Sudden Firm Closures and the Effects on Displaced Workers

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January 15, 2019

Overview

Motivation and Literature

Motivation

Involuntary unemployment spells can have significant costs in terms of wages and probability of future employment.

Several potential mechanisms could explain this result

- Job-specific abilities/match quality are lost: destruction of a job ladder
- Finding a new job takes time, and unemployment spells depreciate human capital
- Negative signaling

However, identification can pose a problem

Literature

Wage effects of firm closures and/or massive layoffs

- Jacobson, LaLonde y Sullivan (AER 1993): seminal identification strategy to study the impact of displacement and alleviate selection bias using massive layoffs that might unrelated to individual workers
- At least 15 published papers used variations of this methodology with data for the US, UK, Portugal, Norway and others
- Active research topic: Flaaen, Shapiro & Sorkin (NBER Nov. 2017), Lachoska, Mas, Woodbury (NBER Jan. 2018)

In general, wage effects are large and persistent (but control groups are crucial (Krolikowski, 2017)).

Definition of the displacement event is also crucial: massive layoffs/firm closures can be anticipated, and affect the composition of the firm's workforce at the moment of displacement.

This paper

This paper tries to make three contributions to this literature

1. Distinguish between unexpected and expected displacements by looking at different types of firm closures.
2. Explore the sources of income losses: heterogeneity across workers and firms characteristics.
3. As far as we know, this is the first paper that analyzes the effects of displacement using data for a developing country.

Overview of main results

Consistent with the previous literature, job displacements are associated to significant and persistent income losses.

However, wage losses vary significantly by characteristics of the displacement event: job losses associated to sudden firm closures are much larger than those found with the standard measure.

Differences in wage losses across worker types appear to be consistent with ideas on human capital specificity/idiosyncratic match quality.

Data

Data I

We use administrative data from Chile's Internal Revenue Service (Servicio de Impuestos Internos, SII), that has unique identifiers for both workers and companies, allowing us to track individuals and firms over time (2005-2017).

Identifiers are anonymized to guarantee confidentiality. All formal firms in the country must report to the SII, so the data is a census of all firms and the complete labor force with a formal wage contract in Chile.

Data II

Each firm must present an annual statement to the SII reporting the sum of wages, overtime wages, labor earnings and any other similar form of income (excluding disability, pensions and retirement payments) for each individual worker with a labor contract.

While the statement (and the income information) is annual, firms must also report the specific months in which a worker was employed in the firm.

Thus, for any given month, we can identify the employment status of an individual worker, and a measure of her average monthly labor income in that year. From the firm side, we can identify the composition of its workforce and wage structure at any particular month.

Data III

Given that we only observe workers when they are employed in a firm, "unemployment" is strictly non-employment in the formal sector. Thus, it can include actual unemployment, inactivity, self employment, informal employment, etc.

The data also contains information on the firm's economic sector. Firms also report information on variables such as sales, intermediate costs, and capital, which can be used to calculate measures of productivity.

Data IV

Tax records do not provide information on worker characteristics. However, we merge the data on workers income and employment status with data from Chilean Civil Registry and Identification Service (Registro Civil e Identificacion) to get information on gender and date of birth.

To preserve the confidentiality of individual tax statements, we never have access to the real firm and worker identifiers (RUTs) in the tax records. SII directly provides the data to the Central Bank with fake identifiers. Merges with other datasets are done directly by SII with the same fake identifiers.

Data IV

Over the complete dataset, we do some additional work:

- For each worker, we define a unique main relationship at any point in time (the one with highest wage)
- Firms with less than 10 workers are dropped
- We try to distinguish actual firm closures from events that look like M&As, in which a significant share of the closing firm's workforce is immediately reallocated in a new firm.

Monthly data is grouped into quarterly data, to generate a full industry coverage linked employer-employee panel for 2005-2017 period on quarterly basis. The annual average number of workers is 5.573.031, employed on average in 252.896 firms.

Identification & results

Estimation strategy

The JLS 1993 seminal paper for displacement literature set the first identification strategy based on a difference in difference feature:

$$E(w_{it}|D_{i,s}=1,I_{i,s-p})-E(w_{it}|Di_{i,v}=0)$$

w_{it}: Earnings of worker i at date t
$D_{i,s}=1$ if worker i was displaced at date s ($D_{i,s}=0$ otherwise)
$I_{i,s-p}$: information available at date $s-p$

Estimation strategy

The estimation strategy developed by JLS 1993 and described in equation 1, will be the basis for all estimations in this paper.

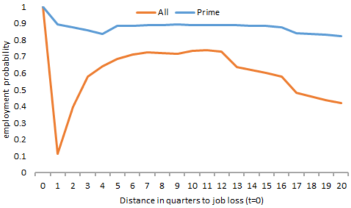
$$w_{it} = \alpha_i + \gamma_t + \beta X_{it} + \sum_{k=-m}^{t} D_{it}^{k} \delta_k + \epsilon_{it} \quad (1)$$

w: Log of the wage received by worker i at period t
α: Worker fixed effect
γ: Time effect
X: Vector of workers observable characteristics (gender and age)
D_k: Dummy representing the distance of the current observation with respect to the displacement event
δ_k: Percentage wage loss or gain k periods before or after displacement, with respect to the control group

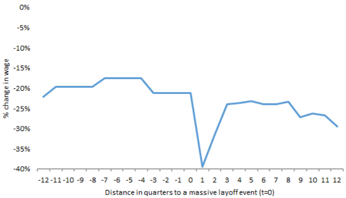
To get a first look at the data, we begin by looking at all job separations. This, all events in which workers that were employed in a given firm in quarter $t-1$ but not in t. We estimate wage effects and employment probability for all workers and a subsample of prime age male workers (25-55 years old). Of course, identification is not clear in this case, as probably most of these transitions are endogenous.

(a) Wage impact

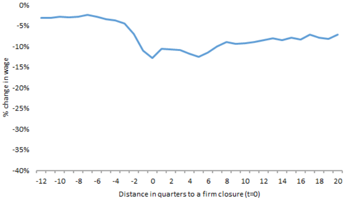
(b) Employment probability impact



(a) Jacobson, LaLonde y Sullivan, 1993



(b) Schwerdt, 2011



The standard approach can be potentially problematic in various dimensions:

1. Control groups including workers that have never been displaced
2. Does not clearly distinguish between early leavers and sinking ship workers
3. Does not identify the informational content associated to firm closures

Our identification strategy

Treatment group

On the firm side:

- Firm closes (this is, it disappears from the dataset)
- Firm must have, at the moment of closure, at least ten workers

On the worker side

- Worker must have at least 12 quarters of tenure at the time of separation
- Worker must leave the firm up to 8 quarters before firm closure
- Worker must be reemployed by the end of sample (2017)

Control group

Workers that are not displaced at the same time as the treatment group but could be displaced in other quarters and have 12 quarters of continuously positive wage in any firm.

Firm closures

We allow for two definitions of firm closure

- **Normal closure**. A firm is observed in period t for the last time
- **Sudden closure**. A firm had no decline on total employment from four quarters before closure until its closing quarter

Basic Stats

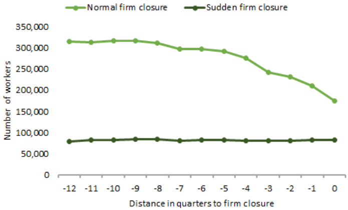
	Treatment (all closures)	Treatment (sudden closures)	Control
Firms			
Observations	4,383	1,511	64,272
Employment (mean)	50	63	82
Wage paid (mean)	465,522	409,227	571,054
Agriculture (share)	9%	11%	10%
Manufacture (share)	14%	14%	11%
Construcion (share)	14%	18%	10%
Wholesale (share)	20%	18%	20%
Professional activities (share)	8%	7%	9%
Workers			
Observations	108,382	42,291	4,811,766
Males (%)	69%	73%	68%
Age (mean)	40.8	40.1	40.8
Wage received (real 2017 CLP, mean)	638,926	671,227	751,821
Tenure (quarters, mean)	19	18	12

Sample characteristics at the closing quarter for treatment groups and sample mean 2008-2014 for control group

Firm leaving timing

As documented by Schwerdt (2011), identification on treatment can be troublesome if the composition of the firm's workforce changes prior to displacement

Figure: Total employment in closing firms

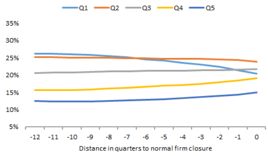


Two effects may arise.

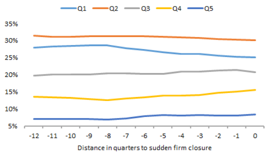
- High-skilled workers, with better job market prospects, might start actively looking for a new job, jumping out the ship as soon as a good chance emerges (get a new job with a similar wage)
- The troubled firm might try to improve its prospect by firing its less productive workers, or those for which firing costs are smaller.

Worker composition by firm type (wage quintiles)

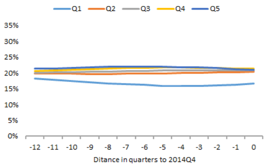
(a) Normal closure firms



(b) Sudden closure firms



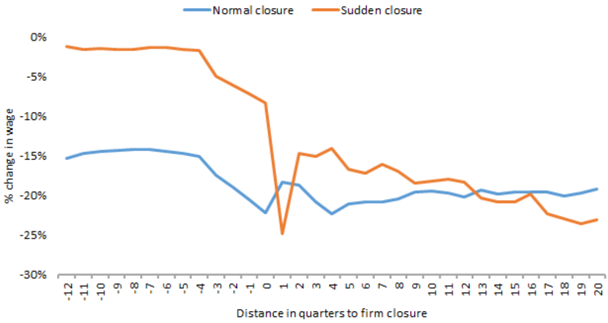
(c) Firms that do not close



- Firms that close suddenly have a different composition relative to other firms
- Wage quintiles from sudden closures firms remain relatively stable as firm approaches the closure event relative to normal firm closures.

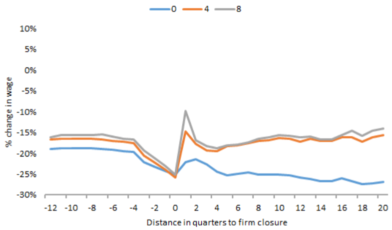
Main Results I: All displacements

Figure: Displaced workers from 0 to 8 quarters before closure

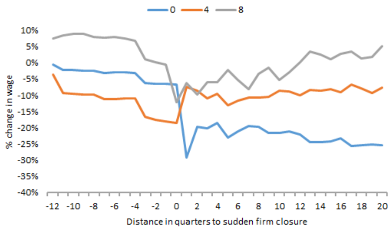


Main Results II: GROSS effects by distance to closure separation. ALL workers

(a) NORMAL closure

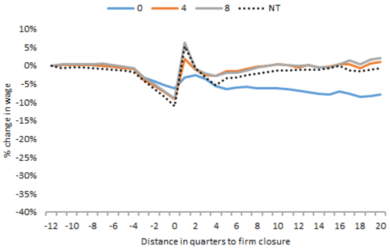


(b) SUDDEN closure

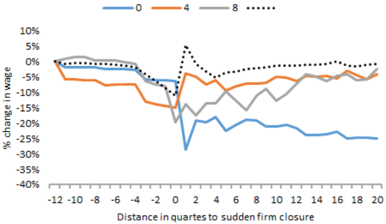


Main Results III: NET effects by distance to closure separation. ALL workers

(a) NORMAL closure

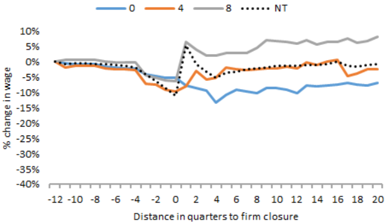


(b) SUDDEN closure

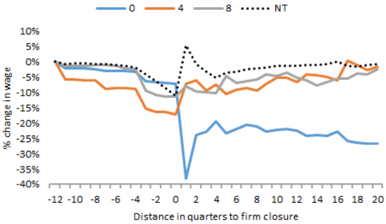


Main Results V: NET effects by distance to closure separation. PRIME workers

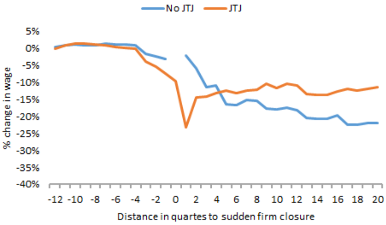
(a) NORMAL closure



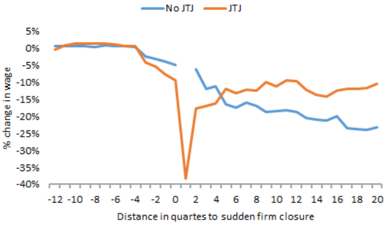
(b) SUDDEN closure



Main Results VI: Wage losses by job to job transitions status



(a) Net wage impact ALL workers



(b) Net wage impact PRIME workers

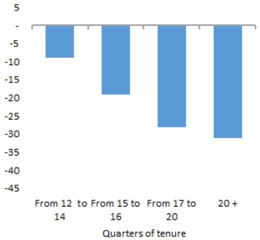
Discussion

- The impact on workers that are displaced at the moment of the event is much larger for sudden closures: expected versus unexpected shocks.
- The exact timing of separation relative to the actual closure plays a crucial role.
- The type of job transition matters: workers that find a new job fast experience large losses in the short run but can recover later.

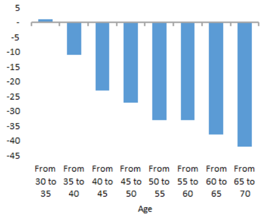
Sources of heterogeneity

Net wage loses (%) by workers characteristics

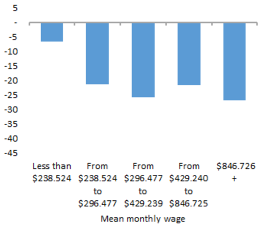
(a) Tenure



(b) Age



(c) Wage received

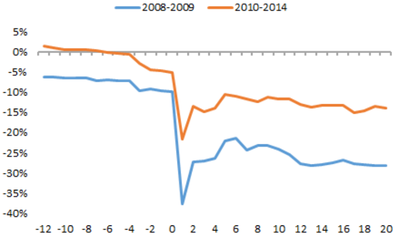


Net wage loses (%) by firm characteristics

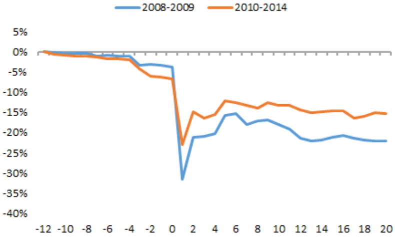
	Quarters after displacement						
	0	1	4	8	12	16	20
	By industry						
Industry stayers	-5%	-26%	-15%	-24%	-26%	-26%	-30%
Industry leavers	-4%	-28%	-19%	-13%	-17%	-19%	-20%
	By size						
Size stayers	-6%	-33%	-18%	-24%	-26%	-29%	-32%
Switch to a bigger size firm	-5%	-20%	-12%	-4%	-8%	-5%	-10%
Switch to a smaller size firm	-6%	-33%	-25%	-27%	-30%	-33%	-34%
	Labor Productivity						
LP Stayers	-7%	-37%	-24%	-21%	-23%	-27%	-28%
Swicth to a bigger LP firm	-6%	-25%	-18%	-20%	-21%	-21%	-22%
Swicth to a smaller LP firm	-5%	-28%	-17%	-17%	-22%	-23%	-27%
	Mean wage paid by firm						
Stayers	-8%	-30%	-15%	-24%	-23%	-24%	-24%
Switch to a bigger mean wage	-6%	-17%	-4%	-8%	-8%	-8%	-11%
Switch to a smaller mean wage	-5%	-53%	-47%	-47%	-49%	-54%	-54%

Net wage loses (%) by year of displacement

(a) Gross wage impact



(b) Net wage impact



Discussion

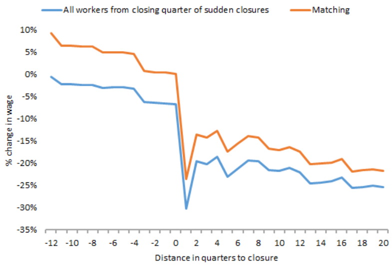
- Wage losses are larger for older workers with larger tenure: consistent with ideas of specific human capital/match quality and the capacity to reinvest in HK/rebuild a job ladder given each worker's life cycle.
- The timing of reentry, and the type of firm in which displaced workers are able to work, appears to be important: we need further analysis.

Matching estimation

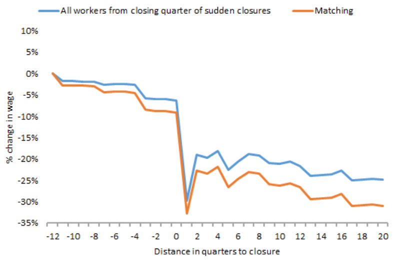
Control group selection by one to one exact matching

For each displaced worker from the sudden firm closures data base, we perform an exact matching on age, gender, ISCI rev 4, firm size (labor force quartiles) and wage group (wagebill quartiles) with individuals on the control group at the quarter of displacement. We are able to match 99.75% of workers.

(a) Gross wage impact



(b) Net wage impact



Conclusions and Future Work

Conclusions

Job displacements can be costly for the future prospects of workers.

Consistent with the previous literature, we find that displaced workers in massive layoffs in Chile experience large and persistent wage losses.

Losses are significantly larger when looking at sudden firm closures, which we think are a better measure of an unexpected shock: workers are (relatively) unprepared for the displacement event.

The timing of separation is important: workers that are able to leave the firm earlier experience relatively smaller effects.

Consistent with ideas of models with on-the-job HK accumulation, job ladders, and match-specific productivity, wage losses are larger for older workers with larger tenure.

Future work

- Build an explicit analytic framework to rationalize our results, in particular in terms of the difference between expected/unexpected displacement
- Analyze in more detail the timing and characteristics of re-employment to separate direct wage effects from composition effects
- Use alternative firm indicators (such as the evolution of sales) to assess the unexpected component of firm closures

Extra tables

Extra table 1: Net wage loses (%) by workers characteristics I

	Quarters after displacement						
	0	1	4	8	12	16	20
				By tenure			
Quartile 1	4%	-14%	-7%	-5%	-6%	-8%	-9%
Quartile 2	-9%	-33%	-24%	-27%	-29%	-26%	-28%
Quartile 3	-4%	-21%	-15%	-12%	-16%	-19%	-19%
Quartile 4	-6%	-20%	-18%	-18%	-23%	-29%	-31%
				By experience			
Quartile 1	-7%	-30%	-22%	-25%	-27%	-24%	-25%
Quartile 2	1%	-12%	-6%	1%	-4%	-9%	-13%
Quartile 3	-4%	-25%	-13%	-11%	-17%	-20%	-19%
Quartile 4	-3%	-14%	-21%	-17%	-18%	-22%	-29%
				By age			
25<age<=30	10%	-5%	-2%	8%	16%	19%	26%
30<age<=35	7%	-13%	-5%	3%	5%	3%	1%
35<age<=40	-2%	-20%	-9%	-13%	-10%	-9%	-11%
40<age<=45	-6%	-26%	-13%	-20%	-19%	-20%	-23%
45<age<=50	-7%	-33%	-20%	-21%	-26%	-27%	-27%
50<age<=55	-7%	-29%	-21%	-24%	-27%	-28%	-33%
55<age<=60	-8%	-33%	-27%	-26%	-33%	-33%	-33%
60<age<=65	-10%	-32%	-28%	-26%	-33%	-39%	-38%
64<age<=70	-10%	-38%	-26%	-25%	-34%	-37%	-42%
age>70	-10%	-20%	-15%	-26%	-33%	-29%	-36%

Extra table 2: Net wage loses (%) by workers characteristics II

	Quarters after displacement						
	0	1	4	8	12	16	20
				By gender			
Female	-6%	-17%	-16%	-18%	-21%	-23%	-23%
Male	-4%	-32%	-18%	-19%	-21%	-22%	-25%
				By wage received			
Decile 1	-33%	-5%	-6%	-3%	-5%	-3%	-3%
Decile 2	-14%	-5%	-7%	-13%	-14%	-12%	-11%
Decile 3	-9%	-7%	-16%	-20%	-22%	-19%	-17%
Decile 4	-7%	-21%	-21%	-23%	-24%	-23%	-25%
Decile 5	-6%	-35%	-29%	-26%	-27%	-25%	-28%
Decile 6	-1%	-24%	-27%	-20%	-22%	-22%	-24%
Decile 7	1%	-17%	-25%	-22%	-25%	-21%	-21%
Decile 8	6%	-15%	-26%	-22%	-25%	-21%	-22%
Decile 9	10%	-9%	-24%	-19%	-21%	-22%	-18%
Decile 10	8%	-14%	-25%	-26%	-32%	-34%	-35%