tilde{w}_{t+1}^j$ are the observed variables in the regression. In the case the econometrician abstracts from misclassification errors, $\tilde{\mu}_t^{ij}$ and $\tilde{w}_{t+1}^j$ can be directly computed from the data as is typically the case in the literature. With misclassification, mobility rates and wages must be corrected for misclassification following, for example, the procedure discussed in Section 4.

Equation (13) is derived from a moment condition and, under the null hypothesis, the error term e_{t+1}^{ij} is independent of any variable in the information set of individuals up to time t . Assuming a known value for β , parameters κ and ν can be estimated using an instrumental variable regression using, for example, lagged values of wages as instruments.⁴² Table 6 shows estimated values of parameters. Column 2 shows estimates of κ and ν using flows and wages obtained with original PSID industry coding data for the years 1971 to 1997, which abstract from misclassification. Similarly, column 3 shows estimates using the mobility and wage measures corrected for misclassification estimated before. The estimates using original coded data suggest large costs of switching industries, around 11 times the mean wages, as mean wages are normalized to one. The estimate for ν using original coded data suggest that idiosyncratic forces affecting workers' mobility decisions are also large, with a standard deviation about 4.6 times the average wage, since switching decisions are influenced by the difference between two idiosyncratic shocks.⁴³ However, note that the effective costs of switching for a worker are the differences between the cost κ and the realization of the idiosyncratic ϵ shock multiplied by parameter ν . The effective cost of switching faced by those that make a transition is much smaller than what the value of κ alone suggests.⁴⁴

Note that the estimates of κ and ν in column 2 Table 6 are quite similar to those obtained by Artuç et al. (2010). Their Table 3, panel II, shows estimates for κ of 13.2 and for ν of

⁴¹Appendix A shows the the derivation of this equation from the model equilibrium conditions. For the estimation wages are normalized so the average wage in the sample is equal to one. Moreover, I assume $\beta = 0.97$.

⁴²It is possible to use other instruments as well, but is important that the instruments are relevant.

⁴³The variance of the idiosyncratic shock ϵ multiplied by ν is $\nu^2 \frac{\pi^2}{6}$.

⁴⁴The intervals in brackets below the estimated parameter values in Table 6 show percentiles 5 and 95 of the distribution of parameter values obtained via block bootstrap. The distribution of parameters obtained via bootstrap is asymmetric and has a heavy right tail due to the non-linear transformation, which has an important effect on the standard errors. Therefore, these central intervals provide a better indication of the variability of the estimates relative to the standard error.

Table 6: Estimates of structural parameters κ and ν

	Using original coding	Corrected for misclassification
Elasticity parameter, ν	2.54 [1.85 - 3.40]	3.45 [2.44 - 6.89]
Cost of industry switching, κ	11.30 [7.33 - 13.69]	17.03 [11.68 - 33.80]

Note: Estimated using equation (13) and yearly information about industry mobility and industry wages, assuming $\beta = 0.97$. Column 3 uses industry mobility and wages corrected for misclassification estimated by EM algorithm using PSID data. See text for details. Sample restricted to SRC individuals between 24 and 64 years old employed at the time of the survey in two consecutive years. IV regressions instrumented using one year lagged values of wages. Intervals in brackets show percentiles 5 and 95 of the distribution of parameter values obtained via block bootstrap.

As discussed in Section 3, misclassification biases the estimates of the costs κ towards zero. The estimates of κ in column 3 of Table 6, which use data corrected for misclassification, are roughly fifty percent larger than those estimated using the original PSID coding shown in columns 2. In addition, the results of the table show that misclassification biases the estimates for ν also towards zero and the estimates using corrected data show values for ν that are approximately forty percent larger than those obtained using the original coding without adjustment. As stressed in Section 3, the estimates of ν critically depend on how misclassification affects some mobility rates relative to others and the sign of the bias for ν is the same as that of the simple example in Section 3.

It is important to highlight that the estimations in Table 6 do not control for worker's characteristics or for potential changes in parameters over time. The next subsection allows for differences in worker characteristics and changes over time in parameters.

5.2 Heterogeneity and time-varying costs of industry switching

Figure 2 and Table 5 show that industry mobility increased over time. In principle, the structural model may account for this pattern with no additional features. If wages change over time in a way that induces workers to reallocate from some industries into others, the simple model with constant parameters κ and ν may be able to rationalize the data. However, it is also possible that, in addition to wage changes, structural parameters, like the cost of switching industries, are changing over time. With lower costs over time, mobility rates would increase.

⁴⁵Artuç et al. (2010) obtain additional estimates under different specifications and data adjustments. Note that annualized (gross) mobility rates in Artuç et al. (2010) are 2.5 times larger than raw mobility rates in the CPS data, and this larger mobility has an important impact on parameter estimates.

I now relax the assumption that costs of industry switching are constant over time. In particular, I assume that the cost of switching industries varies by decade and estimate a model with three different levels of κ . For simplicity, I assume that individuals do not anticipate these changes in κ , and they expect the costs to be constant over time. At the beginning of each decade, workers are “surprised” by the change in this parameter and expect it to remain at that level for all periods in the future. Under this assumption, I can use equation (13) but allowing for different constant terms for each decade.

Table 7 shows the estimation results assuming homogeneous workers, but with switching costs parameters that vary by decade. Parameter ν is assumed fixed for all time periods. The table shows an interesting downward trend in the point estimates of switching costs κ over time, where the costs of switching industries in the 1990s are 16% lower than in the 1970s. However, the confidence intervals around the estimated values are large and statistically it is not possible to reject the hypothesis of constant κ .

Table 7: Estimates of κ with time variation

Elasticity ν	Cost of industry switching, κ		
1969-1997	1969-1980	1981-1990	1991-1997
3.45	18.38	16.43	15.53
[2.44 - 6.89]	[12.82 - 36.75]	[11.31 - 32.79]	[10.42 - 30.28]

Note: IV regressions instrumented using one year lagged values of wages. Estimated using equation (13) with dummy variables for decades and yearly information about industry mobility and industry wages, assuming $\beta = 0.97$. Parameter ν is assumed constant for all decades. Estimation uses industry mobility and wages corrected for misclassification estimated by EM algorithm using PSID data. See text for details. Sample restricted to SRC individuals between 24 and 64 years old employed at the time of the survey in two consecutive years. Intervals in brackets show percentiles 5 and 95 of the distribution of parameter values obtained via block bootstrap.

The estimated values in Tables 6 and 7 of κ and ν are large when compared with average wages. The assumption of homogeneous workers can be biasing upwards the estimates of ν as the model is trying to explain the differences in average mobility rates across industries with differences in average industry wages. It is likely that the averaging across workers compresses the variability in wages and mobility, leading to a flatter slope in the regression, which translates into higher values for ν . In turn, the estimates of the costs κ depend on the value of ν through the estimates of the ratio κ/ν . If the ratio does not change much, higher values of ν imply larger estimates of κ . In sum, controlling for worker heterogeneity can be important for the estimates of structural parameters.

Now I study the effects of misclassification on parameter estimates for workers with different characteristics. As mentioned before, *a priori* there are no clear reasons to expect substantial differences in the probability of misclassification, $\alpha_{j|s}$, for workers with different

demographic characteristics. However, workers do differ in their industry choices, the wage they obtain, and their reallocation decisions. For example, younger workers are paid less on average and tend to switch industries more frequently than older workers. Moreover, the share of employment across industries differs by gender and by education. Then, since misclassification probabilities and mobility patterns differ by industry, the *observed* mobility flows of some groups of workers may be more affected by misclassification than that of others due to their industry choices.

In my analysis, I control for gender, education, age, and time period. In the computation of corrected measures of mobility, age and time are numerical variables that vary by one unit every year. I discretize education into two groups, those with an education of high school or less and those with some years of college or more. Figure 3 shows average (gross) mobility rates using original PSID coding (left panels) and the corrected measures (right panels) estimated with the EM algorithm. Panels (a) and (b) show mobility for men and panels (c) and (d) for women. The different lines in each graph show the evolution over time for workers with different education levels and age.⁴⁶ The patterns that emerge across panels are striking and have been covered in the literature, for example in [Kambourov and Manovskii \(2008\)](#). Younger workers switch industries with a higher probability than older workers. Similarly, less educated workers have a higher switching probability than older workers, and men on average switch with a higher frequency than women. Comparing the left and right panels of the figure, we can gauge the effects of misclassification, where mobility rates tend to be 50 to 100 percent larger when computed using original PSID codes relative to the estimated mobility corrected for misclassification.

[Artuç et al. \(2010\)](#) extends the model to allow workers to age probabilistically from young to old. They estimate structural parameters controlling for worker heterogeneity and age groups. However, using a version of the model with deterministic aging is simpler. Let some of the characteristics of workers evolve deterministically over time and denote these characteristics by a , like age. As before, characteristics τ are invariant over time for a worker. For simplicity, assume structural parameters ν and κ are constant over time, but κ can vary with workers' characteristics. Then, we can write the estimating equation as,⁴⁷

$$\begin{aligned} & \left(\log \left[\mu_t^{ij}(\tau, a) \right] - \log \left[\mu_t^{ii}(\tau, a) \right] - \beta \left(\log \left[\mu_{t+1}^{ij}(\tau, a+1) \right] - \log \left[\mu_{t+1}^{jj}(\tau, a+1) \right] \right) \right) = \\ & = \frac{\beta}{\nu} \left(w_{t+1}^j(\tau, a+1) - w_{t+1}^i(\tau, a+1) \right) - \frac{(\kappa^{ij}(\tau, a) - \beta \kappa^{ij}(\tau, a+1))}{\nu} + e_{t+1}^{ij}. \end{aligned}$$

⁴⁶Note that age is kept constant over time, so the rates are estimated for workers with the same age across different time periods.

⁴⁷See Appendix A for details.

Figure 3: Probability of broad industry switching for different workers
corrected measure vs. original data

Note: Original coding refers to yearly industry mobility computed using original PSID codes (smoothed via linear probability model). Corrected measure are model estimates of industry switching probability corrected for misclassification, estimated via EM algorithm. Averages across industries. See text for details on the estimation method.

Table 8 shows the estimates for different types of workers and time periods. Panel (a) in the table estimates the model parameters using mobility rates and wages computed using original PSID coding. Panel (b) estimates parameters using mobility and wage measures corrected for misclassification. First, comparing the estimates with those of an homogeneous worker assumption, estimates for ν and κ are smaller. Estimates of ν using corrected mobility measures are one-half the ones in Table 6, and estimates of κ are between one-third and one-half, depending on the worker group.⁴⁸ Second, comparing panels (a) and (b) highlights the biases that misclassification produce on parameter estimates. In particular, the estimate of ν is close to 5% larger and estimates of κ can be 50% larger when using corrected measures. Last, estimates of κ align well with the discussion of differences in mobility rates for different groups of workers and different time periods. κ tends to fall over time, but with different levels of intensity for different types of workers. Older and more educated workers have higher estimated values for κ , and similarly for women.

6 Trade shocks: welfare and reallocation

While there is evidence of a substantial bias in parameter estimates, the effect of this bias on the speed of reallocation or on welfare after a shock is not immediately clear. To better understand this, I proceed in two ways. The first exercise is simpler and assumes that wages, and their changes, are exogenous. For this I use the model presented in Section 3, but using the dynamic hat algebra of [Caliendo et al. \(2019\)](#). Since the first exercise is a partial equilibrium model focusing on labor supply only, the second exercise incorporates production and international trade, with a well-specified labor demand. Wages and their changes are the results of trade shocks and general equilibrium across all industries and countries. In both exercises I compare the evolution of labor across industries and the impact on workers' welfare in the United States to a shock that permanently affects wages across sectors in an asymmetric way.

⁴⁸The estimated value of parameter ν in Table 8 using originally coded data is 2.96, with parameter κ varying between 7.4 and 14.6. As a comparison, the estimate of ν in [Artuç et al. \(2010\)](#) allowing for worker observed heterogeneity is 1.6, with estimated κ between 3.5 and 10 (see their Table 8). Note, however, that they do not control for gender differences, they use CPS data, and adjust mobility flows for time-averaging (annualized flow rates).

Table 8: Parameter estimates under worker heterogeneity and time trends

Parameter	(a) Using original coding				(b) Corrected for misclassification			
	1969-1980	1981-1990	1991-1997		1969-1980	1981-1990	1991-1997	
ν		2.96 [1.76 - 4.83]				3.11 [2.17 - 6.51]		
κ								
female	HS or less	young						
		9.36 [4.07 - 12.38]	8.57 [3.67 - 11.42]	7.89 [3.18 - 10.37]	8.32 [5.32 - 19.14]	6.95 [4.21 - 16.71]	5.72 [3.29 - 14.91]	
female	HS or less	old						
		13.67 [8.48 - 23.70]	12.88 [8.03 - 22.66]	12.20 [7.58 - 21.72]	19.37 [13.42 - 40.27]	18.00 [12.52 - 37.70]	16.77 [11.69 - 35.84]	
female	Some college +	young						
		10.33 [5.04 - 14.31]	9.54 [4.60 - 12.91]	8.86 [4.11 - 12.04]	9.47 [6.02 - 21.59]	8.10 [5.12 - 18.85]	6.86 [4.04 - 17.26]	
female	Some college +	old						
		14.64 [9.24 - 25.95]	13.85 [8.83 - 24.88]	13.17 [8.46 - 23.99]	20.52 [14.21 - 43.03]	19.15 [13.29 - 39.99]	17.91 [12.46 - 38.28]	
male	HS or less	young						
		8.90 [3.63 - 11.04]	8.11 [3.12 - 9.98]	7.43 [2.63 - 9.08]	7.15 [4.57 - 16.54]	5.78 [3.43 - 14.16]	4.55 [2.41 - 11.78]	
male	HS or less	old						
		13.21 [7.96 - 22.69]	12.42 [7.54 - 21.62]	11.74 [7.13 - 20.74]	18.20 [12.71 - 37.53]	16.83 [11.81 - 35.61]	15.60 [10.99 - 33.09]	
male	Some college +	young						
		9.87 [4.50 - 13.00]	9.08 [4.11 - 11.84]	8.40 [3.62 - 10.91]	8.30 [5.26 - 18.57]	6.93 [4.20 - 16.61]	5.69 [3.26 - 14.35]	
male	Some college +	old						
		14.18 [8.76 - 24.71]	13.39 [8.31 - 23.67]	12.71 [8.00 - 22.70]	19.35 [13.56 - 40.56]	17.98 [12.59 - 37.93]	16.74 [11.78 - 35.61]	

Note: Estimated using equation (13) and yearly information about industry mobility and industry wages, assuming $\beta = 0.97$. Parameter ν is assumed constant across decades and worker characteristics. Parameter κ varies with worker characteristics (by rows) and decades (by columns) as specified in the text. Worker defined as young if between 23 and 35 years old. Old worker defined between 36 and 63 years old. IV regressions instrumented using one year lagged values of wages. Intervals in brackets show percentiles 5 and 95 of the distribution of parameter values obtained via block bootstrap.

6.1 Exogenous wages

I begin with a simple exercise that focuses solely on labor supply and welfare due to exogenous wage changes. As discussed before, misclassification biases parameter estimates towards zero. The goal of this example is to highlight that different parameter values can lead to important economic differences in the effects of shocks on worker reallocation. In this example, I exogenously increase wages in all sectors except manufacturing by 3%, and decrease manufacturing wages by 3%. I calibrate the initial wage vector of the model to be $w = [0.85, 0.95, 1.08, 0.99, 1.02, 1.09]$ and use two sets of parameter values: $\nu = 2.54$ and $\kappa = 11.3$, which correspond to those in Table 6 using original coded data, and $\nu = 3.45$ and $\kappa = 17.03$, which correspond to the estimates using data corrected for misclassification.⁴⁹

The left panel of Figure 4 shows the yearly evolution of the change in the manufacturing employment share, relative to the initial value, after the change in wages for these two sets of parameter values. In both cases, relative wages in manufacturing fall and workers reallocate out of manufacturing and into other sectors. However, the pace of the reallocation and the total long-run impact on the manufacturing share of employment differ across these parameter values. In particular reallocation happens at a faster rate and the total manufacturing employment drop is larger using parameters estimated with original coded data. By year 30, the differences in the employment share across the two economies is almost 2 percentage points. Since the drop in the manufacturing employment share by that time is between 6 and 8 percentage points, the differences are substantial and the measured effects using estimates obtained with originally coded data are magnified by 30%. The right panel of the figure shows the change in welfare, measured as consumption equivalent, for a worker that starts the period in each of the listed industries.⁵⁰ Since estimated mobility is higher and parameters are lower when using originally coded data, the option value for workers in manufacturing is better. Thus, despite the same wage change in manufacturing in both economies, welfare is not so negatively impacted in the economy that uses estimates from originally coded data. For a worker attached to manufacturing during the period of the shock, the fall in welfare is negligible for the economy with estimates from originally coded data, while the welfare change is equivalent to a drop of 0.5% of consumption in every period when using parameters obtained with data corrected for misclassification. In the other sectors, welfare increases, as wages increase, but the option value is more negatively affected in the model with parameter estimates from originally coded data.

⁴⁹Wages are calibrated to approximate mobility flows and average labor allocation allocation in the data given parameter values.

⁵⁰See Appendix D for the details on the consumption equivalent change in welfare.

Figure 4: Effects of exogenous wage changes under different parameter estimates

Note: Evolution of manufacturing employment in the model with exogenous wage changes under parameter values $\nu = 2.54$ and $\kappa = 11.3$ for original coding, and $\nu = 3.45$ and $\kappa = 17.03$ for corrected for misclassification. In both cases initial wages are $w = [0.85, 0.95, 1.08, 0.99, 1.02, 1.09]$, and the shock increases wages by 3% in all sectors but manufacturing, and decreases manufacturing wages by 3%.

The estimated parameters κ and ν , together with the calibrated values of wages, approximate reasonably well mobility flows and labor allocation observed in the data, but cannot fit them perfectly. This is driven largely by the assumption of a common cost of switching for all sectors. Other than wage differences, different sectors are very symmetric in this economy and is difficult for a single parameter to generate the rich patterns of mobility observed in the data. Moreover, the initial labor allocation measured in the data may not correspond to a stationary equilibrium. As labor adjusts slowly to shocks, shocks that occurred before the initial observed period will still have an impact on the evolution of labor, mobility and wages.

To overcome these potential issues, I employ the dynamic hat algebra developed in [Caliendo et al. \(2019\)](#), which can accommodate arbitrary costs of switching sectors and does not require the economy to be in a stationary equilibrium initially. Conditional on a value for parameters ν and β , the method uses mobility flows and initial labor shares to compute the dynamics of industry employment along the transition and the changes in welfare to an unanticipated wage shock.⁵¹ I assume the same exogenous and unanticipated wage shock as in the previous case. The economy gradually converges to a stationary equilibrium compatible with the new wages.

Figure 5 shows the evolution of the manufacturing employment share in panel (a), and the changes in welfare due to the shock in panel (b), for the two different cases: using es-

⁵¹Appendix C details the equations used in the dynamic hat algebra, which are derived from the structural model of Section 3.

estimates under original coding and estimates corrected for misclassification. Both economies are not in a stationary equilibrium initially and the manufacturing labor share under no shocks is gradually falling over time. Thus, in panel (a), I show the evolution of the manufacturing labor share after the wage shock hits and subtract the evolution of the labor share for the economy with no shock. In other words, the figure shows the change in the labor share due to the wage shock. Similar to the previous case, the economy with parameters and mobility estimated with original coding adjusts faster and reaches a lower level of manufacturing employment than the economy with estimates corrected for misclassification. The magnitudes are smaller than those discussed before, but are still important.⁵² By year 15, differences across these two differently measured economies are close to 0.40 percentage points. Since the drop in the manufacturing employment share is close to 2.7 percentage points, misclassification can alter the estimated impact of the shock by 15%. In the long run, differences are smaller, but the discrepancies persist. Panel (b) shows that estimates of the welfare changes of the shock are also different depending on whether original or corrected data is used. In both cases, welfare increases in all sectors but the increase is smaller for workers initially attached to manufacturing. Relative to the previous case, there is a more pronounced heterogeneity in the welfare effects across sectors, a product of the more flexible structure. However, the effects computed using estimates from data with original coding show a consumption equivalent welfare increase of 0.90%, while the effects computed using corrected data are 0.75%, a difference of almost one-fifth of the magnitude. Wages increase in all other sectors leading to important welfare increases, but the increases are noticeably larger when using the estimates from the data corrected for misclassification. This is a reflection of the lower mobility flows and how, in turn, this lower mobility translates into differences in the option value of moving.

6.2 General equilibrium and trade shock

I now extend the model to include production and characterize labor demand, such that wages endogenously adjust to a trade shock. This exercise is relevant since, unlike the previous cases, the evolution of wages will be affected by the speed of labor reallocation across sectors.

The production side of the general equilibrium model is a simpler version of [Caliendo et al. \(2019\)](#). In particular I calibrate the model for three countries in the world and abstract

⁵²Although the exogenous change in wages is the same in this case and the previous one, manufacturing employment was already in a decreasing trend in the current example, leading to a smaller effect of the same change in wages.

Figure 5: Effects of exogenous wage changes in dynamic hat algebra model

Note: Evolution of the changes in the manufacturing employment share in the dynamic hat algebra model with exogenous wage changes under parameter $\nu = 2.54$ for original coding, and $\nu = 3.45$ for the data corrected for misclassification. In both cases the shock increases wages by 3% in all sectors but manufacturing, and decreases manufacturing wages by 3%.

from modeling regions within countries. Moreover, I abstract from input-output relations across sectors and assume the only factors of production are labor and structures (fixed capital). Other than in the United States, I assume that workers do not face any frictions to reallocate across labor markets, so that in each country there is a unique labor market wage. All labor and goods markets are competitive and prices and wages are determined by supply and demand at each time.

Following [Eaton and Kortum \(2002\)](#) I assume that in each sector there is a continuum of varieties that can potentially be traded across countries. The technology to produce any of these varieties is described by a Cobb-Douglas function with workers and structures as inputs. The total factor productivity of country i and sector j in variety x is $z^{ij}(x)$. I assume that each $z^{ij}(x)$ is the result of an independent Fréchet random draw with dispersion parameter θ and scale parameter A^{ij} . The output for a producer of an intermediate variety with efficiency $z^{ij}(x)$ is,

$$q_t^{ij}(x) = z^{nj}(x)(h_t^{ij}(x))^{\xi^i}(l_t^{ij}(x))^{1-\xi^i},$$

where $l_t^{ij}(x)$, $h_t^{ij}(x)$ are labor and fixed capital (structures) inputs used in variety x , respectively. Parameter ξ^i is the share of structures in production. Structures are in fixed supply in each country and sector, and the total availability is given by H^{ij} . Denote by r_t^{ij} the rental price of structures in country i and sector j , then, by competition and free entry and

exit, the price of producing one unit of variety x is equal to its unit costs,

$$\tilde{p}_t^{ij}(x) = \frac{B^{ij} (r_t^{ij})^{\xi^i} (w_t^{ij})^{1-\xi^i}}{z^{nj}(x)}$$

where B^{nj} is a constant that depends on parameters.

Trade costs are represented by $\lambda_t^{ij,nj}$ and are of the iceberg type. One unit of any variety of intermediate good j shipped from country i to n requires producing $\lambda_t^{ij,nj} \geq 1$ units in country i . If a good is nontradable, then $\lambda = \infty$. Competition across countries implies that the price paid for a particular variety of good j in country i is given by the minimum unit cost of acquiring that variety across countries, taking into account trade costs. That is,

$$p_t^{ij}(x) = \min_n \{ \tilde{p}_t^{nj}(x) \lambda_t^{nj,ij} \}.$$

Intermediate varieties from sector j are needed to produce a final good from sector j , denoted by Q_t^{ij} , according to,

$$Q_t^{ij} = \left(\int (\tilde{q}_t^{ij}(x))^{1-1/\eta^{ij}} dx \right)^{\eta^{ij}/(\eta^{ij}-1)},$$

where $\tilde{q}_t^{ij}(x)$ denotes the quantity of variety x sourced from the lowest cost producer. Competitive behavior implies zero profits at all times.

Given the properties of the Fréchet distribution, the price of the sectoral aggregate good j in country n at time t is (Eaton & Kortum, 2002),

$$P_t^{nj} = \Gamma^{ij} \left(\sum_{i=1}^N \left(B^{ij} (r_t^{ij})^{\xi^i} (w_t^{ij})^{1-\xi^i} \right)^{-\theta} (\lambda_t^{ij,nj})^{-\theta} (A^{ij})^\theta \right)^{-1/\theta}, \quad (14)$$

where Γ^{ij} is a constant. Moreover, the share of varieties that country i sources from country n is given by,

$$\pi_t^{nj,ij} = \frac{(B^{nj} (r_t^{nj})^{\xi^n} (w_t^{nj})^{1-\xi^n})^{-\theta} (\lambda_t^{nj,ij})^{-\theta} (A^{nj})^\theta}{\sum_{m=1}^N (B^{mj} (r_t^{mj})^{\xi^m} (w_t^{mj})^{1-\xi^m})^{-\theta} (\lambda_t^{mj,ij})^{-\theta} (A^{mj})^\theta}. \quad (15)$$

Trade can be imbalanced due to differences across countries between where income is generated and where it is consumed. I assume there is a unit mass of rentiers in each country. Rentiers cannot relocate to other regions. They manage the local structures, rent them to

local firms, and send all the rents to a global portfolio. Rentiers in country n have a total ownership share ι^n of the global portfolio of rents, with $\sum_{n=1}^N \iota^n = 1$. The difference in rental income generated and consumed in country i generate trade surplus equal to $\sum_{j=1}^J r_t^{ij} H^{ij} - \iota^i \chi_t$, where $\chi_t = \sum_{i=1}^N \sum_{j=1}^J r_t^{ij} H^{ij}$ are the total rents in the world.

Workers and rentiers consume a Cobb-Douglas aggregate of all final goods from all sectors, with parameters γ^j , common for all countries. Let X_t^{nj} be the total expenditure on the final good of sector j good in country i . Then, goods market clearing implies

$$X_t^{ij} = \gamma^j \left(\sum_{k=1}^J w_t^{ik} L_t^{ik} + \iota^i \chi_t \right),$$

where $\sum_{k=1}^J (w_t^{ik} L_t^{ik} + \iota^i \chi_t)$ is total income, and the value of the final demand, in country i .

Labor market clearing in country i and sector j implies,

$$L_t^{ij} = \frac{(1 - \xi^i)}{w_t^{ij}} \sum_{n=1}^N \pi_t^{ij,nj} X_t^{nj},$$

while the market clearing condition for structures is,

$$H^{ij} = \frac{\xi^i}{r_t^{ij}} \sum_{n=1}^N \pi_t^{ij,nj} X_t^{nj}.$$

These equilibrium conditions can be manipulated and expressed in changes (hat algebra) to simplify the calibration and the computations. Appendix C presents the details.

I calibrate the general equilibrium model to three countries: the United States, other advanced economies, and the rest of the world.⁵³ I use the same six broad sectors as used throughout the paper. Initial values of trade shares, total expenditures, and value of production are from the World Input-Output Dataset (WIOD), 2013 release, for the year 1997, which is the latest year I have annual data from the PSID.⁵⁴ I calibrate parameter θ to be equal to 4, as estimated by [Simonovska and Waugh \(2014\)](#). I abstract from differences in labor and capital (structures) income share across countries and assume $\xi^i = 0.33$ for all countries, a common value used in macroeconomics. The calibration of parameter ι^n is straightforward using data on trade deficits, total world output and the share of each country

⁵³Other advanced economies include: Australia, Austria, Belgium, Canada, Germany, Denmark, Spain, Finland, France, United Kingdom, Greece, Ireland, Italy, Japan, Korea, Luxembourg, Netherlands, Norway, Portugal, and Sweden. The rest of the world include: Bulgaria, Brazil, China, Cyprus, Czech Republic, Estonia, Hungary, Indonesia, India, Lithuania, Latvia, Mexico, Malta, Poland, Romania, Russia, Slovak Republic, Slovenia, Turkey, Taiwan, and those countries classified as rest of the world in the dataset.

⁵⁴See [Timmer, Dietzenbacher, Los, Stehrer, and De Vries \(2015\)](#) for a description of the data.

in world production.⁵⁵ Finally, I use information about final demand consumption by sector to get parameters γ^j of the Cobb-Douglas consumption aggregator, and use information on trade flows by sector to calibrate π . I calibrate the initial value of the shares of employment by sector for the United States to those in the PSID data. I compute the implicit wages consistent with these labor shares and the total labor income from WIOD.⁵⁶ A normalization is needed to pin down nominal variables. I normalize the price of the final consumption aggregate in the United States is equal to one in every period.

I engineer a trade shock as a decrease in trade frictions. In particular, in period $t = 1$ agents learn that $\lambda_t^{nj,ij}$ for manufacturing goods shipping from the rest of the world into the United States and other advanced economies decreases by 10% each period for 10 years. This captures the large increase in international trade of the recent decade and in particular the large expansion of exports from China into advanced economies since the mid-1990s. In the model, this shock doubles the amount of imports of the United States over this period, while at the same time U.S. exports also expand. Overall, the trade deficit of the United States increases but less than the expansion in imports. All of these movements are consistent with the evolution of aggregate trade variables of the United States in the early 2000s, before the Great Recession. In both economies, the shock is of identical magnitude.

Figure 6 shows the evolution of the change in the manufacturing employment share, in the left panel, and the changes in period-one welfare due to the shock, in the right panel, for two economies, which differ only in the estimates of parameter ν , initial mobility flows and initial employment shares. Similar to the previous cases, the economy calibrated using originally coded data displays a faster employment adjustment to a lower level of manufacturing employment than the economy that uses corrected mobility information. In the initial years of the transition, differences in employment are small, but by year 10, misclassification errors magnify the effects on employment by 0.4 percentage points, or around a 20% difference of the total effect. Measures of welfare are also substantially affected by misclassification. Overall, measures of welfare change less in this exercise than in the previous cases as the level of wages, on average, do not change as much. Despite this differences in levels with the previous exercises, the patterns still hold. In particular, the economy that uses original data for estimates and calibration shows a mildly positive change in welfare due to the trade

⁵⁵The formula is, $\iota^n = \frac{\text{deficit}^n}{\xi(\text{World Output})} + \frac{\text{country}^n \text{ output}}{\text{World Output}}$. The formula is intuitive. Multiplying and dividing the last term by ξ , it becomes the country's generated rents as a share of world rents. A trade deficit is possible when ι is larger than the share of rents the country generates and sends to the global portfolio.

⁵⁶As is usual in the literature, I adjust slightly the first-period value of expenditures/production by sector and country such that, given parameters and initial values of other endogenous variables, the economy is in equilibrium in the first period.

shock for workers initially attached to manufacturing. However, welfare falls more notably in the economy that uses corrected mobility measures. The opposite is true for the other sectors of the economy, which show a larger increase in welfare in the economy that uses corrected mobility measures.

Figure 6: Effects of a trade liberalization in the general equilibrium model

Note: Evolution of the changes in the manufacturing employment share in the general equilibrium model with a decrease in trade frictions between the rest of the world and the U.S. and other advanced economies under parameter $\nu = 2.54$ for original coding, and $\nu = 3.45$ for the data corrected for misclassification. In both cases the shock decreases trade frictions $\lambda^{nj,ij}$ by 10% per year for ten years in manufacturing, for shipments originating in the rest of the world destined for the U.S. and other advanced economies.

While the previous section showed how estimated of parameter values are biased when using uncorrected data, the key insight from all the exercises in this section is that the estimates of the *dynamic adjustment of labor* and the *welfare effects* of a trade shock are biased when using data that is plagued with misclassification errors. Since many works in the trade literature using publicly available data for the United States do not correct mobility flows, one should be cautious in taking the estimated magnitudes at face value.

7 Conclusion

Misclassification errors are prevalent in industry and occupational mobility data and typically exaggerate worker flows across labor markets. The literature has studied this problem, focusing on its causes and possible ways to correct mobility measures. In this paper I focus on the *consequences* of misclassification for estimates of the labor market effects of international trade. Many recent models of international trade with segmented labor markets and costly reallocation critically depend on information about workers' reallocation patterns. In this paper I show how misclassification affects estimates of structural parameter values in this

class of models and propose an econometric framework to jointly estimate misclassification probabilities, corrected mobility matrices, and structural parameters in a unified way.

Under different model specifications, I compare how the estimated effects of a trade liberalization differ on whether the analysis uses corrected or uncorrected mobility measures and biased or unbiased structural parameters. My results show that estimated employment and welfare effects of a trade shock are substantially different. The main conclusion from this paper is that the estimates of the dynamic adjustment of labor and welfare effects of a trade shock are biased when using mobility flows that are subject to misclassification errors, raising an important warning for future research where workers' industry and occupation reallocation is a central part of the study.

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Appendix A: Estimation equation

In this Appendix I derive equation (5) used to estimate structural parameters in a model with no misclassification following [Artuç et al. \(2010\)](#). Combining equations (1) and (2), we get,

$$v_t^i(\tau) = w_t^i(\tau) + \beta E_t [v_{t+1}^j(\tau)] - \kappa^{ij}(\tau) - \nu \log [\mu_t^{ij}(\tau)], \quad (16)$$

which holds for all i and j . As in [Artuç et al. \(2010\)](#), this does not assume perfect foresight and individual form expectations about future variables. Taking the difference of values when industry j is chosen and when industry i is chosen, we get,

$$0 = \beta E_t [v_{t+1}^j(\tau) - v_{t+1}^i(\tau)] - \kappa^{ij}(\tau) - \nu (\log [\mu_t^{ij}(\tau)] - \log [\mu_t^{ii}(\tau)]).$$

Use (16) one period forward for $v_{t+1}^j(\tau)$ and $v_{t+1}^i(\tau)$, where the future industry choice in both cases is industry j and taking differences, we get,

$$v_{t+1}^j(\tau) - v_{t+1}^i(\tau) = w_{t+1}^j(\tau) - w_{t+1}^i(\tau) + \kappa^{jj}(\tau) - \nu (\log [\mu_{t+1}^{jj}(\tau)] - \log [\mu_{t+1}^{ij}(\tau)]).$$

Combining the last two equations, we obtain,

$$E_t \left[\frac{\beta}{\nu} (w_{t+1}^j(\tau) - w_{t+1}^i(\tau)) - \frac{1-\beta}{\nu} \kappa^{ij}(\tau) + \beta (\log [\mu_{t+1}^{ij}(\tau)] - \log [\mu_{t+1}^{jj}(\tau)]) - (\log [\mu_t^{ij}(\tau)] - \log [\mu_t^{ii}(\tau)]) \right] = 0, \quad (17)$$

As argued by [Artuç et al. \(2010\)](#), rational expectations imply that this is a conditional moment that holds when conditioning on any variable known at time t . In particular, parameters can be estimated via the following regression,

$$(\log [\mu_t^{ij}(\tau)] - \log [\mu_t^{ii}(\tau)] - \beta (\log [\mu_{t+1}^{ij}(\tau)] - \log [\mu_{t+1}^{jj}(\tau)])) = \frac{\beta}{\nu} (w_{t+1}^j(\tau) - w_{t+1}^i(\tau)) - \frac{1-\beta}{\nu} \kappa^{ij}(\tau) + e_{t+1}^{ij}, \quad (18)$$

where e_{t+1}^{ij} is a rational expectations error, orthogonal to any variable known at time t . This expression can be estimated using an instrumental variables regression using, for example, lagged values of wages as instruments.

Time variation.— Now, assume that the cost of switching industries varies over time in the following way. Parameter κ is constant over several years and suddenly it changes in an unanticipated way. For example, at the beginning of each decade, workers are “surprised” by change in this parameter and expect to remain at that new level for all periods in the future. Under this assumption, I can use equation (13) but allowing for different constant terms for each decade. At the end of each decade, the expected value of next year’s wages

and mobility would differ from the actual value due to this change in κ , but since the change is unanticipated, it will be captured in the expectation error term.

Evolving workers' characteristics: aging.— Moreover, it is easy to incorporate differences in age. [Artuç et al. \(2010\)](#) extend the model for workers that age probabilistically from young to old. But the expression for deterministic aging is simpler. Let some of the characteristics of workers evolve deterministically over time and denote these characteristics by a , like age. Then, we can write the estimating equation as,

$$\begin{aligned} \left(\log \left[\mu_t^{ij}(\tau, a) \right] - \log \left[\mu_t^{ii}(\tau, a) \right] - \beta \left(\log \left[\mu_{t+1}^{ij}(\tau, a+1) \right] - \log \left[\mu_{t+1}^{jj}(\tau, a+1) \right] \right) \right) = \\ = \frac{\beta}{\nu} \left(w_{t+1}^j(\tau, a+1) - w_{t+1}^i(\tau, a+1) \right) - \frac{(\kappa^{ij}(\tau, a) - \beta \kappa^{ij}(\tau, a+1))}{\nu} + e_{t+1}^{ij}. \end{aligned}$$

Clearly, the value function for the worker may be different the last period of her (work)life, but to the extent that the estimation does not use that period, the equations holds.

Heterogeneous switching costs.— Finally, I discuss how to identify and estimate parameters for the case of heterogeneous switching costs, κ , that vary by origin and destination. It is clear from equation (18) that observables in the left-hand side and the right-hand side vary by origin-destination pairs, ij , and by time. Much of the discussion in Section 3 assumed a single time period in a stationary environment. In this case, if κ varies by origin and destination, parameters ν and κ cannot be separately identified. However, with at least two periods of data and under the assumption of constant parameters (sometimes referred to as constant fundamentals), we can identify costs that vary by origin and destination using a stacked-version of equation (18) over two periods, with origin-destination fixed effects.

I now extend the result of Section 3.1 and show how misclassification errors affect the estimates of the switching costs. As in that section, I use two set of parameters: $\nu = 1.9$ and $\nu = 3.45$. The two set of parameters for the matrix of switching costs are randomly drawn from a uniform distribution with mean 8 and 17.03, respectively, and an upper and lower limit that is $\pm 12.5\%$ relative to the mean. Wages are the same as those assumed in Section 3.1, except that in the second period wages in sector 1 increase by 0.1 and the sector 6 decrease by 0.1.⁵⁷

In the absence of misclassification error, the regression with origin-destination fixed effects recovers the parameters perfectly. Table 9 shows what happen with the estimates with a moderate level of misclassification error ($\psi = 0.005$). As in the case of homogeneous switching costs, in this example the estimates of ν and κ are biased downwards due to the

⁵⁷Note that all that is needed is some change in wages over time to estimate cost parameters by origin and destination. Given the parametric assumptions specified in the model and the assumption that parameters are constant over time, parameters are identified.

errors, with estimated values for ν around 50% lower than the true values and κ between 50% to 67% lower, depending on the case. In this way, the main conclusions of Section 3.1 extend to the case of heterogeneous switching costs, κ , that vary by origin and destination.

Appendix B: Data on mobility and wages

The PSID is a yearly panel (up to 1997) that has detailed information about worker’s demographic characteristics and socio-economic conditions, including labor earnings and the type of job at the time of the interview, including information about industry and occupation. My sample includes individuals 23 to 64 years old in the core Survey Research Center (SRC) sample of the PSID.⁵⁸ Furthermore, I only use individuals that are employed at the time of the survey.

Industries and mobility: Up to 2003, the PSID reports information about the industry of individuals using the codes in the 1970 Census of Population.⁵⁹ Between 1971 and 1980, industry is coded to two digit-level, and three digit from 1981 onwards for the original coding. Retrospective coding starts in 1968 and ends in 1980, and is coded using three-digits codes also following the industry classification from the 1970 Census of Population. Table 10 shows how the original PSID industry codes map into one of the six broad industries used in the analysis.

Moments on industry mobility are computed over two consecutive years for individuals employed in each of those years.

Real wages: I measure real wages using PSID data on nominal wages, salaries, and hours, and deflate them by the Consumer Price Index for all urban consumers (CPI). For hourly workers, nominal hourly wages are taken directly from the PSID data, and are available from 1968 to 1997 for heads and wives. For salary workers, the PSID constructs a measure of hourly wages for salary workers up until 1992 for head and wives. From 1993 to 1997, the PSID reports data on salary and payment period separately. I use these variables to construct an hourly wage following the methodology from before 1993. In particular, to create hourly wage data for salary workers, the salary variable is divided by the typical number of hours worked in an employee’s payment period. For example, an employee with an

⁵⁸The core Survey Research Center (SRC) sample is nationally representative. The PSID has two additional samples: the Survey of Economic Opportunity (SEO) sample, which oversamples low-income households, and immigrant and Latino samples, which oversamples migrant population. I exclude these additional samples from my analysis.

⁵⁹The industry codes in the 1970 Census of Population follow closely the 1967 Standard Industrial Classification codes.

Table 9: The effect of misclassification on parameter estimates for heterogeneous switching costs

Panel A												
True parameter values - true value of $\nu = 1.9$							estimates under misclassification - estimated $\nu = 1.1$					
Ag./Min.	Const.	Manuf.	Trans./Util	W & Retail	Other		Ag./Min.	Const.	Manuf.	Trans./Util	W & Retail	Other
-	7.1	8.0	8.5	8.3	7.7		-	3.8	4.4	4.5	4.4	4.2
Agric./Mining	8.1	-	8.6	7.5	8.9		3.8	-	4.4	4.0	3.9	4.4
Construction	7.2	7.5	-	8.2	7.9		3.1	3.4	-	3.9	3.7	3.9
Manufacturing	7.9	8.9	7.6	7.4	8.1		3.6	4.0	3.9	-	3.7	4.0
Transport/Util	7.6	8.7	7.3	-	8.1		3.5	4.0	3.8	4.0	-	4.0
Wholesale/Retail	8.1	8.8	7.5	8.9	-		3.5	3.9	3.9	4.1	4.1	-
Other serv												
Panel B												
True parameter values - true value of $\nu = 3.45$							estimates under misclassification - estimated $\nu = 1.67$					
Ag./Min.	Const.	Manuf.	Trans./Util	W & Retail	Other		Ag./Min.	Const.	Manuf.	Trans./Util	W & Retail	Other
-	15.1	17.1	18.0	17.6	16.5		-	6.4	7.1	7.5	7.3	7.0
Agric./Mining	17.2	-	18.4	15.9	18.9		6.5	-	7.2	7.0	6.8	7.3
Construction	15.3	15.9	-	17.4	16.9		5.5	5.9	-	6.8	6.4	6.6
Manufacturing	16.7	18.9	16.1	15.8	17.2		5.9	6.4	6.3	-	6.3	6.5
Transport/Util	16.2	18.6	15.5	-	17.2		5.9	6.5	6.2	6.8	-	6.5
Wholesale/Retail	17.2	18.7	15.9	36.7	-		6.0	6.5	6.5	6.9	6.8	-
Other serv												

Note: Parameters estimated by OLS according to equation (18). Each observation is a sector of origin-destination, where origin is different from destination. The example uses 6 sectors, two different time periods with different wages. There are 60 observations in each regression. Panel A shows results for structural parameter values $\nu = 1.9$ and parameters κ as listed on the left matrix in the panel. Misclassification error computed as in Section 3 with $\psi = 0.005$. Panel B shows results for $\nu = 3.45$ and parameters κ as listed on the left matrix in the panel.

Table 10: Broad industry groups

	Original industry coding (1971-1980)	Original industry coding (1981-1997), and Retrospective coding (1968-1997)
	2-digit PSID industry codes	3-digit PSID industry codes
Agriculture/Mining	11; 21	17 - 28; 47 - 57
Construction	51	67 - 77
Manufacturing	30 - 49; 85	107 - 398
Transport/Utilities	55-57;	407 - 479
Wholesale/Retail	61; 62; 69	507 -699
Other services	71 - 84; 86 - 92	707 - 937

Note: Columns 2 and 3 show the mapping between PSID industry codes, which follow the 1970 Population Census, and the broad groups I use in the analysis.

annual salary would have their salary divided by 2000, which is the approximate number of hours worked in a year.⁶⁰ Finally, the wage variables are deflated by the CPI and expressed in dollars of 1979. Finally, for the estimation and the empirical analysis, I normalize real wages so the average wage is equal to one.

Appendix C: Dynamic hat algebra

Here I manipulate equations (1) and (2) and derive the equations employed in the dynamic hat algebra computations. Take differences over two periods using equation (1) under the assumption of no shocks, then,

$$v_{t+1}^j(\tau) - v_t^j(\tau) = \left[\frac{w_{t+1}^j(\tau)}{w_t^j(\tau)} - 1 \right] w_t^j(\tau) + \nu \log \left[\sum_{\ell=1}^J \mu_t^{j\ell}(\tau) \exp(\beta(v_{t+2}^\ell(\tau) - v_{t+1}^\ell(\tau)))^{1/\nu} \right]. \quad (19)$$

Similarly, take the ratio of the expression in equation (2) over two consecutive periods under the same assumption, then

$$\mu_{t+1}^{j\ell}(\tau) = \frac{\mu_t^{j\ell}(\tau) \exp(\beta(v_{t+2}^\ell(\tau) - v_{t+1}^\ell(\tau)))^{1/\nu}}{\sum_{m=1}^J \mu_t^{jm}(\tau) \exp(\beta(v_{t+2}^m(\tau) - v_{t+1}^m(\tau)))^{1/\nu}}. \quad (20)$$

Equations (19) and (20) are special cases of those in Proposition 2 in (Caliendo et al., 2019), but allowing for worker heterogeneity in τ . In period 1, workers are “suprised” by a shock. Denote with a “^”, variables after the shock, then, the following expressions must be used

⁶⁰In some cases, hourly wage, salary wage, and salaries are top coded. I do not use these observations in my analysis.

in that first period,

$$\hat{v}_1^j(\tau) - v_0^j(\tau) = \left[\frac{\hat{w}_1^j(\tau)}{w_0^j(\tau)} - 1 \right] w_0^j(\tau) + \nu \log \left[\sum_{\ell=1}^J \mu_0^{j\ell}(\tau) \psi_1^\ell \exp(\beta(\hat{v}_2^\ell(\tau) - \hat{v}_1^\ell(\tau)))^{1/\nu} \right], \quad (21)$$

$$\mu_1^{j\ell}(\tau) = \frac{\mu_0^{j\ell}(\tau) \psi_1^\ell \exp(\beta(\hat{v}_2^\ell(\tau) - \hat{v}_1^\ell(\tau)))^{1/\nu}}{\sum_{m=1}^J \mu_0^{jm}(\tau) \psi_1^m \exp(\beta(\hat{v}_2^m(\tau) - \hat{v}_1^m(\tau)))^{1/\nu}}, \quad (22)$$

where $\psi_1^\ell = \exp(\beta(\hat{v}_1^\ell(\tau) - v_1^\ell(\tau)))^{1/\nu}$. For periods $t > 1$, the evolution of value function and mobility flows in changes in the economy hit by the shock can be characterized by equations identical to (19) and (20), but with variables with “ $\wedge$ ”. In a similar way, these expressions are a special case of Proposition 3 in [Caliendo et al. \(2019\)](#).

In both these cases, given a sequence of wage changes, a solution is found by imposing the terminal condition $v_T^j(\tau) - v_{T-1}^j(\tau) = 0$, for sufficiently large T , and taking μ_0 as given, for example by measuring flows in the data.

Production

To simplify computations, we can use equilibrium conditions in changes. For this, take ratios of equilibrium conditions (14) and (15) over two consecutive periods, such that,

$$\pi_{t+1}^{nj,ij} = \frac{\pi_t^{nj,ij} \left(\frac{w_{t+1}^{nj}}{w_t^{nj}} \right)^{-\theta(1-\xi^n)} \left(\frac{r_{t+1}^{nj}}{r_t^{nj}} \right)^{-\theta\xi^n} \left(\frac{\lambda_{t+1}^{nj,ij}}{\lambda_t^{nj,ij}} \right)^{-\theta}}{\sum_{m=1}^N \pi_t^{mj,ij} \left(\frac{w_{t+1}^{mj}}{w_t^{mj}} \right)^{-\theta(1-\xi^m)} \left(\frac{r_{t+1}^{mj}}{r_t^{mj}} \right)^{-\theta\xi^m} \left(\frac{\lambda_{t+1}^{mj,ij}}{\lambda_t^{mj,ij}} \right)^{-\theta}},$$

and the changes in the price of the Cobb-Douglas aggregate final good, $P_t^{C,n}$, is,

$$\frac{P_{t+1}^{C,n}}{P_t^{C,n}} = \prod_{j=1}^J \left(\sum_{m=1}^N \pi_t^{mj,ij} \left(\frac{w_{t+1}^{mj}}{w_t^{mj}} \right)^{-\theta(1-\xi^m)} \left(\frac{r_{t+1}^{mj}}{r_t^{mj}} \right)^{-\theta\xi^m} \left(\frac{\lambda_{t+1}^{mj,ij}}{\lambda_t^{mj,ij}} \right)^{-\theta} \right)^{-\frac{\gamma_j}{\theta}}.$$

These two expressions, together with market clearing conditions, characterize equilibrium in each period t for a given value of labor supply in each sector and country, L_t^{ij} .⁶¹

⁶¹As mentioned in Section 6, I normalize nominal variables such that $P_t^{C,n} = 1$ in every period in the United States.

Appendix D: Consumption equivalent welfare changes

I now derive the expressions for the equivalent variation in consumption. Using (1) and (2), we can write the value at period 1 as,

$$v_1^j(\tau) = w_1^j(\tau) + \beta v_2^j(\tau) - \nu \log \left(\mu_1^{j\ell}(\tau) \right).$$

Iterating this expression forward

$$v_1^j(\tau) = \sum_{t=1}^{\infty} \beta^{t-1} \left[w_t^j(\tau) - \nu \log \left(\mu_1^{j\ell}(\tau) \right) \right].$$

Define variables with a “^”, as those corresponding to the equilibrium after an unanticipated shock hits in period 1. Thus, lifetime utility in period 1 after a shock is $\hat{v}_1^j$. The consumption equivalent change in welfare is the scalar $\delta^j(\tau)$, for each j and τ , such that,

$$\hat{v}_1^j(\tau) = \sum_{t=1}^{\infty} \beta^{t-1} \left[w_t^j(\tau)(1 + \delta^j(\tau)) - \nu \log \left(\mu_1^{j\ell}(\tau) \right) \right].$$

In words, this simply says that a change in consumption of δ^j every period in the economy with no shocks, would bring lifetime utility of that economy to the levels of utility of the economy with the shock. Manipulating these equations we get,

$$\delta^j(\tau) = \frac{(1 - \beta) (\hat{v}_1^j(\tau) - v_1^j(\tau))}{w_1^j(\tau)}.$$

Appendix E: Correcting mobility estimates in the Current Population Survey

In this appendix I show how to correct yearly mobility matrices using data from the Current Population Survey (CPS).⁶²

The CPS collects information on individuals for a sampled household at the same address for four consecutive months, stops for eight months, and then surveys them again for another four months. I match individuals with their survey conducted a year before and compute their employment or non-employment status and work industry, accounting for

⁶²I access the CPS data from <https://cps.ipums.org/cps/>. See Flood et al. (2021) for a detailed reference.

any change between interviews as a transition. Since I need information on wages, I use only the Outgoing Rotation Groups, which are the individuals at month 4 and 8 of the survey.⁶³

The procedure to obtain industry and occupation information in the CPS is very similar to the PSID as individuals provide a verbal description on the type of business of their employer and the tasks they perform, which are then independently coded by a professional coder (Bureau, 2015).⁶⁴ As discussed in Murphy and Topel (1987), Moscarini and Thomsson (2007), and Kambourov and Manovskii (2008), industry and occupation information is subject to misclassification errors, which, as in the case of the CPS, greatly inflates mobility rates.⁶⁵

Under the assumption that misclassification probabilities are similar between the PSID and the CPS, which given the similarities in the way individuals are asked to report this information and the way the description is then coded, seems reasonable, then I can use estimates of α from Table 4 to correct mobility in the CPS data. Thus, I implement this using CPS data and the EM algorithm detailed in Section 4, but taking the values of α as given from Table 4.⁶⁶ I adapt equation (8) as follows,

$$\mathcal{L}(\mathbf{d}, \boldsymbol{\tau}, \boldsymbol{\omega} | \hat{p}_j, \hat{p}_{j'|j}, \hat{w}_s, \alpha) = \sum_{n=N_0+1}^N \sum_{j=1}^J \sum_{j'=1}^J \sum_{s=1}^J \sum_{s'=1}^J d_j^n d_{jj'}^n q_{ss'}^n \log [\hat{p}_s(\tau^n) \alpha_{j|s}(\tau^n) \hat{p}_{s'|s}(\tau^n) \alpha_{j'|s'}(\tau^n) f(\log(\omega^n / \hat{w}_s(\tau^n)))],$$

and use equations (9), (10), and (11) to obtain estimates of industry mobility corrected of misclassification.

Table 11 shows mobility rates in the CPS computed using uncorrected data and the estimates corrected of misclassification. In both cases industry mobility increases over these

⁶³ The main limitation with the CPS is that individuals who move to a different address cannot be matched to previous surveys. The match rate over a year is close to 75%. Mortality, residence change, and nonresponse rates are the main drivers of the 25% mismatch rate.

⁶⁴ According to the CPS interviewing manual, Census employees in Jeffersonville, Indiana assign industry codes to individuals based on the business or industry description individuals provide. Similarly, coders assign occupation codes on the basis of the kind of work the specified person usually does and on a description of his/her most important activities or duties.

⁶⁵ In 1994 the CPS introduced dependent coding as a way to reduce the magnitude of misclassification errors. Basically, under dependent coding, individuals are asked to report information on industry and occupation the first time they participate in the sample, while in subsequent months they are asked whether they are still employed with the same firm and performing the same tasks as in the previous month. If that is the case, then codes for the second month are simply a copy of those from the first month, reducing spurious mobility. However, note that dependent coding only helps for individuals that do not change their employer or main tasks from one month to the next, and is only available at higher frequencies, as information on industry and occupation is coded independently in month 5, which will affect all measured mobilities one-year apart.

⁶⁶ Since I have more years of data in the CPS, I allow for a higher order polynomial (order three) in time in the linear probability model used in the EM algorithm. As argued by Moscarini and Thomsson (2007), the patterns of mobility over time are non-monotone, thus a higher order polynomial allows for a more flexible evolution of mobility over time.

years, a pattern also present in the PSID data, as can be clearly seen by the decreasing values in the diagonals of the matrices. Depending on the industry, corrected mobility rates can be two times larger when computed using the raw (uncorrected) data, relative to the corrected estimates.

Note that, since misclassification probabilities do not have a time period attached to it, it is possible to use these same estimates to obtain corrected measures for mobility at higher frequencies, like quarterly or monthly. Moreover, for more recent periods and for those observations which are dependently coded, one can adapt equation (8), treating the dependently coded data as correct.

In sum, this appendix shows that the method proposed in this paper is portable and can be used with data from other surveys, taking the estimated values for the misclassification probability, α , from the PSID. As industry and occupation in the PSID data is coded at three-digits, it is also possible to extend the analysis of this paper to more disaggregate industry and occupation groups, and to use other datasets to obtain mobility rates for more recent time periods.

Table 11: Estimated matrices of industry mobility, $\hat{p}_{s'|s}$ using CPS data
(Selected years, smoothed.)

Panel A: 1983 - original						
	Agric./Mining	Construction	Manufacturing	Transport/Util	Wholesale/Retail	Other serv.
Agric./Mining	0.804	0.029	0.054	0.013	0.054	0.046
Construction	0.009	0.840	0.045	0.030	0.022	0.054
Manufacturing	0.003	0.011	0.929	0.008	0.027	0.022
Transport/Util	0.003	0.016	0.019	0.902	0.021	0.038
Wholesale/Retail	0.005	0.013	0.054	0.011	0.857	0.061
Other serv.	0.001	0.012	0.025	0.009	0.030	0.923
1983 - corrected						
	Agric./Mining	Construction	Manufacturing	Transport/Util	Wholesale/Retail	Other serv.
Agric./Mining	0.907	0.016	0.026	0.001	0.041	0.009
Construction	0.007	0.930	0.044	0.008	0.004	0.008
Manufacturing	0.002	0.011	0.972	0.005	0.001	0.009
Transport/Util	0.001	0.005	0.007	0.961	0.008	0.018
Wholesale/Retail	0.004	0.008	0.003	0.009	0.957	0.018
Other serv.	0.001	0.005	0.015	0.011	0.007	0.962
Panel B: 1989 - original						
	Agric./Mining	Construction	Manufacturing	Transport/Util	Wholesale/Retail	Other serv.
Agric./Mining	0.769	0.041	0.064	0.018	0.067	0.040
Construction	0.012	0.814	0.057	0.023	0.032	0.062
Manufacturing	0.004	0.014	0.901	0.008	0.038	0.034
Transport/Util	0.004	0.017	0.020	0.894	0.022	0.042
Wholesale/Retail	0.006	0.012	0.057	0.016	0.830	0.080
Other serv.	0.003	0.012	0.026	0.012	0.033	0.915
1989 - corrected						
	Agric./Mining	Construction	Manufacturing	Transport/Util	Wholesale/Retail	Other serv.
Agric./Mining	0.885	0.023	0.026	0.003	0.050	0.013
Construction	0.006	0.920	0.050	0.004	0.010	0.010
Manufacturing	0.002	0.011	0.968	0.004	0.001	0.013
Transport/Util	0.001	0.007	0.008	0.945	0.013	0.026
Wholesale/Retail	0.005	0.009	0.005	0.011	0.940	0.030
Other serv.	0.001	0.005	0.018	0.013	0.010	0.953
Panel C: 1996 - original						
	Agric./Mining	Construction	Manufacturing	Transport/Util	Wholesale/Retail	Other serv.
Agric./Mining	0.752	0.040	0.060	0.028	0.064	0.055
Construction	0.009	0.804	0.052	0.025	0.046	0.065
Manufacturing	0.005	0.016	0.878	0.011	0.045	0.045
Transport/Util	0.003	0.021	0.029	0.859	0.031	0.057
Wholesale/Retail	0.009	0.016	0.064	0.019	0.796	0.096
Other serv.	0.003	0.010	0.026	0.013	0.037	0.910
1996 - corrected						
	Agric./Mining	Construction	Manufacturing	Transport/Util	Wholesale/Retail	Other serv.
Agric./Mining	0.874	0.029	0.027	0.003	0.050	0.017
Construction	0.006	0.909	0.052	0.006	0.014	0.014
Manufacturing	0.003	0.015	0.955	0.005	0.002	0.020
Transport/Util	0.001	0.009	0.012	0.920	0.016	0.041
Wholesale/Retail	0.005	0.009	0.005	0.013	0.930	0.037
Other serv.	0.001	0.005	0.018	0.014	0.011	0.951

Note: Fraction of movers in an industry that switch to a different industry. First year industry by row and second year industry by column. Estimated by EM algorithm using CPS data and estimates for α from Table 4, see text for details.