# DOCUMENTOS DE TRABAJO

## Productivity Gaps and Job Flows: Evidence from Censal Microdata

Elías Albagli
Mario Canales
Chad Syverson
Matías Tapia
Juan Wlasiuk

N° 895 Diciembre 2020
BANCO CENTRAL DE CHILE

**BANCO CENTRAL DE CHILE**

**CENTRAL BANK OF CHILE**



Documentos de Trabajo del Banco Central de Chile
Working Papers of the Central Bank of Chile
Agustinas 1180, Santiago, Chile
Teléfono: (56-2) 3882475; Fax: (56-2) 3882231

**Documento de Trabajo**
**N° 895**

**Working Paper**
**N° 895**

# Productivity Gaps and Job Flows: Evidence from Censal Microdata*

Elías Albagli
Central Bank of Chile

Mario Canales
Central Bank of Chile

Chad Syverson
Chicago Booth

Matías Tapia
Central Bank of Chile

Juan Wlasiuk
Central Bank of Chile

## Abstract

A large body of work has highlighted the importance of employment reallocation as a driver of aggregate productivity growth, but there is little direct evidence on the extent and nature of this process. We use an administrative matched employer-employee census for Chile to provide novel insights on the relationship between productivity gaps between firms and job transitions. As expected, the fraction of worker flows reflecting movements from lower- to higher-productivity firms is greater than that of the opposite sign, but only marginally so. Almost half of all transitions occur "down the firm-productivity ladder." This process is also highly heterogeneous across several dimensions. Up-the-ladder flows are more likely for direct job-to-job transitions than those that pass through non-employment. They are also much more likely for young, high-skilled workers, whose job transitions comprise in an accounting sense the lion's share of aggregate productivity growth. Interestingly, workers with higher job turnover rates contribute proportionally the least to aggregate productivity growth. Put together, this evidence is suggests that the productivity benefit of job reallocation might have a net benefit, but this benefit reflects massive and heterogeneous gross flows underneath.

## Resumen

Una extensa literatura ha destacado la importancia de la reasignación de trabajadores como un motor del crecimiento de la productividad agregada. Sin embargo, existe poca evidencia de los detalles de este proceso a nivel de transiciones de empleo de trabajadores individuales. Este artículo usa un censo de datos administrativos de trabajadores-empresas para Chile para entregar nueva evidencia sobre la relación entre diferenciales de productividad entre empresas y transiciones de empleo. De acuerdo a lo esperado, la fracción de flujos de empleo hacia empresas con mayor productividad es mayor que las que ocurren en la dirección opuesta, pero solo marginalmente. Es decir, casi la mitad de las transiciones de empleo entre firmas son "hacia abajo" en términos de productividad. Este proceso también tiene un alto grado de heterogeneidad en varias dimensiones. Las transiciones hacia firmas más productivas son más frecuentes para cambios directos de empleo a empleo que para aquellos cambios que pasan por un período de no empleo. También son más frecuentes para trabajadores jóvenes y de mayores habilidades, cuyas transiciones se asocian contablemente al grueso de las ganancias agregadas de productividad asociadas a la reasignación. De manera interesante, los trabajadores con mayor rotación son los que proporcionalmente contribuyen menos al proceso de crecimiento de la productividad agregada. En resumen, estos resultados sugieren que la reasignación de empleo se asocia a ganancias netas relevantes, pero que esto esconde flujos brutos de trabajadores muy heterogéneos y de gran magnitud.

*We thank seminar participants at the Central Bank of Chile Workshop on Labor Markets and Productivity. The views expressed in this paper are exclusively those of the authors and do not necessarily reflect the position of the Central Bank of Chile or its Board members. Any errors or omissions are responsibility of the authors. Emails: ealbagli@bcentral.cl, mcanales@bcentral.cl, mtapia@bcentral.cl, Chad.Syverson@chicagobooth.edu, jwlasiuk@bcentral.cl.

# 1 Motivation

Labor markets play a key role in reallocating workers across different firms and sectors over time. The ease with which such reallocation responds to shifts in supply and demand primitives at the micro level has considerable influence on businesses' and industries' trajectories, frictional unemployment, and over longer horizons, aggregate productivity growth. On this last point, a large body of work suggests that reallocation of labor and other factors works in the "right direction"–that is, away from less productive and towards more productive firms. In aggregate, this process explains a relevant share of an economy's productivity gains (Foster et al., 2008; Syverson, 2011).

At the same time, however, substantial differences in measured productivity across firms persist. There are surely frictions that limit the speed and completeness of such reallocations.

In this paper we seek to make some headway in understanding how labor market reallocation interacts with the presence of heterogeneous-productivity firms. Through this, we can both quantify its influence on aggregate productivity growth as well as understand the frictions that limit its influence. We address several related questions along the way. First, we know net flows are in the "right" direction. Is that mostly true for gross flows too, or is there significant degree of job churning not conducive to aggregate productivity gains? Second, does the frequency of job flows towards higher productivity firms depend on the type of job flow–for instance, being different for direct job-to-job movements compared to transitions that pass through non-employment spells? Third, are there meaningful differences in such patterns across different types of workers?

We conduct our investigation by leveraging a matched employer-employee census for Chile between 2005 and 2016. Chile is an interesting case study on the dynamics of labor reallocation for several reasons. First, it is a small open economy that has a relevant exposure to relative price shocks, particularly in commodities, so alongside the influence of technological change makes the degree of labor reallocation across firms and sectors significant. In fact, Chile ranks highest among OECD countries in terms of labor turnover, with large job creation and destruction rates at the firm level and short employment spells for individual workers (Albagli et al., 2017). At the same time, as in many other countries, there is a large degree of persistent measured misallocation across Chilean firms, pointing to significant potential productivity gains through employment reallocation (Busso et al., 2013; Bergoeing et al., 2010). This poses a puzzle that leads directly to our core question: if the labor market seems to be very fluid, why are productivity differentials across firms so persistent? Do individual job transitions really correlate with productivity differentials?

Our data set allows us to track job histories of individual workers at monthly frequency and to compute annual firm-level productivity measures across all economic sectors. This enables thus enabling a detailed look into how productivity gaps across firms relate to worker flows between them, as well as a direct quantification of the relative contributions of different worker groups to aggregate productivity gains from reallocation. We highlight three main results. First, while on average individual job transitions across firms are linked to positive firm-productivity gaps and thus contribute positively to aggregate productivity growth, the fraction of all job changes that flow towards the "right" direction ("up" the productivity ladder) is only marginally higher than that occurring in the opposite direction, with almost half (48% in our preferred specification) of all job changes actually moving from higher towards lower productivity firms. This indicates that net reallocation gains in the labor market are extremely noisy and associated to a very large degree of job churning.

Second, we show that up-the-productivity-ladder transitions vary significantly across job flow types and across firm-productivity levels. Specifically, they are more likely for direct job-to-job transitions than for those passing thorough non-employment spells. This is consistent with job-search theory, in the sense that movements that result from on-the-job search should lead to better quality jobs more likely to be available at higher productivity firms. They are also more likely to occur between firms at the high end of the productivity distribution, while job transitions originating from low productivity firms having a smaller chance of moving upwards than that predicted by a completely random benchmark given by their position in the productivity distribution.

Thirdly, and to gain more insights into the nature of these results, we explore the heterogeneity across different types of workers, and quantify their relative contribution to aggregate productivity gains. Job changes lead to significantly larger and more frequent productivity gains for flows of younger workers, workers with high skills, and female workers. In fact, young, skilled workers provide the lion's share of aggregate productivity gains, while the contribution of other groups is modest or even negative. Significantly, workers at the high-end of the job turnover distribution contribute proportionally little to aggregate productivity growth. Overall, we believe this evidence questions whether a high level of job market turnover is an unequivocal sign of efficient resource reallocation leading to faster aggregate productivity growth. Put differently, it may well be the case that job reallocation in countries with labor markets exhibiting less job turnover might contribute more to aggregate productivity growth, to the extent that such reallocation is more systematically related to productivity gaps between firms.

Our paper relates to several strands of literature. The first relates to papers documenting and analyzing the existence of persistent productivity differences across firms, and the potential efficiency gains of unrealized labor reallocation (Hsieh and Klenow, 2009; Restuccia and Rogerson, 2013; Dias et al., 2016). Such work motivates the exercise we perform here, but does not give direct evidence about the nature of the reallocation process implicit in such persistent productivity gaps. A second literature looks more directly at the role of actual employment reallocation across firms as a relevant driver of aggregate productivity growth (De Loecker and Konings, 2006; Foster et al., 2008; Syverson, 2011; Melitz and Polanec, 2015). These papers are closer to the spirit of our analysis, and we add to their insights by directly quantifying up vs. down the productivity ladder flows, as well as the actual contributions to aggregate efficiency gains of different types of job-flows and worker types. A third body of evidence studies the determinants and implications of individual job transitions (Topel and Ward, 1992; Fallick et al., 2011; Davis et al., 2012; Foster et al., 2016) and, more recently, links such transitions to movements along job ladders from the perspective of workers (Menzio et al., 2016; Moscarini and Postel-Vinay, 2018; Bagger and Lentz, 2019; Lise and Robin, 2017). Our results are in general consistent with their findings, but complement them by linking evidence from the point of view of workers to that of productivity gaps between firms.

The structure of the paper is as follows. Section 2 describes our data and methodology. Section 3 presents evidence of overall efficiency gains from job flows, differentiating by job transition type and by firm of origin productivity levels. Section 4 further studies the role of heterogeneity at the worker level, and provides a direct quantification of the relative contribution of different groups to aggregate productivity-gains. Section 5 concludes.

# 2 Data and Methodology

The data comes from two main sources. First, the Chilean tax authority, SII, provides tax records for a census of Chilean firms, available between 2005 and 2016. The annual tax statement (F22) provides information on each firm's balance sheet, including data on sales, expenditures in intermediate inputs, wage bill and capital. Additionally, firms file a labor compensation report (DJ1887) that records the annual compensation paid to each employee, as well as the specific months in which he was employed at the firm. This allows us to build a matched employer-employee dataset in which, for any given month, we can identify the employment status of an individual worker and his average annual earnings, as well as properly track job transitions at a monthly frequency. Since all formal firms must report to the SII, the data covers the complete labor force with a formal wage contract, representing roughly 60% of all employment in Chile. All data are anonymized to ensure confidentiality regarding firm's and worker's identities.

To complement the tax data, we use information from the Chilean Civil Registry and Identification Service (Registro Civil e Identificación), which we match with the SII data to obtain workers' information on gender and date of birth.

We apply a set of filters over the raw data to obtain the final dataset for our empirical analysis. First, we drop from the sample all firms that have only one employee for an entire year, as it seems likely that they represent some form of self-employment rather than an actual firm with workers in the spirit of our exercise. We also drop from the sample all workers employed in those firms. Second, we want to avoid spurious job transitions, in which workers move to a "new" firm with a different tax ID that is actually directly linked with the previous firm (this includes cases in which the firm tax ID changes, M&As, or separations of a single firm into several business entities for tax purposes). We address this by excluding from the set of transitions all cases in which a significant share of a firm's workforce jointly reallocates to another firm (whether existing or new). Third, we must take a stance with workers that are employed in more than one firm at a given month, and identify their main job. We classify the main job as the one with the longest current tenure and, if two or more job have the same tenure, we choose the one with the highest average monthly earnings[1]. Finally, as we want to focus on full-time jobs but have no information on hours, we drop all job relations in which the worker gets less than the minimum wage for 80% of his tenure, as they are probably part-time jobs.

We calculate average labor productivity at the firm level as a measure of annual value added (from form F22) divided by the number of workers in a given calendar year[2],

[1]From an initial set of 48 million labor relations, we drop 8% of them as secondary relations.

[2]For consistency with the concept of labor productivity, we include all workers that were employed

weighted by the number of months in which each worker was employed (from DJ1887)[3]. Thus, average labor productivity is defined at an annual level, and remains fixed throughout the calendar year. As our arrangements imply that each employed worker has only one job relationship at every point in time, we define job transitions as changes in the identity of the worker's main relationship. Transitions can occur directly over consecutive months or indirectly over non-consecutive months. Given that our data only covers wage employment in the formal sector, we cannot refer to gaps in the worker's employment history as unemployment spells, but rather as periods of non-employment.

As we do not have data on formal education, we use workers earnings over time to classify them across skill groups. We follow the methodology proposed by Borovičková and Shimer (2017)[4], who define the workers' skill type as the expected wage he should receive in an employment relationship, conditional on accepting the job. This provides a measure of the market's valuation of the workers skills, either reflecting human capital acquired through formal education or labor market skills acquired through experience.

First, we compute the wage residual from a regression of the logarithm of monthly real earnings that worker i obtains by working in firm j on year t ($w_{ijt}$), on time-varying observable characteristics: indicator variables for the year ($d_t$), and for the age and gender of each worker ($d_{(a,g)}$), as shown in equation 1. The idea to use the wage residual as a measure to identify high and low-type workers is to remove the effects of aggregate wage growth (with time indicators) and of the age-gender wage growth profile (with age-gender indicators).

$$w_{ijt} = \beta_0 + \beta \sum_{t=2005}^{2016} d_t + \delta \sum_{a,g} d_{a,g} + \varepsilon_{ijt} \tag{1}$$

Then, we average this residual through each workers' employment history to obtain an unbiased estimator of workers' type ($\hat{\lambda}_i$) weighted by the total months worked ($t_{it}/T_N$)[5].

$$\hat{\lambda}_i = \frac{\sum_{m=1}^{M_i} t_{it}\varepsilon_{it}}{T_i} \tag{2}$$

Finally, using this measure of (lifetime) wages we rank workers in quintiles weighted by their employment share. This rank uses the distribution of all workers that were employed during the sample, and orders them according to their wage history. Given that

in the firm at any given month, regardless of whether they had multiple relationships.

[3]For robustness, we also use firm balance sheet information and the methodology in Ackerberg et al. (2015) to obtain measures of TFPR and the marginal revenue productivity of labor. While we do not present the results using this alternative definition of productivity for the sake of brevity, results throughout the paper are qualitatively similar and available upon request.

[4]Qualitative results throughout the paper are robust to simpler methodologies, such as directly comparing average labor earnings over the sample within gender-cohort groups.

[5]The only difference with Borovičková and Shimer (2017) is that we use yearly frequency data on wages and months worked to compute the worker type average.

the methodology has already removed the time component of wages, we can directly compare workers, and therefore obtain a time-invariant ranking.

We also look at worker job histories to classify workers based on their employment behavior in terms of average tenure/job turnover. In particular, controlling for age and gender, we want to distinguish between workers that have relatively few jobs (and therefore have long tenures with a small degree of turnover) and workers that have short employment spells and change jobs frequently[6]. We classify workers in five average tenure quintiles.

## 3 Job transitions and productivity sorting patterns

We begin our analysis with a very simple question: how do individual worker transitions between two firms relate to differences in labor productivity?

For each transition, we calculate a productivity gap, the difference between the log of average labor productivity in the destination firm and the log of average productivity in the initial firm. This provides a measure of the direction of any given transition - whether the worker went up or down the productivity job ladder - as well as the magnitude of the difference between both firms. Results are presented in Table 1.

Table 1: Job Transitions and Productivity Gaps

| | Average Productivity Gap (1) | p25 (2) | p50 (3) | p75 (4) | Share Upward Trans. (5) | Transitions (6) |
|---|---|---|---|---|---|---|
| ***Panel A: All transitions*** | | | | | | |
| All | 7.6 | -62.5 | 5.2 | 76.1 | 52.4 | 11,017,590 |
| Job-to-Job | 15.9 | -51.4 | 8.3 | 78.2 | 54.2 | 4,160,740 |
| Job-N-Job | 2.6 | -69.7 | 2.9 | 74.9 | 51.2 | 6,856,850 |
| ***Panel B: Yearly-adjusted productivity*** | | | | | | |
| All | 5.2 | -65.0 | 3.0 | 73.5 | 51.4 | 11,017,590 |
| Job-to-Job | 15.6 | -51.7 | 8.0 | 77.9 | 54.0 | 4,160,740 |
| Job-N-Job | -1.2 | -73.3 | -0.5 | 71.0 | 49.8 | 6,856,850 |

Note: Productivity measured as log average labor productivity. Productivity gaps are defined as the difference between the firm of destination and the firm of origin for any given job transition. "Upward transitions" are defined as job transitions with a positive productivity gap.
Source: Authors' calculations based on Chilean IRS data.

[6]In particular, we regress the job tenures for each labor relationship on worker age and gender. We then use the average residuals for each worker build a ranking of average job tenures net of age-gender effects

Panel A presents the results of this exercise across the 11 million transitions in our sample. Consistent with the notion that reallocation is a factor behind productivity growth, on the aggregate job transitions are associated to reallocation gains, with the average productivity gap between firms being 7.6%. However, this aggregate result holds an enormous degree of heterogeneity. This is clear in the large dispersion of the distribution of productivity differentials: while the 25th percentile in the distribution is associated with transitions in which workers move to a firm in which labor productivity is 62.5% smaller, the 75th percentile are transitions with a productivity gain of 76.1%. An implication of this dispersion is that the share of job transitions that move up the productivity ladder is barely above 50%: in fact, 47.6% of all transitions are to firms that are less productive than the initial firm. At a first glance, this is a striking result: while net reallocation flows are directed towards more productive firms, this process involves an enormous degree of churning. The data suggests that a relatively modest degree of productivity-enhancing reallocation requires massive gross employment flows, with a very large degree of turnover [7].

To our knowledge, there is little available evidence to contrast our results with. A notable exception is the work by Stoyanov and Zubanov (2012), who study reallocation flows for the manufacturing sector of Denmark. Their focus is different from ours, as their interest is on the potential externalities of workers from productive firms moving to less prodcutive firms, rather than provinding a comprehensive characterization of reallocation at the worker level. However, they do mention the share of upward transitions in their data –at 55%. This figure is somewhat higher than ours, but in the same ballpark as the results presented here. Theoretically, even in a frictionless world in which all job transitions were efficient, some transitions down the firm-productivity ladder might be motivated by a better firm-worker match, and/or from other non-pecuniary motives that might drive worker reallocation across different firms. Nonetheless, the fact that the frequency of upward flows is only marginally higher than that of a completely random reallocation benchmark –a 50% unconditional change of moving up or down the firm-productivity ladder– strikes us as rather surprising, and probably warrants more work in this area to the extent that micro data allowing such computations becomes increasingly available in other countries.

The presence of search frictions in the reallocation process provides an additional insight. Direct job-to-job transitions, in which the worker changes jobs in consecutive months, are likely to represent voluntary movements to better matches, consistent with the idea of on-the-job search introduced by Burdett and Mortensen (1998). To the extent that match qualities correlate positively with measures of firm-level productivity, there should be a link between direct job-to-job transitions and the notion that workers can move upwards through a productivity ladder. On the other hand, the outcome of indirect job transitions, in which the worker goes through a non-employment spell, is likely to be more uncertain[8] A non-employed worker that experienced an involuntary separation might end up accepting a worse match than his previous job, as long as it satisfies his

[7]As mentioned earlier, we make the same exercise using other measures of labor productivity, such as the Marginal Revenue Productivity of Labor (MRPL) obtained using the estimates of TFPR derived methodology in Ackerberg et al. (2015), as well as measures of average labor productivity demeaned by sector averages and year effects. Results are qualitatively the same and available upon request.

[8]Recall that our data only identifies employment in the formal sector. Therefore, we cannot identify whether an employment gap is associated to unemployment, a job in the informal sector, or the worker dropping out of the labor force.

reservation wage. Thus, the correlation between indirect transitions and productivity-enhancing reallocation is likely to be weaker.

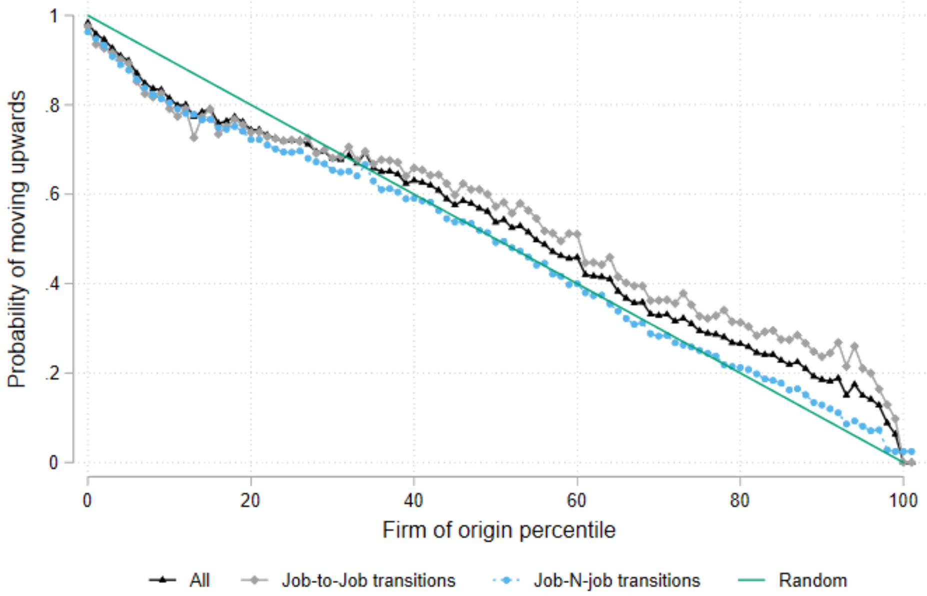
The results in Table 1 confirm this intuition. Job-to-job transitions, which account for 37% of all transitions in our sample, are associated to larger average productivity gaps, and the whole distribution of productivity differentials shifts to the right. In fact, job-to-job transitions account for almost 80% of the aggregate productivity gains, providing credence to the notion that workers that change jobs directly are more likely to climb productivity ladders. However, the share of upward transitions, while larger, is still relatively close to 50%, indicating that even for direct transitions the reallocation process is very noisy, and associated to large turnover.

Panel B addresses a potential concern on the previous exercise. As discussed earlier, our data defines firm productivity by calendar years. Therefore, transitions that occur between calendar years compare productivity measures across different points in time. The secular growth of aggregate productivity across time implies that the true productivity gaps for year-to-year transitions can be overestimated. Therefore, we adjust productivity across years by accounting for annual productivity growth. As expected, average productivity gaps are smaller for both groups, although the effect is much more important for indirect transitions, for which productivity gaps from reallocation now become slightly negative.

To have a better assessment on whether job transitions relate systematically to productivity enhancing reallocation, and to see whether reallocation patterns vary across firms with different productivity levels, Figure 1 looks at worker transitions along the productivity distribution of their initial firms. If reallocation movements across firms were entirely unrelated to productivity differentials, job transitions should move along the 45-degree line that starts from the origin, as the conditional likelihood of moving to a more productive firm would (mechanically) only depend on the productivity percentile of the worker's initial firm. This is, if conditional reallocation was completely random, a worker employed in the median firm would have exactly the same chance of moving up or down the productivity ladder. As the figure shows, actual reallocation patterns depart from the random benchmark, but rather modestly so, and vary significantly along the productivity distribution. Movements up the productivity ladder are more frequent among workers employed in firms in the upper half of the productivity distribution, especially those in the upper 20%, implying that reallocation is more intense among more productive firms. In contrast, workers moving at the lower tail of the productivity distribution are more likely to move downwards the productivity ladder than if they moved randomly.

It is also interesting to notice that, in the bottom end of the distribution, job-to-job and indirect transitions look virtually identical: there seems to be no systematic difference between changing jobs directly or indirectly in terms of the likelihood of moving up the productivity ladder. Conversely, job-to-job transitions look very different from indirect transitions at the upper end of the productivity distribution. While for workers in high-productivity firms indirect transitions lie (almost) along the random reallocation benchmark, job-to-job transitions have a much higher likelihood of leading to movements up the job ladder. This also indicates that poaching is operating within the set of more productive firms, with important productivity-enhancing job-to-job flows between firms

Figure 1: Conditional probability of moving to a more productive firm




Note: Job transitions are sorted by labor productivity of the firm of origin. For each percentile of this distribution, the figure plots the share of transitions to a more productive firm.
Source: Authors' calculations based on Chilean IRS data.

in the first two deciles of the productivity distribution.

# 4 Individual job transitions and worker heterogeneity

The previous section provided a general overview of reallocation flows across the universe of individual transitions, and characterized how these patterns varied along different types of transitions and the productivity distribution of firms. We now take an additional step and provide evidence on the way in which heterogeneity across workers relates to systematic differences in the reallocation process.

## 4.1 Reallocation patterns by worker groups: firm-level evidence

To get a first glance at the role of worker heterogeneity in employment transitions and productivity gaps, we replicate the exercise in Haltiwanger et al. (2018), who look at job-to-job flows between low and high productivity firms in the US across different worker categories. This provides an analysis at the firm level, rather than at the worker level as the rest of the papers, but provides some insights that can motivate the latter part of our analysis.

Haltiwanger et al. (2018) classify firms in productivity quintiles, and focus on net job-to-job flows at low productivity firms (firms in the first quintile) and high productivity flows (firms in the fifth quintile). Their results show that net job-to-job flows are consistent with productivity-enhancing reallocation: they are negative for low productivity firms - on the net, their workers are being poached by other firms -, while they are pos-

Table 2: Poaching Patterns by Worker Types

| | Share in the economy | **Low Productivity** Net Job-to-job | **Low Productivity** Ratio | **High Productivity** Net Job-to-job | **High Productivity** Ratio |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| ***Panel A: by age*** | | | | | |
| Less than 25 | 13.0 | 25.7 | 1.98 | 14.1 | 1.08 |
| Age 25 - 34 | 31.1 | 45.3 | 1.46 | 47.1 | 1.52 |
| Age 35 - 44 | 26.5 | 20.3 | 0.77 | 24.6 | 0.93 |
| Age 45 or older | 29.4 | 8.8 | 0.30 | 14.2 | 0.48 |
| ***Panel B: by workers' type*** | | | | | |
| Low wage | 23.4 | 11.7 | 0.50 | 7.7 | 0.33 |
| Q2 | 23.3 | 27.7 | 1.19 | 21.1 | 0.90 |
| Q3 | 20.6 | 32.7 | 1.59 | 31.5 | 1.53 |
| Q4 | 17.3 | 27.9 | 1.62 | 39.8 | 2.30 |
| High wage | 15.4 | 10.9 | 0.71 | 37.9 | 2.47 |

Note: Following Haltiwanger et al. (2018), we define High (Low) productivity firms as the top (bottom) quintile in the firms' labor productivity distribution and estimate net poaching (job-to-job) transitions by age and skill categories.
Source: Authors' calculations based on Chilean IRS data.

itive for high productivity firms. However, poaching from high-productivity firms is not homogeneous across all types of individuals, but focused on younger and educated workers.

Patterns for Chile are very similar to their results, which indirectly also provides a check on the validity of our data. Consistent with the evidence for the US, net job-to-job flows are negative (positive) for low (high) productivity firms across all worker categories, reinforcing the idea that on the net reallocation enhances productivity, as documented in the previous section. More interestingly, as presented in Table 2, poaching is far from being uniform across all workers.

Panel A presents poaching patterns across 4 age groups: workers younger than 25, workers between 25 and 34, workers between 35 and 44, and workers older than 45. Column (1) presents the share of total employment by these age groups, while Column (2) presents the distribution of workers that are poached away from low-productivity firms. The age distribution of workers poached from low-productivity firms is very different from the age distribution of employment, as reflected in the ratios in Column (3). 70% of workers that are poached away are younger than 35, although this group only represents 43% of employment. Workers over 45, who are almost 30% of employment, represent a scanty 8% of the workers that are poached. Poaching from high-productivity firms, presented in Columns (4) and (5), tells a similar story, with more than 60% of poached workers being younger than 35.

Panel B focuses on workers with different skills, as proxied by the lifetime-earnings quintiles defined in Section 2. Once again, poaching patterns are far from homogeneous. Poaching efforts from high-productivity firms clearly focus on workers from the upper half of the skills distribution, while worker losses for low-productivity firms are concentrated on the medium-part of the skills distribution.

Overall, the results in Table 2 indicate that worker heterogeneity can lead to systematic differences in reallocation patterns. These differences are consistent with existent theory and evidence on labor market dynamics, and are similar to the evidence found for the US in Haltiwanger et al. (2018).

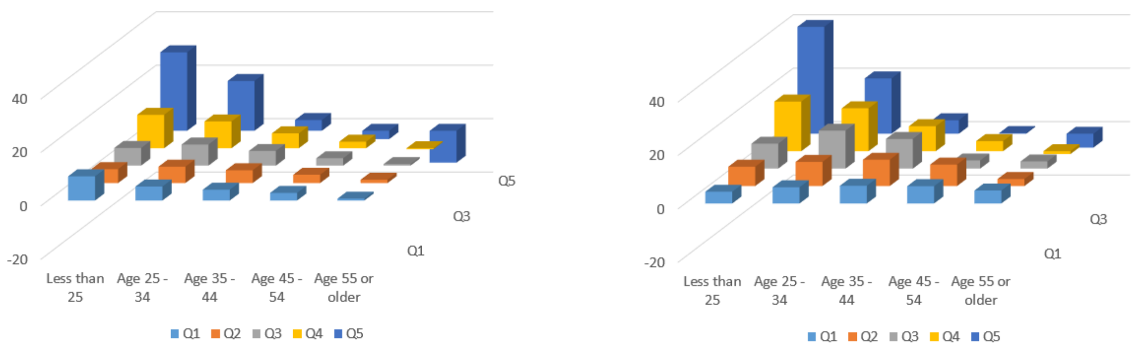
## 4.2 Reallocation patterns by worker groups: worker-level evidence

A long literature (Topel and Ward, 1992; Menzio et al., 2016; Lagakos et al., 2018) has analyzed the importance of the life-cycle of workers in understanding employment dynamics and the evolution of earnings. Job mobility is larger at the early stages of the employment life-cycle, a fact that is consistent both with the notion that young workers are starting to build up their job ladders and with the idea that transitions are relatively costless as they have not accumulated a significant amount of sector or firm-specific human capital. Additionally, the growth in lifetime earnings is specially strong in the first decade, a result that points to rapid accumulation of skills and the ability to rapidly move towards better jobs. Workers on the second half of their work life, on the other hand, move significantly less, experience flatter earnings profiles, and can suffer significantly from job displacement, as they lose human capital/fall down the job ladder, and do not have enough time left to recover. Therefore, it is not surprising that younger workers play a leading role in the process of reallocating employment towards more productive firms. Similarly, there are various reasons for which movements up the productivity ladder might be more likely for workers in the upper end of the ability distribution. For example, complementarities between high-productivity firms and high-skilled workers will naturally lead to sorting as an equilibrium outcome.

To complement our novel results on job transitions on the previous section with worker characteristics, we classify workers across five age groups (less than 25, 25-34, 35-44, 45-54, more than) and, as before, across skills quintiles. We use this classification to define 25 age-skills groups. We take advantage of our data to introduce one additional dimension, and further divide the sample between men and women. This is an interesting dimension for an economy like Chile, in which the gender wage gap is large and female labor participation, while growing, is still low.

Figure 2: Productivity gaps by worker characteristics

(a) Males (b) Females




Note: The figure plots average productivity gaps resulting from job transitions, averaged by worker type group.
Source: Authors' calculations based on Chilean IRS data.

Figure 2 presents a graphical representation of the average productivity gaps associated to the job transitions of workers in the gender-age-skill groups. Differences across groups are striking. Consistent with our prior, productivity differentials are significantly larger for young, skilled workers, being the largest for workers younger than 35 in the top skill quintile. Productivity gaps decline monotonically with age, becoming almost negligible for workers over 45. Productivity differentials are very negative for high-skilled male workers over 55, a result that reflects that a large share of those transitions are non-voluntary, and associated to the destruction of valuable job ladders. Interestingly, productivity gaps are consistently larger for female workers, suggesting a systematic gender-based difference in the process of labor reallocation.

Overall, the results in this section indicate that job transition patterns vary significantly across workers, with productivity-enhancing reallocation being the strongest - by a significant margin - among young, high-skilled workers. We now use these results to provide a decomposition of productivity gains from reallocation, identifying the relative contribution of each group.

## 4.3 Taking stock: decomposing aggregate gains from job reallocation across different groups

Table 3 presents the contributions of different worker groups to aggregate reallocation gains in the economy. To the best of our knowledge, this decomposition of aggregate reallocation across worker characteristics is novel to the literature, and provides a quantitative assessment of the microeconomic structure that underlies macroeconomic reallocation. Column (1) decomposes the economy's average productivity gain from job transitions (7.56%) into the absolute contributions of age groups (Panel A), worker skill quintiles (Panel B) and gender (Panel C). Panel D incorporates information from the worker's job history, and sorts workers in terms of their average job tenure.

For each worker category, we calculate the contribution as the group-specific average productivity differential from job transitions weighted by the group's share in the total number of job transitions in the economy. Column (2) presents the relative importance of each group for total reallocation, while Column (3) is each group's share of job transitions. Column (4) is the ratio of (2) and (3), which by construction also equals the group's average productivity differential relative to the aggregate differential. As suggested by the analysis in Figure 2, there is a very large degree of heterogeneity across different types of workers. Almost half of the economy's reallocation gains are associated to the job transitions of young workers between 25 and 34 years old, a number that jumps to almost 80% when the youngest group (under 25) is included: productivity-enhancing reallocation is a young person's game. Job transitions of workers over 45 year old contribute a meager 4,7% , once again reflecting the fact there is a very strong life-cycle effect over reallocation patterns, such that transitions are actually associated to negative average differentials for workers over 55.

Column (4) highlights, as indicated earlier by Figure 3, that these results do not only reflect that the mobility of workers younger then 35 is higher and they are therefore associated to a larger share of overall job transitions (53.6%). Younger workers experience transitions with larger average productivity differentials, an outcome that declines monotonically with age. Young workers sustain productivity-enhancing reallocation on the aggregate because they move more frequently across jobs and because, conditional on moving, they are more likely to move to a firm with larger productivity[9]. As discussed in the previous section, these age-specific reallocation patterns closely relate to the literature on life cycle income profiles (Lagakos et al., 2018; Menzio et al., 2016), which highlights that wage gains - likely associated to a significant extent with successful job transitions towards better matches- are especially relevant over the first decade of work experience.

The decomposition by worker skills shows that 53.4% of all reallocation gains come from the top two quintiles, although they only represent 37.6% of transitions. In fact, although workers in the top quintile move relatively infrequently (accounting only for 16% of all transitions), they explain more than a quarter of aggregate productivity gains. As shown in Column (4), average productivity differentials are positive for all quintiles, but they grow monotonically along the skills ladder, highlighting that, conditional on switching jobs, more skilled individuals are more likely to move to a firm with larger labor productivity[10]. These patterns highlight the importance of productivity job ladders, especially among more skilled individuals, as a relevant driver of reallocation in the economy.

The third panel replicates the exercise distinguishing between male and female workers, and finds that although female workers represent only 20.7% of job transitions in the economy, they account for 30.3% of aggregate productivity gains from reallocation.

Finally, the fourth panel looks at the contribution of workers with different average tenures across their employment history. Workers on the first two quintiles, which have relatively short employment spells and tend to change jobs frequently, account for 61% of all transitions[11]. However, they only account for 32% of total reallocation gains. The bulk

[9] As mentioned earlier, they are also more likely to move directly through job to job transitions.

[10] This is also reflected in the fact that they are more likely to move to a new job directly.

[11] The relationship between average tenure and turnover, while negative, is not perfect, as workers with short tenures can also have longer non-employment spells and therefore hold fewer jobs. That explains

Table 3: Decomposition of Average Productivity Gains from Reallocation

| | Weighted average productivity gains | Share of productivity gains | Share of job transitions | Gains to Transitions Ratio |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| ***Panel A: by age*** | | | | |
| Less than 25 | 2.24 | 29.2% | 18.3% | 1.59 |
| Age 25 - 34 | 3.73 | 48.5% | 35.3% | 1.38 |
| Age 35 - 44 | 1.35 | 17.6% | 24.8% | 0.71 |
| Age 45 - 54 | 0.40 | 5.2% | 15.4% | 0.33 |
| Age 55 or older | -0.04 | -0.5% | 6.2% | -0.08 |
| Total | 7.69 | | | |
| ***Panel B: by worker skill quintiles*** | | | | |
| Low skill | 0.64 | 8.4% | 15.4% | 0.54 |
| Q2 | 1.34 | 17.5% | 24.3% | 0.72 |
| Q3 | 1.60 | 20.8% | 22.8% | 0.91 |
| Q4 | 2.10 | 27.3% | 21.6% | 1.26 |
| High skill | 2.01 | 26.2% | 16.0% | 1.63 |
| Total | 7.69 | | | |
| ***Panel C: by gender*** | | | | |
| Male | 5.36 | 69.7% | 79.3% | 0.88 |
| Female | 2.33 | 30.3% | 20.7% | 1.46 |
| Total | 7.69 | | | |
| ***Panel D: by job tenure quintiles*** | | | | |
| Short job tenure | 0.89 | 11.6% | 28.8% | 0.40 |
| Q2 | 1.65 | 21.4% | 32.2% | 0.67 |
| Q3 | 2.12 | 27.5% | 22.9% | 1.20 |
| Q4 | 2.30 | 29.9% | 13.7% | 2.19 |
| Long job tenure | 0.74 | 9.6% | 2.5% | 3.81 |
| Total | 7.69 | | | |

Note: Productivity measured as log average labor productivity. Weighted average productivity gains is group's average productivity gaps weighted by the group's share in total job transitions.
Source: Authors' calculations based on Chilean IRS data.

of reallocation comes from quintiles 3 and 4, who contribute 57.4% of all gains although they only represent 36.4% of job movements. Workers on the fifth quintile by definition seldom change jobs, and therefore represent a meager 2.5% of job transitions in the economy. Despite this, they provide almost 10% of the overall productivity gains. This is shown more clearly by the gains-to-transitions ratio, which increases strongly along the tenure groups, even more so than across skill levels. Average productivity gains associated to workers that hold on longer to their jobs are much larger than gains from workers who change jobs frequently, highlighting that very active job churning might not be an indicator of productive reallocation.

# 5 Conclusions

The evidence in this paper provides a complete and novel characterization of the relationship between individual job transitions and the aggregate process of employment reallocation that increases productivity by moving workers towards more productive firms. Our results suggests that this process has a complex structure, and that labor market's ability to reallocate workers away from less productive and into more productive firms involves an enormous amount of labor turnover, with a very large share of job transitions not leading to productivity gains. Productivity-enhancing job transitions are not uniformly distributed, but exhibit significant and systematic differences across the distribution of firms and workers, drawing more heavily from young, high-skill workers. Moreover, workers who churn jobs more frequently contribute proportionally the least to productivity growth from labor reallocation, stressing that a highly fluid labor market need not be an unequivocal sign of economy-wide efficiency gains.

why workers in the second tenure quintile have slightly more transitions than workers in the first quintile.

# References


**Ackerberg, Daniel A, Kevin Caves, and Garth Frazer**, "Identification properties of recent production function estimators," *Econometrica*, 2015, *83* (6), 2411–2451.

**Albagli, Elías, Alejandra Chovar, Emiliano Luttini, Carlos Madeira, Alberto Naudon, and Matias Tapia**, "Labor Market Flows: Evidence from Chile Using Micro Data from Administrative Tax Records," *Working Papers Central Bank of Chile*, 2017, *812.*

**Bagger, Jesper and Rasmus Lentz**, "An empirical model of wage dispersion with sorting," *The Review of Economic Studies*, 2019, *86* (1), 153–190.

**Bergoeing, Raphael, Facundo Piguillem, and Norman V Loayza**, *Why are developing countries so slow in adopting new technologies? The aggregate and complementary impact of micro distortions*, The World Bank, 2010.

**Borovičková, Katarína and Robert Shimer**, "High wage workers work for high wage firms," Technical Report, National Bureau of Economic Research 2017.

**Burdett, Kenneth and Dale T Mortensen**, "Wage differentials, employer size, and unemployment," *International Economic Review*, 1998, pp. 257–273.

**Busso, Matías, Lucia Madrigal, and Carmen Pagés**, "Productivity and resource misallocation in Latin America," *The BE Journal of Macroeconomics*, 2013, *13* (1), 903–932.

**Davis, Steven J, R Jason Faberman, and John Haltiwanger**, "Labor market flows in the cross section and over time," *Journal of Monetary Economics*, 2012, *59* (1), 1–18.

**Dias, Daniel A, Carlos Robalo Marques, and Christine Richmond**, "Misallocation and productivity in the lead up to the Eurozone crisis," *Journal of Macroeconomics*, 2016, *49*, 46–70.

**Fallick, Bruce, John Haltiwanger, and Erika McEntarfer**, "Nonemployment Duration and the Consequences of Job Separations," *Unpublished. Accessed November*, 2011, *15*, 2011.

**Foster, Lucia, Cheryl Grim, and John Haltiwanger**, "Reallocation in the great recession: cleansing or not?," *Journal of Labor Economics*, 2016, *34* (S1), S293–S331.

**_ , John Haltiwanger, and Chad Syverson**, "Reallocation, firm turnover, and efficiency: Selection on productivity or profitability?," *American Economic Review*, 2008, *98* (1), 394–425.

**Haltiwanger, John, Henry Hyatt, and Erika McEntarfer**, "Who moves up the job ladder?," *Journal of Labor Economics*, 2018, *36* (S1), S301–S336.

**Hsieh, Chang-Tai and Peter J Klenow**, "Misallocation and manufacturing TFP in China and India," *The Quarterly Journal of Economics*, 2009, *124* (4), 1403–1448.

**Lagakos, David, Benjamin Moll, Tommaso Porzio, Nancy Qian, and Todd Schoellman**, "Life cycle wage growth across countries," *Journal of Political Economy*, 2018, *126* (2), 797–849.

**Lise, Jeremy and Jean-Marc Robin**, "The macrodynamics of sorting between workers and firms," *American Economic Review*, 2017, *107* (4), 1104–35.

**Loecker, Jan De and Jozef Konings**, "Job reallocation and productivity growth in a post-socialist economy: Evidence from Slovenian manufacturing," *European Journal of Political Economy*, 2006, *22* (2), 388–408.

**Melitz, Marc J and Sašo Polanec**, "Dynamic Olley-Pakes productivity decomposition with entry and exit," *The Rand Journal of Economics*, 2015, *46* (2), 362–375.

**Menzio, Guido, Irina A Telyukova, and Ludo Visschers**, "Directed search over the life cycle," *Review of Economic Dynamics*, 2016, *19*, 38–62.

**Moscarini, Giuseppe and Fabien Postel-Vinay**, "The cyclical job ladder," *Annual Review of Economics*, 2018, *10*, 165–188.

**Restuccia, Diego and Richard Rogerson**, "Misallocation and productivity," *Review of Economic Dynamics*, 2013, *16* (1), 1–10.

**Stoyanov, Andrey and Nikolay Zubanov**, "Productivity spillovers across firms through worker mobility," *American Economic Journal: Applied Economics*, 2012, *4* (2), 168–98.

**Syverson, Chad**, "What determines productivity?," *Journal of Economic literature*, 2011, *49* (2), 326–65.

**Topel, Robert H and Michael P Ward**, "Job mobility and the careers of young men," *The Quarterly Journal of Economics*, 1992, *107* (2), 439–479.

| **Documentos de Trabajo**<br>**Banco Central de Chile** | **Working Papers**<br>**Central Bank of Chile** |
|---|---|
| NÚMEROS ANTERIORES | PAST ISSUES |
| La serie de Documentos de Trabajo en versión PDF puede obtenerse gratis en la dirección electrónica:<br><br>www.bcentral.cl/esp/estpub/estudios/dtbc.<br><br>Existe la posibilidad de solicitar una copia impresa con un costo de Ch$500 si es dentro de Chile y US$12 si es fuera de Chile. Las solicitudes se pueden hacer por fax: +56 2 26702231 o a través del correo electrónico: bcch@bcentral.cl. | Working Papers in PDF format can be downloaded free of charge from:<br><br>www.bcentral.cl/eng/stdpub/studies/workingpaper.<br><br>Printed versions can be ordered individually for US$12 per copy (for order inside Chile the charge is Ch$500.) Orders can be placed by fax: +56 2 26702231 or by email: bcch@bcentral.cl. |

DTBC – 894
**The potential impact of financial portability measures on mortgage refinancing: Evidence from Chile**
Carlos Madeira

DTBC – 893
**Macroprudential Policy and the Inward Transmission of Monetary Policy: the case of Chile, Mexico, and Russia**
Georgia Bush, Tomás Gómez, Alejandro Jara, David Moreno, Konstantin Styrin, Yulia Ushakova

DTBC – 892
**Labor Earnings Dispersion in Chile: Decomposition, Dynamics and the Role of Firms**
Rosario Aldunate, Gabriela Contreras, Matías Tapia

DTBC – 891
**Determinantes del rating soberano: el caso de Chile**
Natalia Gallardo, Mauricio Hitschfeld

DTBC – 890
**The impact of the Covid public policies on the Chilean households**
Carlos Madeira

DTBC – 889
**Surveying the survey: What can we learn about the effects of monetary policy on inflation expectations?**
Michael Pedersen

DTBC – 888
**Does the Exposure to the Business Cycle Improve Consumer Perceptions for Forecasting? Microdata Evidence from Chile**
Fernando Faure, Carlos A. Medel

DTBC – 887
**Railroads, specialization, and population growth in small open economies: Evidence from the First Globalization**
Andrés Forero, Francisco A. Gallego, Felipe González, Matías Tapia

DTBC – 886
**High Dimensional Quantile Factor Analysis**
Andrés Sagner

DTBC – 885
**Heterogeneous Paths of Industrialization**
Federico Huneeus, Richard Rogerson

DTBC – 884
**Does the Commodity Super Cycle Matter?**
Andrés Fernández, Stephanie Schmitt-Grohé, Martín Uribe

DTBC – 883
**Twitter-Based Economic Policy Uncertainty Index for Chile**
Andrés Sagner, Juan Sebastián Becerra

DTBC – 882
**Corporate-Sector Functional Currency: An International Comparison**
Jorge Fernández, Fernando Pino, Francisco Vásquez

DTBC – 881
**Back testing fan charts of activity and inflation: the Chilean case**
Jorge Fornero, Andrés Gatty

BANCO CENTRAL
DE CHILE