



Desarrollo y Sociedad

ISSN: 0120-3584

revistadesarrolloy sociedad@uniandes.edu.co

Universidad de Los Andes

Colombia

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On the Benefits and Costs of Job Reallocation in Colombia
Desarrollo y Sociedad, núm. 57, 2006, pp. 123-162
Universidad de Los Andes
Bogotá, Colombia

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On the Benefits and Costs of Job Reallocation in Colombia*

Sobre los beneficios y costos de la reasignación de puestos de trabajo en Colombia

Juanita González Uribe**

Abstract

This article measures gross creation, destruction, and reallocation of jobs inside the Colombian Manufacturing Industry between 1982 and 1998. We characterize job reallocation as a source of adjustment both in productivity dynamics and on workers welfare. Consistent with previous research, we find evidence of productivity enhancing factor reallocation. However, we also find evidence of significant welfare losses for displaced workers. Our most novel results are the negative effect of displacement, sector change and unemployment duration on post-job-change wages. The event of sector change seems to spur considerable sector specific skills losses which offset any potential positive effects of sector change, such as the purge of the displacement stigma. In brief, our results show that on balance depreciation and

* The author thanks Marcela Eslava, John Haltiwanger, Michel Janna, Adriana Kugler and Maurice Kugler for helpful comments. This paper was developed within the context of the project "Market Institutions, Firm and Job Turnover, Competition and Productivity: An Analysis of Colombia", supported by the Tinker Foundation.

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This paper was received December 12, 2005 and accepted April 6, 2006.

stigma effects dominate productive search outcomes in the determination of post-unemployment wages. We conclude that at least a fraction of job reallocation is socially inefficient.

Key words: input reallocation, worker displacement, productivity dynamics.

JEL Classification: D24, J65, J24.

Resumen

Este trabajo mide la creación, destrucción y reasignación de puestos de trabajo en la Industria Manufacturera Colombiana entre 1982 y 1998; y caracteriza este fenómeno como una fuente simultánea de ajuste en la dinámica de la productividad y en el bienestar de los trabajadores. Los resultados muestran que la reasignación de puestos de trabajo tiene un impacto positivo sobre la productividad pero también constituye pérdidas significativas en el bienestar de los trabajadores. Nuestros hallazgos más interesantes son el efecto negativo de los eventos de desplazamiento, cambio de sector y duración del desempleo sobre los salarios poscambio de trabajo. En resumen, el trabajo muestra que la depreciación del capital humano y el estigma social asociados al desplazamiento dominan la búsqueda productiva en la determinación del salario posdesempleo. Concluimos que por lo menos una fracción de la reasignación de puestos de trabajo es socialmente ineficiente.

Palabras clave: reasignación de factores, desplazamiento de trabajadores, dinámica de productividad.

Clasificación JEL: D24, J65, J24.

Introduction

In the last twenty years, changes in technology and consumer demand, international competition, structural reforms and some deep recessions contributed to large-scale job reallocation in Latin America (IADB, 2004). Although recent evidence shows that efficient reallo-

cation of inputs across businesses is closely connected to aggregate productivity growth (Eslava et al., 2004), it is also true that corporate downsizing has added large numbers to the figures of employee displacement. Concerns about both the plight of experienced workers losing jobs for the sake of aggregate productivity, and about productivity-restricting worker protection, give rise to an important public policy debate.

Following Davis and Haltiwanger (1992), this article measures gross creation, destruction and reallocation of jobs across establishments of the Colombian Manufacturing Industry between 1982 and 1998. In addition, we show the positive impact of this labor reallocation on productivity dynamics using prior estimates of plant level productivity (Eslava et al. 2004) and a modified dynamic productivity decomposition based on Foster et al. (2002). And last, using a new data set, derived from the Continuous Colombian Household Survey, we quantify the impact of displacement on workers' welfare by estimating long-term earnings losses and post-displacement earnings determinants, in the spirit of Addison and Portugal (1989).

Our principal findings are as follows. First, using the productivity decomposition mentioned above, we find that job reallocation across manufacturing sectors amounts to 20% of productivity growth in the Colombian manufacturing sector. Second, using data from the Continuous Colombian Household Survey, we find that both the average wage loss and unemployment duration for a displaced¹ worker inside the Colombian manufacturing sector are larger than for a worker who loses his job for reasons different to displacement. The difference amounts to approximately 15% of the minimum legal wage and to 2.6 more months of unemployment while searching for a new position. Third, we find that the length of unemployment duration, and both, displacement and sector change, negatively affect post-job-change wages. Our linear regression results suggest that on balance depreciation and stigma effects dominate productive search outcomes in the determination of post-unemployment wages. We conclude that at least a fraction of job reallocation is socially inefficient.

¹ We consider as displaced a person who is currently employed and responded that his/her previous job loss was due to "a plant closing or a restructuring of his/her former employer". The non-displaced category includes causes of job loss unrelated to job reallocation.

The goal of this study is to show the existence of both productivity gains and welfare costs from job reallocation in the Colombian Manufacturing industry. To this end and because of data restrictions, we are forced to draw upon two different data sets to assemble a more accurate picture of job flows. These available data sets differ in terms of sampling frequency, sampling unit, extent of industrial coverage and particularly important, in time period. In spite these differences, and although both phenomena must be interpreted separately, this study contributes to the current literature by finding and exploiting a link between two previously unrelated literatures, plant-level industrial dynamics and welfare economics; and by measuring the extent and impact of job reallocation in a developing country.

This study improves our understanding of job reallocation and its impact on the economy, especially the costs of job displacement. However, to inform public debate and decision making, we need to know more. Matched employer-employee data with information on turnover (quits, layoffs, firings, recalls, hiring) and on the evolution of earnings would help answer questions about firm's decisions to lay off workers and about long-term effects of displacement. Unfortunately this data is not available for Colombia. Hence, this study's worth is twofold. On the one hand, it is the first attempt to acknowledge welfare costs as well as productivity gains derived from establishment-level reallocation processes in the Colombian Manufacturing Industry. On the other hand, it is a call for the need to construct matched employer-employee data in Colombia in order to fully assess the impact of policy measures in the subject.

The rest of the paper proceeds as follows. Section I reviews some of the relevant literature related to firm heterogeneity and worker displacement costs. Section II measures establishment-level job flows. Using establishment level and household level data respectively, Section III and Section IV examine the effects of job flows on productivity dynamics and on workers' welfare. Finally, Section V provides the main conclusions.

I. Related literature

Market economies undergo continual creation and destruction of jobs. Existing plants expand and contract their factor use, new plants create jobs, and plants that shut down destroy them. Academics and policymakers alike recognize the existence of large job reallocation figures. However, there is less agreement about the benefits of factor reallocation.

Theoretical literature on industrial dynamics, such as the models of *creative destruction* by Schumpeter (1950), *passive learning* by Jovanovic (1982) and *vintage capital* by Jovanovic and MacDonald (1994) among others, argue in favor of beneficial factor reallocation. These models claim that even if within firm productivity is immutable, an effective selection mechanism across firms may lead to productivity enhancing net entry and reallocation across continuing firms. The idea is that although managers may not be able to affect the productivity of their establishments, they may be able to perceive their relative efficiency levels, and, if they are responsive to the associated market signals, they may downsize or expand appropriately (Brown and Earle, 2003).

Empirical evidence based on these models suggests a significant role for reallocation in productivity dynamics. For the U.S. manufacturing sector, Baily et al. (1992) find that factor reallocation accounted for a third of the productivity gains in a ten year period. Similarly, using Korean and Taiwanese data, Aw et al. (2002) report productivity differentials between entering and exiting firms as an important source of growth of aggregate productivity. For the Chilean manufacturing industry (1979-1986) Levinsohn and Petrin (1999) find that most of the increase on aggregate productivity is due to net entry and to resource reallocation, while declines are generally triggered by decreases on average firm productivity rather than by between or net entry effects. Similarly, Bartelsman et al. (2004), using firm level data across 24 countries, conclude that the contribution of net entry represents between 20% and 50% of total aggregate productivity growth. While the exit effect is always positive, the entry effect tends to be negative for most countries of the OECD and emerging economies. Finally, for Colombia, the study of Liu and Tybout (1996) finds an uneven role

for net entry in the Colombian manufacturing industry between 1977 and 1985. In most periods, exiting firms are approximately 10% less productive than the average; hence, their exit traduces into aggregate productivity gains. In recent studies, such as Medina et al. (2002) and Eslava et al. (2004,2005), newfound evidence on the efficient role of factor reallocation is reported.

Nevertheless, theory also suggests downsides of reallocation. For instance, job reallocation imposes large costs on workers when forced to switch employers and shuffle between employment and joblessness². This is because much of the burden of reallocating jobs across regions, industries and plants inevitably falls upon them. Addison and Portugal (1989) and Kletzer (1998) show how displacement frequently translate into large welfare losses. They identify two major loss sources. First, displaced workers experience immediate costly spells of unemployment together with adjustment and searching costs. Second, wages can be permanently affected and hence workers can experience losses beyond initial unemployment (Jacobson et al., 1993).

Theory suggests various reasons why permanent wage reductions might arise. Workers that are forced to leave their jobs and that possess skills that are specially suited to their positions are likely to be less productive, at least initially, in their subsequent jobs. Previous on-the-job investment in firm specific human capital, and/or costly searches resulting in particularly good matches with their old firms, are permanently lost. Also, unemployment stigma effects can scar workers indefinitely. If a social stigma is inflicted upon the unemployed, such as associations to laziness and inefficiency, workers might get caught in unemployment traps (Addison and Portugal, 1989).

Empirical evidence on the subject is large. Addison and Portugal (1989) find that the length of unemployment is a potent source of reduced earnings since it is possible that workers may suffer from deprecia-

² Theoretical models of microeconomic adjustment, however, recognize that factor reallocation might be perverse even in terms of productivity growth. Factors such as credit market imperfections (Barlevy, 2001), institutions, regulations and tax laws (Hopenhayn and Rogerson, 1993; Bertola and Rogerson, 1997), competition from foreign and domestic rivals (Melitz, 2000) and negotiations between employers and labor organizations (Mortensen and Pissarides, 1994), can lead to inefficient job reallocation.

tion of their human capital that, coupled with stigma effects, may lower expected wages. The authors also find that wage consequences of a change in industry and occupation are profound. This is because an individual's ability to retain human capital or to retain hierarchical standing depends a great deal on finding a new job in the same industry and occupation (Kletzer, 1998).

Jacobson, LaLonde and Sullivan (1993) compare changes in displaced workers' earnings to those of workers who lose their job for reasons different to displacement. They find that high tenure workers incur in large losses when they separate from distressed firms. Losses exhibit great variability among workers displaced from different industries, sizes of firms and local labor market conditions. Finally, an important part in the earnings changes following job loss is the inability to find a new full-time job.

This study links two previously unrelated literatures, plant-level industrial dynamics and welfare economics. In the spirit of both Levinsohn and Petrin (1999) and Jacobson, LaLonde and Sullivan (1993), it attempts to acknowledge productivity gains as well as welfare costs derived from establishment-level reallocation processes in a developing country.

II. Job flows

In this section we measure gross and net rates of job reallocation in the Colombian Manufacturing Industry following Davis and Haltiwanger (1996). We begin by specifying more precisely our definition of job and worker reallocation.

Gross job creation (GCR) is defined as total employment gains from new establishments and expanding incumbents as a fraction of average sector employment. Analogously, gross job destruction (GDR) represents total employment losses from shrinking and dying establishments as a percentage of average sector employment. Introducing some notation we can write GCR and GDR rates in sector s at time t as

$$GCR_{st} = \sum_{\substack{e \in E_{st} \\ g_{et} > 0}} \left(\frac{x_{et}}{X_{st}} \right) g_{et} \quad GDR_{st} = \sum_{\substack{e \in E_{st} \\ g_{et} < 0}} \left(\frac{x_{et}}{X_{st}} \right) |g_{et}|$$

where E_{st} is the set of establishments in sector s at time t , x_{et} is the number of employees of establishment e at t , and g_{et} is the growth rate of establishment e at time t , defined as the change in establishment employment from $t-1$ to t , divided by X_{st} (the average employment in sector s between $t-1$ and t). This growth rate measure lies in the closed interval $[-2,2]$ and is symmetric around zero³.

Three useful measures can be constructed using the rates of GCR and GDR. First, net employment growth corresponds to the difference between job creation and job destruction (Davis et al. 1996). Second, we define gross job reallocation as the sum of GCR_{st} and GDR_{st} , which can be interpreted as the maximum worker reallocation associated to job flows. Finally, excess job reallocation represents the part of job reallocation above the amount required to accommodate net employment changes. It equals the difference between gross job reallocation and the absolute value of net employment growth.

A. Data description

Our data come from the Eslava et al. (2004) EHKK database constructed using the Colombian Annual Manufacturers Survey (AMS) for the years 1982 to 1998. The EHKK is an unbalanced panel of Colombian plants with more than 10 employees, or sales above a certain limit (around US\$35,000 in 1998). It includes information for each plant on: physical quantities and prices of output and inputs; capital stock; production and non-production workers and total labor hours; and estimates of total factor productivity. A more thorough description of the measurement of each variable can be found in Eslava et al. (2004).

B. Magnitude and time variation

Job creation and destruction rates provide information about employment dynamics that is unavailable from more aggregate labor statistics. For any given level of aggregate employment growth, higher rates

³ The size-weighted frequency distribution determines the weight to attach to each growth rate value in the calculation of job creation and destruction rates (Davis et al. 1996).

of job reallocation translate into larger numbers of workers forced to change jobs, which on the one hand might induce aggregate productivity gains as workers move from less productive to more productive firms, but on the other hand can translate into welfare losses for workers. This is because as employment opportunities shift across locations, parallel shifts are undertaken by workers. Displaced workers are forced to find employment at different establishments, and sometimes even at different sectors, or to become unemployed or leave the labor market and become inactive.

Table 1 Annual flows as a percentage of employment, 1983-1998.

	Average	Standard Deviation	Minimum	Maximum
Job Creation	10.2	1.6	7.3	13.1
Job Destruction	11.4	2.6	7.5	16.0
Job Reallocation	21.6	3.1	16.7	28.0
Net Employment Growth	-1.2	2.9	-7.2	3.8
Excess Job Reallocation	20.4	3.1	14.5	26.1
Minimum Worker Reallocation	12.0	2.1	8.5	16.0

Source: Author calculations.

Using the EHKK and own calculations of job reallocation, Table 1 reports summary statistics for rates of job creation, job destruction, job reallocation, net employment changes and excess job reallocation, and the minimum worker reallocation required to accommodate job reallocation⁴ for the Colombian manufacturing sector. Job flow measures reflect plant level annual employment changes.

The key message conveyed by Table 1 is the substantial magnitude of gross job flows (and their similarity to U.S.A data, see Davis and Haltiwanger, 1996). On average, 11.4 percent of manufacturing jobs were destroyed over a twelve-month interval during the 1983-1998 period. Twelve-month job creation rates averaged a slightly lower 10.2 percent of manufacturing jobs. These two figures reflect the net shrink-

⁴ To obtain a lower bound, the chance of double counting job losers who move directly to new jobs at expanding establishments in the same sector is eliminated by choosing the maximum value between job creation and job destruction. That is the minimum worker reallocation in sector s , $MWR_{st} = \max\{GCR_{st}, GDR_{st}\}$, represents the minimum worker change rate in direct response to job reallocation in sector s .

age of manufacturing employment between 1982 and 1998 of 1.2 percent. Job reallocation figures reveal that approximately one in five manufacturing jobs are either destroyed or created over an average twelve-month interval (21.6 percent of employment). Excess job reallocation, the part of job reallocation above the amount required to accommodate net employment changes, averages 20.4 percent and throughout the whole period never fell below 14.5 percent.

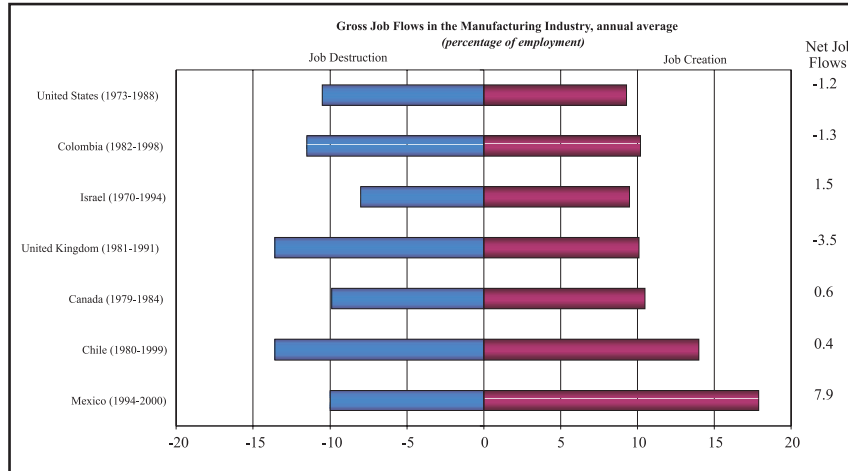
Table 1 sheds some light on how reshuffling of employment opportunities across plants affects workers. According to it, in an average year, the amount of worker reallocation induced by job reallocation is bounded between 12.0 and 21.6 percent of employment. That is, a large number of workers must change jobs every year and face the costs associated with such transitions. Are the productivity gains associated to this churning large enough to make up for these potential costs? Matched employer/employee data, which is unavailable for Colombia, is needed in order to fully answer this question. Given data constraints, however, this study calculates productivity gains associated with reallocation using the EHKK data as source, and costs for displaced workers using a different one.

To provide some perspective on cross-country levels of job creation and destruction, Figure 1 depicts gross job flows in the manufacturing industries of different countries and periods. An interesting result, taking into account the vast differences on labor legislation among countries, is that there is no large deviation in the levels of job reallocation between Latin American and developed countries.

C. Concentration and persistence

The rates of job reallocation reported in the figures and tables above trigger two additional questions on the concentration and persistence of these rates. First, what role does net entry of plants play in the creation and destruction of jobs? Second, do the high rates of creation and destruction of jobs reflect permanent or temporary employment changes? Consequences of job creation and destruction on worker reallocation depend in large part on the answers to these inquiries. The present value of welfare loss is larger if job destruction is persistent and concentrated on exiting plants. This is so because both phenomena lower the probability of job reopening.

Figure 1. Gross job flows in the manufacturing industry, annual average.



Source: Author calculations, IADB (2004) and Davis, Haltiwanger and Schuh (1996).

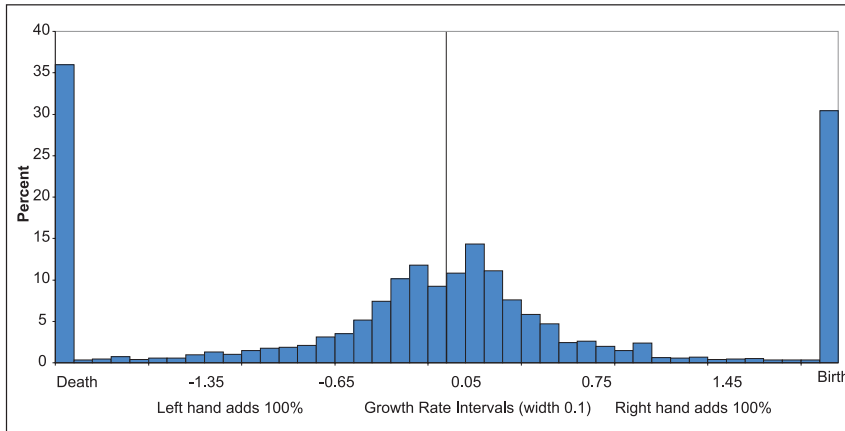
Figure 2 displays the distributions of job creation and job destruction by absolute values of establishment level employment growth rates for the 1983-1998 period. For instance, the right half of Figure 2 plots the fraction of job creation accounted to establishments experiencing growth rates in different intervals between 0 and 2. A final category corresponding to establishment growth of 2, shows the fraction of job creation accounted for by new establishments. The left half of Figure 2 provides a symmetric partition of destruction rates⁵.

The central message depicted is the crucial role of net entry in job reallocation. Births and deaths alone account for approximately 30.5 and 36.0 percent of job creation and destruction respectively. Furthermore, Figure 2 shows that establishments experiencing dramatic growth rates ($|g_{et}| > 0.25$) account for 44.4 percent of job creation and 43.0 percent of job destruction. Finally, Figure 2 reveals that job destruction relative to job creation is more concentrated in plants with dramatic employment changes. In conclusion, both job creation and destruction are concentrated in establishments that experience large employment changes, but concentration is larger for job destruction.

⁵ Recall that the growth rate defined above is symmetric around zero and lies inside the closed interval $[-2, 2]$.

These results imply that a large part of job destruction inside the manufacturing industry occurs in massive layoffs, augmenting expected wage loss due to an excess of labor supply.

Figure 2. Job creation and destruction partitioned by establishment growth rate.



Source: Author calculations.

Table 2 Persistence rates for job creation and destruction. (% Annual job flow measures).

Year	Job Creation		Job Destruction	
	1 year	2 years	1 year	2 years
83	67.1	54.1	83.6	62.0
84	63.4	59.3	86.5	64.0
85	73.9	69.4	83.5	60.0
86	78.2	69.0	74.3	65.0
87	71.7	65.0	81.9	67.0
88	72.3	66.2	81.8	66.0
89	73.6	65.9	79.4	64.0
90	69.5	57.3	80.0	63.0
91	66.4	61.1	79.6	64.0
92	73.2	64.4	80.6	66.0
93	66.5	55.5	82.8	59.0
94	60.3	48.8	80.2	63.0
95	70.2	63.0	86.0	75.0
96	71.2	54.4	83.2	76.0
97	66.9		87.9	
Simple mean	69.6	61.0	82.1	65.3

Source: Author calculations.

Table 2 shows persistence rates that underlie our measures of job creation and destruction. Following Davis et al. (1996) we define the n -period persistence of job creation as the percentage of newly created jobs at time t that remain filled at each period through time $t+n$ ⁶. Analogously, job destruction persistence is defined as the percentage of destroyed jobs at t that do not reappear at any subsequent period through $t+n$. One-year persistence of job creation and job destruction range from 60 to 78 percent and 74 to 88 percent respectively. These figures mean that approximately 7 out of 10 newly created jobs survive at least one year, and 5.5 out of 10 newly created jobs survive at least two years. These ranges show high persistence of job creation and destruction activities and are very similar to those calculated by Davis et al. (1996) for the United States, where one-year job creation and destruction persistence ranged from 61 to 81.7 percent and 72.2 to 87.2 percent respectively.

The persistence of establishment-level employment changes bears directly on worker reallocation. If rates of job creation and destruction reflect short-lived changes, then temporary reallocation of workers is sufficient to handle the job reallocation figures. On the contrary, if changes are persistent, then the associated reshuffling of jobs must generate permanent joblessness and worker reallocation. Table 2 suggests that worker reallocation associated to job reallocation in the entire sampling period 1983-1997 had permanent character, intuitively augmenting welfare costs associated with displacement. As the figures above show, job destruction is more persistent than job. One-year persistence of job destruction ranges from 74.3 to 87.9 percent, and two-year persistence ranges from 60 to 76 percent. Hence, the effect on expected wage loss is twofold, not only are the persistence rates of job destruction high, which means that the probability of a lost job to reopen is low, but also created jobs tend to disappear more easily than a lost job tends to reopen. This means that the probability of finding a

⁶ Let $E_{e,t}$ denote time t employment at establishment e . Newly created jobs at e in t equal $E_{e,t} - E_{e,t-1}$, assuming positive growth. If $E_{e,t+1} \geq E_{e,t}$, then all of these newly created jobs are present in $t+1$. If $E_{e,t+1} \leq E_{e,t-1}$, then none of the newly created jobs are present in $t+1$. If $E_{e,t+1} \in [E_{e,t-1}, E_{e,t}]$, then $E_{e,t+1} - E_{e,t-1}$ of the newly created jobs are present in $t+1$. Carrying out this calculation for all growing establishments in t and dividing the result by GCR_t gives the persistence rate in $t+1$ (Davis et al., 1996).

new job is less than the probability of losing one, rising expected wage losses.

III. Impact of job reallocation on productivity growth

Evidence reported above implies two important results: large job reallocation rates reflect uneven establishment-level adjustments and net entry explains an important fraction of job rotation. An open question is whether the observed job reallocation increases industrial total factor productivity; that is, if it generates aggregate benefits.

Total factor productivity is not an observable variable; its successful study depends on the accuracy of its estimation technique. In the past few years new methodologies have been designed in order to account for simultaneity biases and omitted variable issues present in traditional estimates (González, 2004). An important number of authors have implemented these new methodologies for Colombia (Medina et al., 2003; Eslava et al., 2004; Echavarría et al., 2005).

Nevertheless, standard estimations reported in productivity studies are usually aggregated to a level which makes it difficult to see how productivity is really changing. In order to better understand what underlies the industry-level changes in productivity it is useful to decompose those changes into their causes.

A. Aggregate productivity decompositions

In this section we propose a new measure and decomposition of industrial productivity, alternative to that proposed by Baily et al. (1992). We start with our new definition of aggregate industrial productivity. Traditional measures of aggregate productivity weight establishments by output. $P_t = \sum_i \theta_{i,t} p_{i,t}$. Hence, aggregate productivity P_t corresponds to the weighted mean of establishment productivity p_{it} , using output shares θ_{it} as weights. Although this measure is very intuitive, it does not tell much about input changes, or more specifically, about job reallocation across establishments. This is because an increase in output is not necessarily driven by employment movements. Our alternative measure of aggregate productivity uses labor shares instead of output shares in its calculation, which serves our purpose much better.

This new measure though, demands a whole new interpretation. Now, aggregate productivity responds not only to idiosyncratic productivity changes but to expansions or contractions of the different establishments' labor force⁷. For example, consider the case when aggregate productivity rises during a determined span of time. This rise might occur because jobs are reallocated to more efficient plants, i.e. efficient plants attract workers from other establishments, or because each plant in the industry becomes more productive even though no job reallocation took place. Industry-level productivity can also increase if entrants are more productive than the average incumbent or if less efficient firms exit, as entries and exits imply employment changes. Hence, productivity growth in the industry reflects simultaneously employment adjustments among the incumbents, and the effect of entry and exit on employment shares. It is worth to note that in our new measure of aggregate productivity, labor intensive establishments are more important in terms of their contribution to aggregate productivity than capital intensive plants, a fact that must be kept in mind while analyzing results.

Following Foster et al. (2002) we decompose changes in this new measure of aggregate productivity into five terms reflecting all interactions between job reallocation and productivity changes. The decomposition is as follows

$$\Delta P_t = \sum_{i \in C} \theta_{i,t-1} \Delta p_{i,t} + \sum_{i \in C} (p_{i,t-1} - P_{t-1}) \Delta \theta_{i,t} + \sum_{i \in C} \Delta p_{i,t} \Delta \theta_{i,t} + \sum_{i \in N} \theta_{i,t} (p_{i,t} - P_{t-1}) - \sum_{i \in X} \theta_{i,t-1} (p_{i,t-1} - P_{t-1})$$

where P_t is labor-weighted average productivity, p_{it} and θ_{it} are the productivity and labor share of establishment i , respectively. C, N and X represent the set of continuing, entering and exiting plants, respectively.

The first term in this decomposition represents a within plant component that reflects plant level productivity changes weighted by initial

⁷ Expansions and contractions of the labor force are associated to changes in the marginal productivity of capital, which contributes to total factor productivity.

labor shares in the industry⁸. The term can be either positive or negative: for a given distribution of shares firms can become more or less productive. The second term represents a between plant component that reflects changing labor shares, weighted by the deviation of initial plant productivity from the initial productivity index. This term can also be either positive or negative, reflecting respectively, increasing or decreasing shares for relatively more productive firms. The third term is a cross-term (covariance type), which reflects if more productive plants tend to increase their labor shares and vice-versa. Finally, the last two terms represent the contribution of entering and exiting plants respectively⁹.

B. Data description

In this section we decompose aggregate productivity using the estimates of plant level productivity for the Colombian manufacturing industry by Eslava et al. (2004), found in the EHKK data base mentioned in section II.A. Eslava et al. (2004) estimate total factor productivity for each establishment as the residual from a capital-labor-energy-materials (KLEM) production function. Since productivity shocks are likely to be correlated with inputs Eslava et al. (2004) present IV estimates, where demand-shift instruments (which are correlated with input use but uncorrelated with productivity shocks) are used. The authors construct Shea (1993) and Syverson (2003) type instruments by selecting industries whose output fluctuations are likely to function as approximately exogenous demand shocks for other industries. In addition, they use as instruments one- and two-period lags of the demand shifters just described, energy and materials prices, and government expenditures (excluding investment) in the region where the plant is located. A more thorough description of the plant level productivity estimation can be found in Eslava et al. (2004).

⁸ Analogue to Levinsohn and Petrin's "true productivity case".

⁹ The second term together with the last two are the analogues of Levinsohn and Petrin's "rationalization case"

C. Results

Table 3 shows the results of our aggregate productivity decomposition. The third column of Table 3 shows the contribution of job reallocation among continuing plants to aggregate productivity. For all sub-periods, except 1982 to 1985¹⁰, job reallocation across continuers is productivity enhancing. Especially so for the period 1994 to 1998, where 47 percent of the increase of aggregate productivity was due to job reallocation from less productive to more productive continuing units, offsetting the decrease of 0.57 percent on average productivity. For the whole sample job reallocation across continuing manufacturing plants amounted to 20 percent of productivity growth in the Colombian manufacturing sector.

Table 3. Dynamic decomposition of Colombian manufacturing total factor productivity 1982-1998.

Year	Change in Weighted TFP	Within	Between	Cross	Entry	Exit
82-85	1.66% (33%)	0.55% (-14%)	-0.23% (8%)	0.13% (26%)	0.42% (-48%)	-0.79%
85-88	11.95% (83%)	9.92% (5%)	0.59% (1%)	0.05% (14%)	1.69% (3%)	0.31%
88-91	7.31% (52%)	3.81% (19%)	1.44% (-12%)	-0.88% (25%)	1.86% (-14%)	-1.08%
91-94	-8.87% (125%)	-11.12% (-22%)	1.97% (-4%)	0.37% (7%)	-0.65% (6%)	-0.56%
94-98	4.11% (-14%)	-0.57% (47%)	1.94% (12%)	0.50% (9%)	0.38% (-45%)	-1.86%

Notes: Numbers in parenthesis add up horizontally to 100 and correspond to the percentage of contribution from each column to the total change in productivity. *Source:* Author calculations.

Columns five and six summarize the contribution of entry and exit to aggregate productivity changes. A negative sign in column five implies that the average productivity of entering plants was less than the initial aggregate productivity, negatively affecting overall efficiency. On the other hand, a negative sign in column six implies that the average productivity of exiting plants was less than the aggregate productivity, which translates into aggregate productivity gains for the

¹⁰ The sign of this coefficient can be largely due to the cycle. During 1981-1986 Colombia experienced a large recession that can bias the results of the decomposition.

industry. As both columns show, we find evidence of productivity enhancing net entry. For the whole period, except 1985 to 1988, firms that exit the sample (reduce their number of workers to zero) are less productive than the average. Similarly, entering firms are more productive than the average for the whole period except during 1991 and 1994. Interestingly, during that period, the positive effect of job reallocation across continuing establishments together with exit of less productive firms, were not enough to offset the fall in average productivity of 11.12 percent and the entry of inefficient establishments.

The results of productivity decompositions, thus, reveal two related phenomena. Increases in aggregate productivity are associated with improvement in allocative efficiency, both through reallocation of existing jobs and through the contribution of entry and exit. These findings suggest that, consistent with previous studies, job reallocation across continuing establishments and net entry (at the three digit level) account for a large share of aggregate productivity growth over the 1980's and 1990's in the Colombian manufacturing industry. We conclude, that job reallocation is productivity enhancing, more productive firms expand their number of job positions while less productive firms close them. How do these gains in aggregate efficiency compare to workers' welfare losses? We try to answer this question in the next section.

IV. Welfare costs of worker displacement

The forces that drive worker flows from one job to another and from employment to joblessness fall into two broad categories. The first category is associated with events or circumstances that induce workers to reallocate themselves among a given set of jobs and establishments, the second, with events that alter the distribution of available jobs among establishments (Davis et al., 1999).

The first category includes job-to-job movements for reasons of career advancement, family relocation, job satisfaction and quality of the worker match. It also includes labor force entry and exit for reasons of health, schooling, child-rearing and retirement (Davis et al., 1999). On the other hand, the second category encompasses the many

forces that impinge on the spatial distribution of labor demand such as the restructuring of firms and industries (Davis et al., 1999). These forces drive establishment-level job creation and destruction, which in turn cause workers to change employers and shuffle between employment and joblessness. In this way the second category gives rise to both job and worker flows (Davis et al., 1999).

Given data that matches workers to their employers and follows each over time, one can directly quantify the connection between worker flows and job flows. Matched worker-employer longitudinal data make it feasible to precisely characterize the relationship between these two types of flows and hence assess the importance of job reallocation as a driving force behind worker reallocation; meaning that we could measure the impact of job reallocation on workers' welfare.

In the absence of suitable matched worker-employer data for Colombia, one can use data on employers to at least place bounds on the amount of worker reallocation induced by the reshuffling of job opportunities, as was done in section II.B. with the EHKK data base. However, no further analysis can be made using this source, since it virtually has no information on employee characteristics, making it impossible to follow individuals after a job is destroyed. For this reason, it is necessary to draw upon a different data set with information on worker characteristics in order to quantify the impact of job reallocation on workers' welfare.

In this section we construct a new dataset using raw data from the Continuous Household Survey (CHS), in order to partially make up for our lack of matched employer-employee data and assemble a more accurate picture of the impact of job flows on welfare.

A. Data description

Our data come from the Continuous Household Survey (CHS) for the years 2001 to 2003. The CHS is a rotating panel of Colombian households that includes information for each household member summarized in six different modules. Each month a different group of households is selected to answer the survey. The first module includes general information on location and type of household as well as char-

acteristics of each household member, such as: age, gender, education attainment and marital state. The second module characterizes the labor force and classifies each household member as currently studying, employed, unemployed or inactive. Information on job search is included in this module too.

The third module describes the main job of the employed. This module includes information on industrial classification, type of job, type of contract, social security, tenure, wages and other sources of income. In addition, during the second quarter of the year, the third module is extended to include information on previous jobs. A complementary set of questions which includes data on industrial classification of previous job, duration of time in between jobs and importantly, reason for job change, allows us to select those workers whose transition within the industry is precisely due to job destruction.

The fourth and fifth modules describe secondary jobs for the employed and the unemployed, respectively. Finally, the last module describes the inactive.

In order to quantify the impact of job reallocation on workers' welfare we look in our data base for workers who can be linked to job destruction. These workers would correspond to individuals who have previously become unemployed because their position was closed by their former employer, and may or may not have find a new job. Unfortunately, the CHS includes no information for the unemployed on reasons for leaving their previous job; hence we are unable to identify unemployed workers that stemmed from job destruction. Because of this, our analysis will focus on currently employed individuals who report having a previous job, and whose reason for leaving the previous job corresponds to job destruction. Workers who lost their job because their position was closed and haven't been able to find a job are ignored in this study. Hence, the costs of job reallocation quantified in this section must be interpreted as a lower bound of real costs.

For this section, we define displaced workers to be currently employed individuals who were involuntarily separated from their jobs by mass layoff or plant closure, rather than because of individual performance. We argue that only these worker flows can be interpreted as induced

by job reallocation. Hence, although other types of worker flows, such as movements of temporal workers, constitute an interesting research area, our focus will be on worker flows stemming only from job reallocation. Thus, we only count as displaced a person who is currently employed and responded that his/her previous job loss was due to “a plant closing or a restructuring of his/her former employer”. Other causes of job loss, quits or firings for cause, are not considered displacements, since they are unrelated to job flows¹¹.

Our operational definition of displacement and the survey as a whole are ambiguous in some ways, so that results must be interpreted with caution. For example, an individual displaced from a job and rehired into a different job with the same employer is still considered displaced. In addition, the distinction between quits and displacement can become blurry in a situation where wage changes induce some workers to quit, and thus not to be counted as displaced (Kletzer, 1998). The survey collects information on only one job loss for each individual, but over several years multiple job losses are possible and not unusual (Kletzer, 1998), meaning that the survey will understate the amount of job displacement. Individuals are surveyed just once, providing information on one post displacement point in time, rather than about their experience over time (Kletzer, 1998).

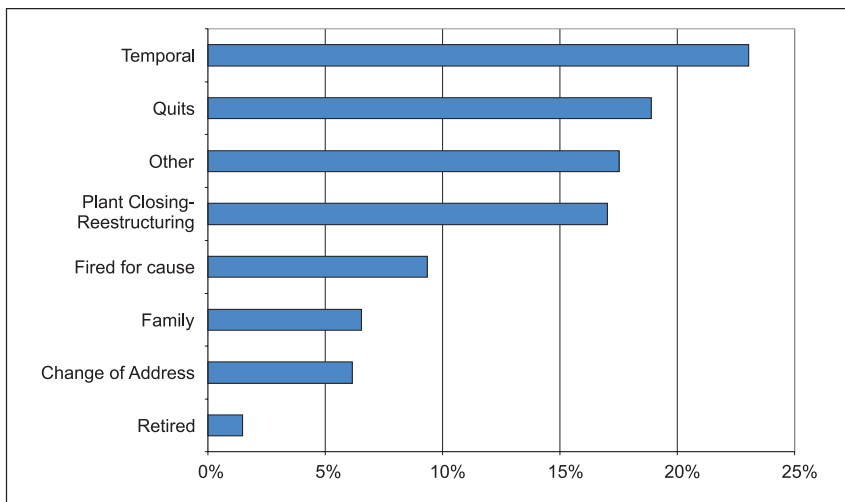
Furthermore, the CHS includes no information on past wages or past tenure and relies on retrospective information going back up to eight years, which might cause recall bias, specifically on unemployment duration and job type. Finally, the it's rotating nature makes longitudinal use difficult.

While these concerns need to be kept in mind, the fact that our data is part of the CHS means it shares the CHS' strengths. In particular it draws upon a large, random sample of 100,000 households, which is weighted to be representative of the Colombian work force. In addition, one major advantage of the CHS is that it contains information on completed spells of unemployment as well as on current tenure.

¹¹ Although it might be true that part of the worker flows induced by termination of temporal contracts can be related to job flows, there is no reliable information regarding that matter in the CHS. Hence, our results must be interpreted as lower bounds of total costs.

Our aim in this part of the paper is to estimate and describe the impact of displacement, as defined above, on workers welfare; especially, the relationship between unemployment duration and post displacement wages, which reflects whether productive search outcomes dominate depreciation and stigma effects of unemployment or not. To this end we use only data on respondents who have at least one job and in the past had a previous position, (we include non-displaced workers¹² as a control group) 45,400 individuals in total, and calculate wage losses using data on current wages and constructing approximate previous wages.

Figure 3. Fraction of workers with previous jobs CHS 2001-2003, by reason for job loss.



Source: author calculations.

Currently employed workers that report having a previous job are characterized in Figure 3 through job loss rates by reason of job loss. For example, the rate of job loss due to displacement is calculated by dividing the number of workers who currently have at least one job and who lost their previous job due to “a plant closing or a restructur-

¹² A non-displaced worker corresponds to an individual who is currently employed and had a previous job, and responded that his/her previous job loss was due to something different than “a plant closing or a restructuring of his/her former employer”.

ing of his/her former employer”, over the total number of workers who lost a job and are currently employed. As Figure 3 shows, 17% of our sample corresponds to displaced workers.

1. Pre-displacement wages

With the rich information on current job characteristics collected in the CHS, we can calculate approximate individual-level wages for previous jobs, using a standard matching procedure. This represents an enormous advantage with respect to other sources of data, as the use of a sector wage as an approximate previous wage is a common source of measurement error, due to individual heterogeneity.

The first step to construct previous wages is to calculate sector wage means controlling by gender, education attainment, type of job and experience. We divide our sample into two-hundred and fifty classes (two genders, five education attainment levels, five job types, and five experience levels¹³) in order to control for fixed effects. We do this exercise for the reported wages using appropriate deflators with base December 2001. The controlled average wage mean for sector s , of job type t , for g (*gender*) employees with level e of education attainment and level ϵ of working experience is:

$$\bar{w}_{s,e,\epsilon,t,g} = \sum_{\substack{e \in E \\ \epsilon \in \Sigma \\ t \in J \\ \text{if } g=m}} \frac{w_{i,s,e,\epsilon,t,g}}{N_{s,e,\epsilon,t,g}} \quad \text{where } 31 \leq s \leq 39, 1 \leq e, \epsilon, t \leq 5$$

Where $g=M,F$ (i.e. male or female) and $w_{i,s,e,\epsilon,t,g}$ is the wage of worker i , who belongs to sector s , has a job of type t , an experience of ϵ , and a level e of education attainment, and $N_{s,e,\epsilon,t,g}$ is the total number of employees at sector s , with job of type t , an experience of ϵ , gender g and a level e of education attainment. Table 4 presents sector average means of the controlled wages $w_{i,s,e,\epsilon,t,g}$.

¹³ The five job types are private or public employee, domestic employee, boss, non-remunerated family member and self-employed. Levels of experience are classified according to tenure: number of years in current establishment and include less than one year, one year, five years, ten years and more than ten years.

Table 4. Sector average monthly wages (Colombian 2005 pesos).

Sector	
Non- manufacturing sectors	518,103
Food, Beverages and Tobacco (31)	464,918
Textile, Apparel and Leather (32)	391,744
Lumber (33)	416,725
Paper and Printing (34)	759,347
Chemicals (35)	720,659
Non-metallic minerals (36)	630,355
Iron and Steel basic industries (37)	705,418
Fabricated Metals and Machinery (38)	547,351
Miscellaneous (39)	454,462
Manufacturing Sector	493,009

Notes: This table presents sector averages of $w_{i,s,e,t,g}$, i.e CIIU2 controlled wages. *Source*: author calculations.

After we construct controlled sector means we obtain an index of relative importance for each worker by dividing his/her current wage over the corresponding (controlled) sector wage mean. The importance of worker i (dev_i), relative to the rest of g (male/female) employees of sector s (where s is current sector), that have a job of type t , an experience of ϵ and a level e of education attainment is:

$$dev_i = \frac{w_i}{\bar{w}_{s,e,\epsilon,t,g}}$$

Finally, using this measure of relative importance or deviation we approximate previous wages by assuming the worker had same importance status in his/her previous job and so we deviate previous controlled sector mean by this index. Hence, the previous wage for individual i , who used to work at sector z and had job of type Γ before changing jobs, and has a current level e of education attainment is¹⁴:

$$\hat{w}_{i,z,e,\Gamma,g} = dev_i * \bar{w}_{z,e,\Gamma,g}$$

¹⁴ One possible bias of our estimation is that people may change their level of education attainment after they change jobs. This is so, because people might quit a job in order to pursue further studies or decide to study while searching for a new job. Since the CHS provides no information on level of education during previous job we assume people not only keep their same relative importance but also the same level of education attainment. *Source*: author calculations.

B. Wage losses and impact of displacement on workers' welfare

Section III above showed that in Colombia the continuous reallocation of the labor force is an important key for productivity growth. Nevertheless, the process of reallocation can span large welfare losses if displaced workers remain unemployed for long periods of time or if displaced workers are forced to accept lower paying jobs. Hence, job reallocation, particularly job destruction, can have a perverse effect on worker's welfare. This section compares displaced and non-displaced workers in terms of the impact of job loss on welfare.

1. Unemployment spells

Unemployment spells and their associated monetary losses, together with searching costs make up the first stage losses of displacement. However, since displacement involves a combination of losing an established job and the need to seek for reemployment, expected wages can also be permanently affected if losses of job-specific or firm-specific human capital increase the risk of permanently lower wages for workers. Consequently, workers can also end up "scarred" by displacement if they continue to earn less or to be unemployed for longer periods of time than their non-displaced counterparts.

For displaced and non-displaced workers we calculate average unemployment duration corresponding to the amount of time respondents report to have spent unemployed while changing jobs. Table 5 depicts summary statistics for duration of unemployment spells by sectors.

Table 5 shows similarities between unemployment spells for displaced and non-displaced workers; both vary by sector and are highly volatile. However, displaced workers present consistently larger unemployment spells than their non-displaced counterparts (except for iron and steel basic industries). On average, displaced workers from the manufacturing industry spend 12.0 months looking for a job, 2.6 months more than non-displaced workers. These results suggest that displacement scars workers, meaning that a social stigma against displacement tends to lower reemployment probabilities.

Table 5. Duration of unemployment spells by sector of origin (2001-2003), measured in months.

Sector	Mean	
	Displaced (1)	Non-Displaced (2)
Non-manufacturing sector	10.4	8.9
Food, Beverages and Tobacco (31)	13.7	10.2
Textile, Apparel and Leather (32)	11.6	10.4
Lumber (33)	9.8	5.6
Paper and Printing (34)	14.6	10.1
Chemicals (35)	11.4	8.9
Non-metallic minerals (36)	9.3	9.2
Iron and Steel basic industries (37)	6.9	7.5
Fabricated Metals and Machinery (38)	11.4	7.5
Miscellaneous (39)	12.8	7.3
Manufacturing Sector	12.0	9.4
Number of Observations	7,606	37,797

Notes: Column (1) and column (2) report sector average duration of unemployment between jobs for displaced and non-displaced workers respectively. Unemployment spells correspond to the number of months reported being jobless in between working positions by displaced workers. The minimum number of months reported for each sector was zero while the maximum was 8 years for all except one of the sectors which reported 6 years. Since the maximum allowed time to report as unemployed is 8 years, we interpreted 8 years observations as outliers and were removed to avoid biased estimations (218 observations). *Source:* author calculations.

Monetary losses from these unemployment spells correspond to potential earnings if the individual had remained employed (opportunity cost). Table 11 shows sector average monetary losses for unemployment. These were constructed using approximate wages for previous jobs (as explained in 5.1) and multiplying these with reported unemployment duration for each worker.

Table 11 shows evidence of large monetary losses from unemployment spells. For comparison, we measure those opportunity costs in terms number of minimum legal wages. These costs correspond to what the literature identifies as short term monetary losses due to temporary (in between jobs) unemployment and are interpreted as a lower bound of costs from job loss¹⁵. As we expected, displaced workers present larger monetary losses from unemployment than non-displaced workers. Both, larger unemployment duration and higher wage losses

¹⁵ Monetary losses calculated as above correspond to lower bound losses since the probability of ever finding a new job is not one.

for displaced workers, reflect on these numbers¹⁶. For workers inside the manufacturing industry, monetary losses for the displaced range between 11.1 and 31.7 minimum monthly wages, meaning that on average they lose 4.4 more minimum wages than their non displaced counterpart while unemployed in between jobs. Table 11 shows some important quantitative differences between displaced and non displaced workers: the sectors of Food, Lumber, Paper, Non-Metallic Minerals, Iron and Steel and Miscellaneous, show monetary losses for displaced workers which are more than twice than those for non-displaced ones.

Table 11. Monetary unemployment losses (Colombian 2005 pesos).

Sector	Opportunity cost (1)		Number of minimum Legal wages (2)	
	Displaced	Non-Displaced	Displaced	Non-Displaced
Non-manufacturing sectors	5,475,608	4,093,229	14.4	10.7
Food, Beverages and Tobacco (31)	7,276,860	4,637,420	19.1	12.2
Textile, Apparel and Leather (32)	4,299,977	3,840,529	11.3	10.1
Lumber (33)	3,999,109	2,051,097	10.5	5.4
Paper and Printing (34)	11,045,315	5,864,107	29.0	15.4
Chemicals (35)	6,165,613	6,112,635	16.2	16.0
Non-metallic minerals (36)	8,001,078	5,200,404	21.0	13.6
Iron and Steel basic industries (37)	11,418,648	3,343,328	29.9	8.8
Fabricated Metals and Machinery (38)	5,455,707	3,781,151	14.3	9.9
Miscellaneous (39)	4,757,515	2,755,116	12.5	7.2
Manufacturing Sector	5,862,400	4,281,835	15.4	11.2
Number of Observations	7,606	37,797	7,606	37,797

Notes: The numbers on column (1) correspond to average monetary unemployment losses and are calculated as the product between individual unemployment duration and adjusted previous wage. Column (2) is calculated by dividing the monetary unemployment loss by the monthly minimum legal wage of 2005 (381,500 Colombian pesos). *Source*: author calculations.

Monetary losses stemming from job loss refer not only to the opportunity cost of unemployment but also to permanent wage reductions. Literature on welfare costs points to wage reductions as a long-term consequence of displacement. One could think on two rationales for

¹⁶ The reported difference on months of unemployment between displaced and non displaced workers for the manufacturing sector corresponds to 27.7%. On the other hand, the reported difference for the same groups in terms number of minimum legal wages lost is 36.97%. This difference is explained average wages. On average, displaced workers have larger adjusted previous wages. Further study might tackle this issue by exploring differences on lost job characteristics between displaced and non-displaced workers.

this phenomenon. The first one is related to lower labor productivity due to loss of job specific skills. For example, a worker who is forced by displacement to seek and accept a job inside a different sector might lose specific skills that were useful in previous jobs and assured wage premiums, but are meaningless for the new sector (or job) (Kletzer, 1998). The second rationale is related to stigma effects from unemployment. If firms tend to layoff low-performance workers, or at least it is believed that they do, displaced workers might suffer from a low performance stigma, reducing their market value and forcing them to accept lower paying jobs.

Evidence for Latin America has favored the first hypothesis as a reasonable explanation for this phenomenon. Kaplan et al. (2004) found that in Mexico, qualified workers suffer from larger wage losses relative to non-qualified workers. Similarly for Brazil, Menezes Filho et al. (2003) found that long term wage losses from displacement were larger for both highly qualified workers and small firm employees, reflecting the loss of specific job skills.

We calculate long-term monetary effects of displacement as permanent wage differentials for workers. Since the CHS has no information on pre-displacement wages, we calculate approximate wage changes as the difference between reported current wages and adjusted pre-displacement salaries constructed as explained in section IV.A.1. Table 7 reports sector average wage differentials $\Delta w_i = w_i - \hat{w}_{i,z,e,\Gamma,g}$, a negative sign of this difference implies a permanent wage loss, while a positive sign implies a permanent wage gain. Table 7 summarizes our findings.

Our results indicate that permanent monthly income changes due to involuntary worker displacement imply large costs even at the two-digit sector classification of the manufacturing industry. As we expected, these losses are higher for displaced workers compared to their non displaced counterpart. On average, displaced workers from the manufacturing industry suffer permanent reductions of their monthly wages that account to 0.19 minimum legal wages; 0.15 more legal wages than non displaced workers. The wage gap is even wider for workers outside the manufacturing industry; 0.17 more legal wages.

Whether this phenomenon is due to a social stigma effect on displacement, or because of job specific skills, cannot be determined from this information. Section IV.C expands these issues.

Table 7. Average wage changes by original sector, 2001-2003. (Colombian 2005 pesos).

Sector	Displaced		Non Displaced	
	Displaced	Displaced	Displaced	Displaced
	Wage differential (1)	% minimum wage (2)	Wage differential (3)	% minimum wage (4)
Non-manufacturing sectors	-67,952	-18%	-7,935	-2%
Food, Beverages and Tobacco (31)	-48,276	-13%	-41,023	-11%
Textile, Apparel and Leather (32)	-12,839	-3%	-9,250	-2%
Lumber (33)	3,256	1%	57,777	15%
Paper and Printing (34)	-233,801	-61%	-141,352	-37%
Chemicals (35)	-250,344	-66%	-203,123	-53%
Non-metallic minerals (36)	-143,755	-38%	12,012	3%
Iron and Steel basic industries (37)	-1,116,418	-293%	-43,855	-11%
Fabricated Metals and Machinery (38)	-51,373	-13%	-58,720	-15%
Miscellaneous (39)	42,205	11%	53,028	14%
Total Manufacturing	-67,117	-18%	-13,712	-4%
Number of Observations	7,606	37,797		

Notes: Column (1) and column (3) present sector averages of wage differentials between reported current wages and adjusted CHS sector average wage, for displaced and non displaced workers respectively. Columns (2) and (4), show the corresponding fraction of a minimum legal wage of this wage differentials. This fraction is calculated by dividing the wage differential by the monthly minimum legal wage of 2005 (381,500 Colombian pesos). Reported wages are deflated by the PCI (base November 2005). *Source:* author calculations.

2. Post-displacement working conditions

The consequences of displacement on welfare depend not only on the probability of finding a new job promptly, but also on the probability of finding a similar position. Imagine two workers who face the same risk of unemployment. At time t their corresponding employers go through a restructuring process and leave them involuntarily unemployed. After a certain amount of time, one of them finds a job similar to the one lost, while the other ends up accepting a lower paying job offer. The effect on welfare is very different in both cases. For this reason, it is useful to study not only the risk of unemployment, but the conditions under which displaced workers find new jobs. This is es-

pecially true in transition economies such as Colombia, where the lack of an efficient social security system might cripple the means for an efficient job search (IADB, 2003).

What kind of jobs do displaced workers find? And do displaced workers really accept jobs with lower wages? Given data availability, we can only assess whether workers move to jobs in sectors that pay in average less than their original sectors. Table 8 shows worker mobility across sectors. The manufacturing sector with largest fraction of worker persistence is Lumber; 35% of its displaced workers remain (find a new job) in that sector after displacement. On average, only two out of ten displaced workers inside the manufacturing industry find new jobs in their previous sectors. Table 8 yields one additional result, the sector who receives the largest amount of displaced workers from the manufacturing sector belongs to the non-manufacturing industry. As Table 8 shows, on average six out of ten displaced workers in the manufacturing industry find jobs outside the industry, particularly in the Construction sector (further breakdown of this table is available upon request).

Table 8. Displaced worker mobility, 2001-2003.

Original \ Resultant	Non-manuf.	(31)	(32)	(33)	(34)	(35)	(36)	(37)	(38)	(39)	N
Non-manufacturing sectors	86%	3%	4%	1%	1%	1%	1%	0%	2%	1%	5545
Food, Beverages and Tobacco (31)	75%	14%	3%	0%	1%	1%	0%	0%	3%	1%	457
Textile, Apparel and Leather (32)	56%	2%	34%	1%	2%	3%	1%	0%	1%	1%	696
Lumber (33)	55%	3%	4%	35%	1%	1%	0%	0%	1%	1%	147
Paper and Printing (34)	58%	4%	5%	0%	27%	2%	1%	0%	3%	0%	110
Chemicals (35)	65%	3%	6%	1%	2%	20%	0%	0%	2%	1%	171
Non-metallic minerals (36)	81%	2%	1%	2%	0%	1%	10%	3%	1%	0%	126
Iron and Steel basic industries (37)	40%	0%	10%	0%	0%	0%	0%	20%	30%	0%	10
Fabricated Metals and Machinery (38)	63%	3%	8%	2%	0%	1%	2%	3%	16%	1%	212
Miscellaneous (39)	75%	5%	5%	0%	0%	1%	0%	0%	6%	9%	132
Number of Observations	6104	296	522	109	83	143	74	18	179	78	

Notes: Each figure shows percentage of workers (from total workers that originally belonged to the sector in each row) who moved to the corresponding sector in the column. *Source*: author calculations.

Worker mobility across sectors by itself is not necessarily negative for welfare. If displaced workers move to sectors that pay higher av-

erage wages, sector change can actually be welfare enhancing. However, sector change can also be associated to job-specific or firm specific human capital losses, increasing the risk of permanently lower wages for workers. To follow up this point, Table 9 shows the fraction of displaced workers who move to sectors that have a lower average wage. The number of workers who change sector is positively correlated to the number of workers who lose in terms of average income. The sector of origin with the largest fraction of workers who accept a lower paying average is: Non-Metallic Minerals, the second largest expelling sector. The sectors of Food, Textile and Lumber present low percentage of workers who move to sectors with lower average wages, which reflects the low average wages of these sectors (see Table 4).

Table 9. Percentage of displaced workers who accept lower paying jobs 2001-2003.

Sector of origin	% lower sector wage (1)	% of workers that change sector (2)	Number of Observations
Non-manufacturing sectors	9%	14%	5545
Food, Beverages and Tobacco (31)	4%	86%	457
Textile, Apparel and Leather (32)	0%	66%	696
Lumber (33)	4%	65%	147
Paper and Printing (34)	73%	73%	110
Chemicals (35)	78%	80%	171
Non-metallic minerals (36)	87%	90%	126
Iron and Steel basic industries (37)	80%	80%	10
Fabricated Metals and Machinery (38)	76%	84%	212
Number of Observations			7474
Pearson Correlation = 0,3794			

Notes: Column (1) shows percentage of workers who move to sectors with lower sector-average wage. These wages were constructed using the reported wages and corresponding sector of the occupied in the CHS. The sector with lowest sector average wage is Textile, Apparel and Leather (32), which explains the 0% reported in column (1). Column (2) shows total fraction of workers who moved to a different sector. *Source:* author calculations.

Before turning to the long-term impact of displacement, we first analyze changes in employment status. Latin America data shows that a large fraction of unemployed workers find new jobs by becoming self-employed: 28 percent in Argentina and 15.7 percent in Mexico (IADB, 2003). In contrast, only 7 percent of the unemployed become self employed in the OECD countries.

Table 10. Job status, fraction of workers, 2001-2003.

	Employee (1)	Independent (2)
Employee	62%	38%
Number of Observations		6141

Notes: The CHS classifies the occupied into five categories: private and public employee, independent worker, boss, and non-remunerated family workers. In the table above employee corresponds to both private and public employees, while independent corresponds to workers classified as independent. *Source*: author calculations.

Table 10 shows percentage of displaced workers that retain employment status. 62 percent of displaced employees in Colombia find post-displacement jobs as employees, while 38 percent change their employment status to independent workers. These results suggest that self-employment is a natural response to displacement. However, self-employment may lack some key features of regular employment, such as social security, which might translate in the long run into additional welfare costs.

Summarizing the evidence presented above, a fairly convincing case can be made that post-displacement sector changes imply lower average wages and hence long-term monetary losses. However, average-wage changes do not take into account a number of factors that determine post-displacement wages such as unemployment duration. The next section focuses on this issue.

C. Job displacement, post-unemployment wages and duration of unemployment

The goal of this section is to identify the determinants of adjustments in earnings following job change. To this end, Addison and Portugal (1989) used a post displacement earnings function. Our approach is different from theirs in two ways. First, we use an unrestricted sample that includes both displaced and non-displaced workers in order to compare both earnings equations and estimate the impact of displacement. Second, our data lacks some key variables of their specification such as previous tenure and previous earnings. For instance, we are unable to test whether the general training component of the return to tenure on the first job is fully captured by the age or experience variable, and we are unable to control for individual heterogeneity by conditioning the post-job-loss wage equation on the pre-job-loss wage.

Consider the following representation of the earnings function

$$(1) \ln(W_i) = \alpha_1 U_i + \alpha_2 \text{Tenure}_i + \alpha_3 D_{dis} + \alpha_4 D_{sec} + \alpha_5 D_{dis} * D_{sec} + x_i \beta + u_i$$

where W_i is the post-job-change monthly salary, U_i is unemployment duration of the last transition measured in months, tenure_i corresponds to experience in current job measured in months, D_{sec} and D_{dis} are dummy variables that represent the events of sector change and displacement respectively, x_i is a vector that includes both, individual characteristics such as gender, age, education and gross domestic product of corresponding geographic region to control for aggregate wage behavior in each region; and sector dummies to control for fixed industrial effects. Finally u_i is a disturbance term.

Note that in equation (1) we allow unemployment duration to affect post-job-change wages. The expected sign is not straightforward. On the one hand, the standard productive-search model predicts, given a constant reservation wage and no human capital depreciation nor stigma effects, that longer spells of unemployment tend to yield higher post-unemployment wages (Stigler, 1962). This is so because unemployment in these models is seen as the natural and optimal transition; the suitability of the employer-employee match increases with time of search. On the other hand, it is also true that unemployed workers may suffer some depreciation of their human capital (Kletzer, 1998) that coupled with stigma effects may be expected to lower wages (Addison and Portugal, 1989). This is especially true for displaced workers that can suffer from additional social stigma and might get caught in unemployment traps. Finally, a declining reservation wage will also yield a negative association between wages and duration of unemployment (Addison and Portugal, 1989)¹⁷, also less efficient searchers may find themselves unemployed for longer durations and still obtain lower wages on reemployment (Mincer, 1986).

The general approach implied by equation (1) is thus likely to provide richer insights into displacement and unemployment effects on wages.

¹⁷ Addison and Portugal (1989) mention as theoretical reason for declining reservation wages, finite lives, income constraints and exhaustion of benefits.

Our focus will be upon the estimates of the displacement, tenure and unemployment duration coefficients. Equation (1) was estimated by OLS and standard errors were corrected with White's procedure. Results are presented on Table 11, numbers in parenthesis correspond to standard errors. All coefficients are significant at the 0.05 level or better, and of the expected sign.

We find that returns to education and experience are positive as expected; the average wage increase is 7.2 percent for every year of additional tenure. Nonlinearities in age are low but significant. The average post-job-change wage of a male worker is 8.55 percent larger than for a female worker. Our more notable findings are the negative effects of displacement, sector change and unemployment duration on the post-job-change wage. We find that the post-job-change average wage decreases 5.26 percent for every year of unemployment. This result contradicts the productive-search model meaning that unemployment stigma effects and human capital depreciation seem to offset the better match outcomes associated to longer spells of unemployment.

Displacement versus job change not related to job reallocation, reduces expected post unemployment wage in 5.18 percent if the displaced worker does not change sector¹⁸. This result implies that the displacement stigma reduces expected wage. If a worker is displaced and he/she finds a job in a different sector the expected post displacement wage falls in 10.97 percent¹⁹. On the other hand, if a worker changes sector but is not displaced the reduction of the post unemployment wage is 11.86 percent. These results indicate that loss of specific skills associated to sector change translate into lower expected wages for both displaced and non displaced workers and that sector change has a larger impact on post-job-change salaries than displacement. This effect could be associated to the skills that the employer is able to perceive in the worker. If a worker changes sector the em-

¹⁸ The coefficients reported for the displacement, sector change and crossed dummies, are calculated using the antilog of numbers shown in Table 11 following the standard procedure for semi-log linear regressions.

¹⁹ Statistical significance of the total effect of displacement and sector change (the sum of the three dummies: displaced, sector change and the cross effect) was tested with an F-test, and found to be statically different from zero.

ployer can infer less information on the workers' general abilities. This means that the impact of loss of specific skills is so negative that it offsets any potential positive effects of a change of sector such as a vanished displacement stigma.

Table 11. Post-job-change wage equation.

Regressor	
Constant	10.569 (0.053)
Age	0.022 (0.002)
Age ²	-0.000 (0.000)
Male	0.082 (0.011)
Education	0.249 (0.006)
Tenure	0.006 (0.000)
Regional GDP	0.000 (0.000)
Unemployment Duration	-0.004 (0.0005)
Displaced	-0.0532 (0.0219)
Sector Change	-0.1263 (0.0123)
Displaced *Sector Change	0.059 (0.027)
R ²	0.10
Number of Observations	28,508

Note: numbers in parenthesis correspond to standard errors. All coefficients are significant at the 0.05 level. Regional and sector dummies are not reported. *Source:* author calculations.

One interesting, additional result is that the effect of sector change alone and the combined effect of sector change and displacement are statistically equal. The loss of specific skills derived from sector change seems to dominate all other effects. In brief, our results imply that on balance, depreciation and stigma effects dominate

productive search outcomes and that the loss of sector specific skills lowers expected wages.

V. Conclusions

This article measures gross creation, destruction, and reallocation of jobs inside the Colombian Manufacturing Industry between 1982 and 1998. We find that on average one in five manufacturing jobs is either destroyed or created over a twelve-month interval. These figures are similar to those reported for the United States in previous studies and reflect relatively large job flows.

We characterize job reallocation as a source of adjustment both in productivity dynamics and on workers welfare. On the one hand, job reallocation can be productivity enhancing, this is so because although managers may not be able to affect the productivity of their establishments, they may be able to perceive their relative efficiency levels, and, if they are responsive to the associated market signals, they may downsize or expand appropriately (Brown and Earle, 2003).

Consistent with previous research, we find evidence of such productivity enhancing factor reallocation. Job reallocation across manufacturing sectors represented 47% of the aggregate productivity increase of the Colombian manufacturing industry during the period 1994 to 1998. On average, 20% of productivity growth in the Colombian manufacturing industry for the period 1982 to 1998 can be attributed to job reallocation. However, job reallocation also imposes large costs on workers when forced to switch employers and shuffle between employment and joblessness. This is so, because much of the burden of reallocating jobs across regions, industries, and plants inevitably falls upon them. We find evidence of larger earnings losses for displaced workers compared to non-displaced workers inside the Colombian manufacturing industry that amount to 15 percent of the minimum legal wage. On average, displaced workers last 2.6 more months unemployed while searching for a new position than their non displaced counterparts.

We stress the importance of displacement, sector change and unemployment duration on the evolution of post-job-change wages. Our

most novel results are that the estimated decrease for each year of unemployment in the post-job-change wage is approximately 5.26 percent and that the event of displacement reduces expected post-unemployment wage (per hour) in 5.18 percent if the displaced worker does not change sector. This last result implies that the displacement stigma reduces expected wage. On the other hand, if a worker is displaced and he/she finds a job in a different sector the expected post displacement wage falls in 10.97 percent. Similarly, if a worker changes sector but is not displaced the reduction of the post unemployment wage is 11.86 percent. In brief, our results imply that on balance, depreciation and stigma effects dominate productive search outcomes and that the loss of sector specific skills lowers expected wages.

The policy implications of our results are not straightforward. Should policy favor larger flexibility in job cuts in order to allow for productivity enhancing reallocation at the cost of earning losses for displaced workers? Or should policy favor instead protection of the employed by restricting job cuts and lose potential productivity gains? Furthermore, should policy efforts move towards subsidizing displaced workers? The debate is far from settled. Although this study improves our understanding of job reallocation and its impact on the economy, in order to inform public debate and decision making, we need to know more. Matched employer-employee data with information on turnover (quits, layoffs, firings, recalls, hiring) and on the evolution of earnings is essential to move further in investigating this issue. This study merely intends to show the existence of both productivity gains and welfare costs from job reallocation, and no comparison on the magnitudes of both effects has been given. In order to reach stronger conclusions one would need a data set that links job flows to worker characteristics in order to investigate both phenomena simultaneously and avoid additional distortion stemming from differences in cycle²⁰. Although the current structure of the statistical data bases stands in the way of efforts to pool data resources, this study strongly advocates a restructuring of existing data resources that would facilitate and improve policy evaluations on the subject.

²⁰ Industrial data used in this paper correspond to an expansive period (1982-1998) for the Colombian economy, while the period of study for the household data corresponds to a recession (2001-2003). Biased results can stem from differences in cycle, hence a data set with coinciding periods of study for both phenomena is desirable.

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