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Selective Firing and Lemons

by

Michele A. WEYNANDT*)

Working Paper No. 1405

March 2014

Supported by the
Austrian Science Funds

FWF

The Austrian Center for Labor Economics and the Analysis of the Welfare State

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Selective Firing and Lemons?*

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March 24, 2014

Abstract

This paper uses the Austrian Social Security Register (ASSD) to explore what information firms infer from the three common types of displacement: individual layoffs, individuals displaced due to a closure and individuals displaced due to a mass layoff. I bring together two strands of the literature, namely signaling and sorting and contribute to it in three ways. First I test whether the individual layoffs are the least productive, second I investigate whether individual layoffs are perceived as "lemons" (with a specific focus on the high ability individuals) and third I raise the question whether the "lemon" exists in the resulting matching pattern. Using the Abowd et al. (1999) model I show that the individual layoffs are the least productive measured by the person fixed effect. I confirm the signaling argument of Gibbons and Katz (1991) that individual layoffs are perceived as "lemons" also for high ability individuals, but I reject the argument of Gibbons and Katz (1991) against the matching model (Becker, 1973). Using three different measures of sorting, I find that the matching changes differentially for the different layoff groups. This leads to the tentative conclusion that both sorting and signaling take place after an individual job loss.

JEL-Classification: E24, J40, J63, J65

Keywords: Labor Markets, Employment, Wages, Displacement

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1 Introduction

"To hire somebody is frequently to purchase a lottery" - Spence (1973)

Among others, Spence (1973) recognized that information asymmetries, which may even resemble a lottery, are crucial for the labor market and its employment dynamics. The focus of the current work is on what information firms infer from the three common types of displacement: individual layoffs, individuals displaced due to a closure, and individuals displaced due to a mass layoff. I thereby bring together two strands of the literature, namely the literature on signaling and sorting. The contribution to the literature is threefold: first I test whether the individual layoffs are the least productive, second I investigate whether individual layoffs are perceived as "lemons" (with a specific focus on the high ability) and third I raise the question whether the "lemon" exists in the resulting matching pattern.

The signaling literature suggests that an agent/individual conveys information about her type (in our case ability) to another principal/party (the firm in our case). Akerlof (1970), Spence (1973) and Greenwald (1986) are examples of papers, which have considerably formed our knowledge about signaling models in the context of wages, mobility and eduction. As individual ability is incompletely observed by a firm, I try to disentangle if either the firms infer information from the layoff type or if the individual grasps the opportunity to find a better matching firm. The idea of a better match follows the sorting idea (assortative matching). We talk about assortative matching if more matches of certain workers and firms are observed than random matches. Becker (1973) is a prominent example of the matching model for the marriage market.

Other than the prominent "lemon" example in Akerlof (1970) for the used car market, Gibbons and Katz (1991) (in the following referred to as GK) have shaped our expectations of what we should find when comparing individual layoffs with closures, as the individual layoffs always experience a wage penalty, after being laid off. This is also the case for Austria as we can see in Figure 1, which plots the wage profiles for the layoff types five years before and five years after displacement, where year 0 is the displacement year. Looking at the individual layoffs wage profile, a clear kink labeled "lemon" by GK at year 1 is visible. Already in the second year of re-employment, individuals have caught up from this drop in re-employment wages. Nevertheless, on average individuals suffering from an individual layoff never seem to catch up with the individuals displaced due to a plant closure.

GK set up an asymmetric information model and test it empirically. The first assumption that GK make, in order to derive their theoretical prediction, is that firms have leeway when determining whom to layoff. Thus, an individual layoff may be stigmatized compared to an individual losing her job due to a firm closure where no such stigma is attached. The first contribution of this work is to test whether the least able are laid off individually. In order to perform this test, I follow the seminal work of Abowd et al. (1999) (in the following referred to as AKM) where I estimate a simple wage regression with a person and a firm fixed effect. The person and firm fixed effects are used as a heterogeneity measure.[1] This measure allows me to show that the individuals suffering from a closure are more heterogeneous in terms of their productivity than the individuals laid off due to a mass layoff, which in turn are more

[1]Following Card et al. (2013b) closely, I apply AKM to the Austrian Social Security registers and I am able to show that the identification restrictions are met.

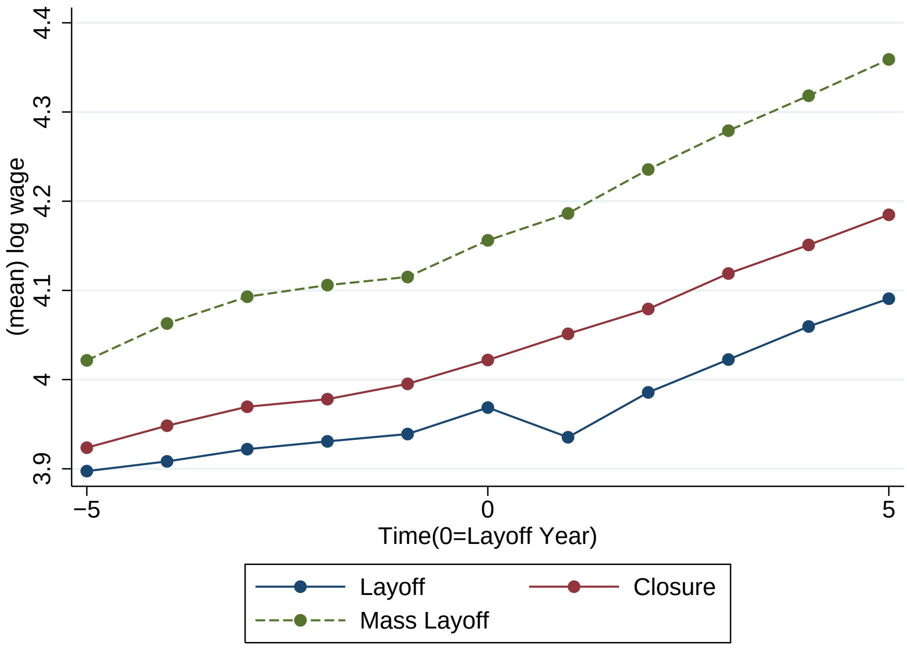


Figure 1: Mean Wages Re-employed Individuals by Layoff Type

heterogeneous than those individually laid off. This finding supports the assumption frequently made in the literature.[2]

The second contribution of my paper is the replication of GK. As equilibrium outcome of GK asymmetric information model, re-employment wages of the individually laid off are smaller than those of the closure individuals. This leads to the main conclusion that individual layoffs are perceived as “lemons”. Replicating GK, I find that a stigma is attached to being individually laid off for the case of Austria. This significantly negative effect of being fired is robust to the inclusion of a control for firm size and other controls such as region and industry.[3]

Combining Krashinsky (2002), who claims that individual layoffs have more to lose, and Hu and Taber (2005), who split their sample by race and gender and thereby put more weight on the heterogeneity of the individuals, I take the GK formulation a step further and add an analysis for high productivity

[2]Since the seminal work of AKM, there are only a few papers which deal with inference on the fixed effects, Serafinelli (2012) and Card et al. (2013a) are two examples of papers that split the firm fixed effects into e.g., quintiles and make inference based on these.

[3]Other papers which replicate GK are for example: Grund (1999), Doiron (1995), Stevens (1997). Grund (1999) uses German Data, but does not find any evidence in favor of signaling. Doiron (1995) replicates GK for Canada. Stevens (1997) tries to replicate the findings for the US using the PSID, and does find smaller wage changes for the closing types, but much of it can be explained by the wage losses in the year prior to the actual closure event. Song (2007) and Borowitz (2010) on the other hand claim that it is all about recall bias when using the Displaced Worker Supplement to the CPS (which is the Data used by GK), while Nakamura (2008) extends the finding over the business cycle.

individuals.[4] The analysis of the high ability individuals shows that indeed they have the most to lose, since they are not able to overcome the stigma of being individually laid off and still pay a wage penalty compared to the closure group. This result supports GK signaling argument that the individual layoffs are perceived as "lemons".

Furthermore, I raise the question whether individual layoffs have a chance of ending up at a high wage firm (HWF) (measured by the firm fixed effect from the AKM model). My findings are reconcilable with Gibbons et al. (2005), who show that unobserved ability does not explain intra-industry wage differentials and find that high-wage sectors employ high skill workers and thus also offer higher returns to workers' skills. I find that compared to individuals suffering from a closure, individual layoffs are less likely to end up at a HWF, while a high ability individual layoff is more likely to end up at a HWF. This result may point toward exploitation, since HWF still hire individual high ability layoffs, but they offer them a lower wage.

The main concern with GK empirical finding, is that it can be reconciled with a sorting model. Replicating their argument against sorting, I am not able to reject the matching model. Therefore, the third contribution of this paper, is to see whether there is matching before the displacement and how and if it changes thereafter. There have been numerous suggestions on how to measure matching, the AKM model allows to analyze the correlation between the worker and firm fixed effect, as Abowd et al. (2004) have done for the US (finding a zero correlation) and for France (finding a negative correlation). These results reject the assortative matching model of Becker (1973).[5]

The consistently close to zero or even negative correlation between the person and firm fixed effects is consistent with a model known as as the "piece rate model"; a model based on Burdett (1978) and extended with worker heterogeneity. Lopes de Melo (2013) applies AKM to the Brazilian data an rejects the "piece rate model", then develops a measure of sorting based on Shimer and Smith (2000) which extends the search model of Becker (1973) by introducing search frictions. In these two models, complementarities in production are the main force that drive assortative matching.[6] As noted in Eeckhout and Kircher (2011) as well, the model of Shimer and Smith (2000) allows to infer the strength of the sorting, since high skill workers work for high productivity firms in case of positive assortative matching (or low productivity firms in case of negative assortative matching) as a consequence of this, they have high skilled co-workers. Thus the correlation between the person effect and the average over the coworkers person effect is a promising way to measure the intensity of sorting in the economy.

To measure sorting, this paper uses three distinct measures; the firm fixed effect, the correlation

[4]Krashinsky (2002) explores an alternative hypothesis, claiming that individual layoffs have more to lose, since they get laid off by larger firms. Introducing controls for firm size, removes the difference between individual layoffs and closure types for his case. Hu and Taber (2005) find the "lemons" effect for some groups but a reversed result for others, pointing towards statistical discrimination.

[5]Haskel et al. (2005) find that more productive firms hire more productive workers applying AKM to the UK (positive correlation) and Irzano et al. (2008) applying AKM to Italy find that the firm's productivity is positively related to skill dispersion within the occupational status groups and negatively to the skill dispersion between groups.

[6]Other papers related to this strand of literature are e.g., Bagger and Lentz (2008), Lise et al. (2012). We refer the reader to Lentz and Mortensen (2010) for a good overview of the labor market models with worker and firm heterogeneity.

between the person and the firm fixed effect as well as the correlation between the person effect and the average of the co-worker person effect. I then compare the amount of matching before displacement with the amount of matching thereafter. In a world where the signal contains no information, I expect the "lemon" to be invisible in the resulting matching pattern. Meaning that the matching measure should change in a similar way for the different layoff groups. If the signal distorts the resulting matching pattern, I should observe a difference between the change in matching before and after displacement. Applying the sorting measures to the ASSD, I find that the matching changes differently for the different layoff groups. This leads to the tentative conclusion, that both sorting and signaling play a role. Assortative matching plays a role, as the sorting measures are always different from zero, while signaling plays a role, because the effects change differently for the different groups.

The remainder of the paper is structured as follows. In Section 2, the underlying theory and empirical framework are discussed. Section 2.1 discusses the GK model, while Section 2.2 gives a short overview of the AKM model. Section 2.3 then talks about the possible sorting mechanism. Section 3 presents the linked employer-employee data of the Austrian Social Security Registers, and discusses the displacement sample. Section 4 presents the results, where Section 4.1 provides the reader with the results on the heterogeneity while Section 4.2 discusses the signaling versus sorting evidence. Section 5 concludes.

2 Theoretical and Empirical Framework

As discussed above, the analysis for signaling follows Gibbons and Katz (1991), while part of the sorting is based on Lopes de Melo (2013). Section 2.1, describes the signaling according to GK and the possible sorting explanation of their findings. Section 2.2 describes the heterogeneity measures, allowing to differentiate between a high and low ability individual and a high and low wage paying firm. Section 2.3 discusses the different measures of sorting and what could be a possible mechanism to disentangle signaling and sorting.

2.1 Signaling according to Gibbons and Katz (1991)

GK provide a theoretical analysis of an asymmetric information model for layoffs. The model describes the labor market as an uncertain environment with informational frictions, where it is assumed that the firm has discretion over whom to layoff. Then the firm's desire to retain a worker, signals that the worker is of high ability, and therefore the market will bid up the wage of the retained worker. However, this effect will represent an adverse effect for individual layoffs, and therefore they will receive lower re-employment wages. The equilibrium outcome of their model for re-employment wages is: $\omega_{\text{closure}} > \omega_{\text{individual layoff}}$. GK conjecture and empirically show, using the displaced worker supplement to the CPS, that individual layoffs compared to displacements due to plant closures exert a negative signal for the workers ability, by earning lower re-employment wages.

The problem with this finding, also mentioned in their paper, is that sorting could be another consistent explanation. The sorting consistent example that they give, see also Figure 2, is that if there is an industry A which is sensitive to ability, and at the beginning of the period all the seemingly high ability individuals work in A. While industry B is insensitive to ability, and all the seemingly low ability individuals work in B. Then over time endogenous mobility will improve the quality of the match. If moves from A to B are labeled as a layoff, and those from B to A as a quit, it generates the exact same prediction as the signaling model.

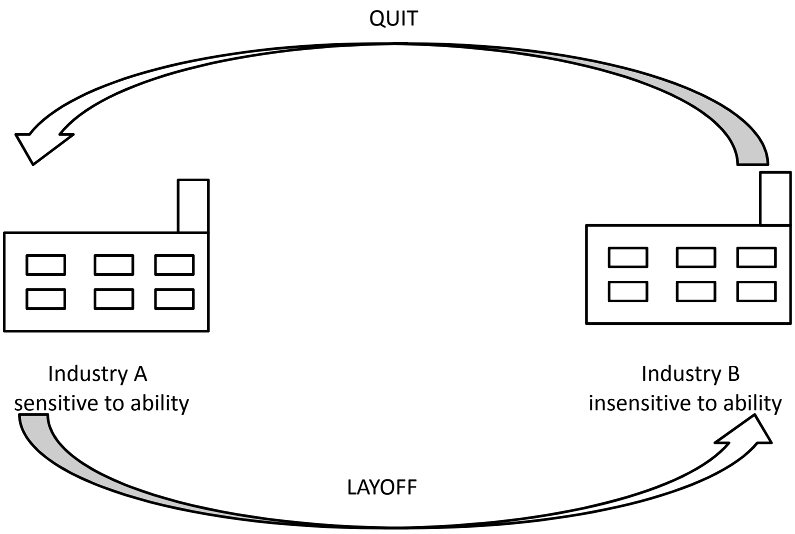


Figure 2: Possible Sorting Mechanism in the GK model

GK test the matching model by including an industry switch dummy, and an interaction between the industry switch dummy and the layoff dummy. They interpret the drop of the significance on the layoff dummy as evidence that sorting (matching) is not the dominant mechanism.

As GK asymmetric information model is used as the framework for the analysis, I will replicate their findings using (and expanding) their empirical specification;

$$\underbrace{\Delta\omega}_{\omega_{\text{post}}-\omega_{\text{pre}}} = \delta_1 1(\text{Layoff}) + \beta X \tag{1}$$

where the prediction that $\delta_1 < 0$ is testable, 1() represents the indicator function and X are other control variables.[7] To replicate GK findings on the symmetric information story, the following empirical

[7] In the empirical section I control for a quadratic in age, age at first employment, firm size, firm operation duration, unemployment duration since labor force participation (LFP), employment duration since LFP, tenure at the closing firm, wage at first job, number of employment spells and number of unemployment spells.

specification will be estimated:

$$\omega_{\text{post}} = \delta_1 1(\text{Layoff}) + \gamma_1 1(\text{Switch Industry}) + \gamma_2 1(\text{Switch Industry} * \text{Layoff}) + \beta X \tag{2}$$

Laid off individuals switching industry should receive especially low re-employment wages; $\gamma_2 < 0$ for the finding to be in line with a matching model. GK find that: $\gamma_2 > 0$ and small in magnitude and therefore exclude matching as a possible explanation. To take GK a step further, I first include mass layoffs when estimating equation (1) resulting in the following specification;

$$\Delta\omega = \delta_1 1(\text{Layoff}) + \delta_2 1(\text{Mass Layoff}) + \beta X \tag{3}$$

and then take it even a step further and include an indication of whether or not the individual is a high ability type individual (HA).

$$\Delta\omega = \delta_1 1(\text{Layoff}) + \delta_2 1(\text{Mass Layoff}) + \delta_3 1(\text{HA}) + \delta_4 1(\text{HA} * \text{Layoff}) + \delta_5 1(\text{HA} * \text{Mass Layoff}) + \beta X \tag{4}$$

With this specification, the question whether a high ability individual is able to overcome his layoff stigma may be answered by testing; $\delta_1 + \delta_3 + \delta_4 \geq 0$. A high ability individual has potentially the most to lose, and therefore this specification allows to test whether there is a stigma attached to being laid off.

In this context, the question may be raised whether a laid off individual (L) even has a chance of being hired at a high wage firm (HWF). To do so I estimate a logit model of the following form:

$$Pr((HWF) = 1) = \lambda_1 1(\text{L}) + \lambda_2 1(\text{ML}) + \lambda_3 1(\text{HA}) + \lambda_4 1(\text{HA} * \text{L}) + \lambda_5 1(\text{HA} * \text{ML}) + \beta X + \epsilon \tag{5}$$

which answers, whether an individual layoff is more likely to end up at a HWF than a closure, and whether and individual layoff, which is also of high ability is more likely to end up at a HWF.

2.2 Measure of Productivity and Sorting

In order to measure a workers productivity, which is unobserved to an econometrician and which is partly unobserved to the firm, I will use the worker fixed effect from an Abowd et al. (1999) type wage decomposition. Productivity may only be partly observed to the firm since for example education is observable and easy to clearly communicate to a hiring firm. Furthermore in order to know whether a firm is paying higher wages, the firm fixed effect of the Abowd et al. (1999) wage decomposition is used;

$$\begin{aligned} \omega_{it} &= \underbrace{\alpha_i + \Psi_{J(i,t)}}_{\text{Fixed Effects}} + x_{it}^{'}\beta + \underbrace{\eta_{iJ(i,t)} + \varsigma_{it} + \epsilon_{it}}_{\text{Random Effects}} \\ &= \alpha_i + \Psi_{J(i,t)} + x_{it}^{'}\beta + r_{it} \end{aligned} \tag{6}$$

where α_i is a time-invariant worker component, $\Psi_{J(i,t)}$ a time-variant establishment component, $x_{it}^{'}\beta$ a linear index of time-varying observable characteristics, $\eta_{J(i,t)}$ is a mean zero random match component,

ς_{it} is a unit root component of individual wage and ϵ_{it} is a mean zero transitory error.[8] All the error terms go into the same random effects component, r_{it}. α_i will be used as a measure of the individual's ability, while $\Psi_{J(i,t)}$ will be used as a ranking of the firm (high wage paying or low wage paying). Following Card et al. (2013b), α_i can also be interpreted as the portion of the individual's earnings power that is fully portable across employers. It is a combination of skills and other factors that are rewarded equally across employers. $\Psi_{J(i,t)}$ captures the proportional pay premium that is common to all employees at workplace j (i.e., all individuals for whom $J(i,t) = j$). This could be rent sharing, efficiency wage premium or strategic wage posting behavior. For more information on the AKM model, and it's identification, I refer the reader to the Appendix A.1 and to Card et al. (2013b).

2.3 Sorting

As briefly mentioned in the introduction, to take the possible matching explanation of the signaling model of GK a step further, matching will be evaluated by different measures. A first impression on sorting is given by the firm fixed effects at the displacement firm and at the re-employment firm. It is an indicator of how the displaced individuals sort themselves into the new firms - as the firm fixed effect represents a ranking of the firms. Furthermore, I will take a look at the correlation of the person and firm fixed effects, as suggested by Abowd et al. (2004). The recent literature by Lopes de Melo (2013), Eeckhout and Kircher (2011), Lentz and Mortensen (2010), to name a few examples, state that one cannot identify the sign of the sorting based on the AKM model. They show that the correlation between the person and the firm fixed effect is biased downwards and therefore mostly zero and may even be negative in some datasets. Due to this bias a distinction between positive assortative matching (PAM) and negative assortative matching (NAM) is not possible.[9]

These papers nevertheless show that the strength of the sorting can be identified, which is arguably the more important measure in economics. Lopes de Melo (2013) shows that the worker-coworker correlation is a good measure of the strength of the sorting. In his model, the high skilled workers work for the high-productivity firms in the case of PAM (or the low-productivity in the case of NAM). A consequence of this, is that they have high-skill co-workers. Therefore the correlations between their own person effect and the mean coworker person effect, $\mathrm{Corr}(\theta_i, \tilde{\theta}_{j(i,t)})$, measures the intensity of the sorting in the economy. θ_i denotes the worker fixed effect and $\tilde{\theta}_{j(i,t)}$ is the mean value of θ among the co-workers.

If I assume for the moment that there is PAM in the Austrian data, then the high type workers match with the high type firms.[10] As the goal is to distinguish between signaling and sorting, the rele-

[8]The seminal work by Abowd et al. (1999) provides an empirical approach on how to computationally tackle the estimation of worker and firm fixed effect with an empirical investigation of France. Haltiwanger et al. (1999) is an example of the application to US data. Up until Abowd et al. (2002) a direct identification of the worker and firm fixed effect was not possible, but based on Abowd et al. (2002) a direct identification is straightforward through the largest connected set, which lead to a vast literature based on the fixed effects. Woodcock (2008) building on Woodcock (2006) added to the discussion by showing that a wage decomposition in the spirit of AKM which fails to control for unobserved worker, firm and match heterogeneity can be misleading. Cardoso (1999) and Card et al. (2013b) are just a few examples of papers that employ AKM to analyze wage inequalities in Portugal and Germany.

[9]With PAM (NAM), a high skill individual will sort herself into a high (low) productivity firm and a low skilled individual into a low (high) productivity firm.

[10]Please keep in mind that I cannot infer whether there is PAM or NAM without productivity data. This is

vant stigma arises from the individual layoff, while no such stigma is attached to an individual displaced by a plant closure. In order to see, whether the resulting matching is affected by the "lemon", this paper takes a closer look at the firm fixed effects, and the different correlation measures as suggested by the literature, before and after the displacement. If the "lemon" plays a role, the difference should be affected; meaning that the difference between pre- and post displacement matching should differ for the closure group and the individual layoff group.

3 Data

This paper uses the Austrian Social Security Database (ASSD) which covers the universe of private sector workers covered by the social security system between 1972 and 2009. The ASSD provides daily information on employment, registered unemployment, total annual earnings paid by each employer, and various individual characteristics of the workers as well as information on employers such as geographical location, industry, and size. For a thorough overview of the data, I refer the reader to Zweimüller et al. (2009).

In the ASSD, the firms are associated with an employer identifier reported in every employment spell of the worker. The current analysis uses only information on male blue and white collar workers in the years 1980-2009. In order to estimate the person and firm fixed effects, I run AKM on a larger sample than the one that is used for inference on sorting and signaling (which only includes displaced individuals).[11] First one main job per year per individual is selected, with a wage and a firm number. If there are overlapping spells, the longest spell is selected as a main spell. To replicate GK a few more restrictions are put on the sample.

In order to use the firm closures as an entry to unemployment, I first create a sample of closing firms. Fink et al. (2010) identify entry and exit of firms using a worker flow approach that follows clusters of workers moving across entities. They also show that their firm definition is comparable to the official firm statistics of Austria.[12] To obtain the individuals affected by a firm closure, firms operating in construction and gastronomy are excluded for seasonality reasons. I only consider male blue and white collar workers who are displaced due to a closure and which comply with the following restrictions. The individual must have been employed in the last quarter of the firm operation, she must have worked at least a year for this firm (to make sure she is unaware of the closure), and her age at displacement must be between 15 and 55 years of age.

To identify mass layoffs, I proceed in a similar fashion. The initial definition is again based on Fink et al. (2010) in the sense that a certain amount of employees is laid off between two quarter dates. To identify the significant drop, the following assumptions are made: for firms with 11 to 20 employees, the firm size has to decline by at least 6 individuals for it to be counted as a mass layoff. For firms with 21 to 100 employees, the firm size has to decline by 10 individuals in order to be recognized as a mass

assumed right now to explain what could possibly happen. Mendes et al. (2010) find for example PAM in Portugal, but they have productivity data and are able to estimate a flexible specification for the productivity.

[11] For more information on the AKM sample, see Appendix A.1.1.

[12] It is secured, that the firm shuts down and it is not just a rename, a spin off or a take over.

layoff, while for a firm with more than 100 employees, the firm size needs to decline by 30%.[13] To obtain the individuals affected by a mass layoff, again firms operating in the construction and the gastronomy sector are excluded. The male blue or white collar worker needs to be employed at the mass layoff firm for at least a year, and must have been between 15 and 55 years old at the displacement.[14]

In order to identify an individual layoff I proceed in a different way than for the mass layoffs and the firm closures. First an employment spell has to be identified which is followed by an unemployment spell. If there are less than 28 days between the two spells, then it is defined as a layoff and not a voluntary quit. This is done in similar fashion in e.g., Gruetter and Lalive (2009). The individual layoff sample may be a negatively selected group of individuals since they may have the worst characteristics, but this is the sample needed in order to replicate GK. I have to exclude voluntary quits, since I want to test whether being laid off really signals lesser ability, or whether it may be self selection. As before the individuals need to have worked for at least a year at the displacement firm and must have been between 15 and 55 at the age of displacement.

Furthermore I only keep those individuals for whom I have a firm fixed effect at the layoff job and at the re-employment job, if the worker finds a new job, and where the worker has a person fixed effect. After this selection the sample contains $98,249$ individual layoffs, $26,461$ mass layoffs and $19,983$ job losses due to a firm closure. Table 1 shows the number of job-to-job moves, compared to job-unemployment-job moves and job-unemployment moves. As an example there are no job-to-job moves in the individual layoff group, due to its definition. Overall the displacement sample contains 21.5% of job to job moves, where 12.46% stem from the mass layoffs and the rest from the closures. If the wages on the re-employment firm and on the layoff firm are analyzed 10.01% of the displacement observations are lost. These individuals may drop out of the labor force or remain unemployed or may have found a job outside of Austria at the time of my last observation point. Furthermore, these numbers may be larger than the actual number of individuals, since some individuals may have suffered from multiple layoffs. The displacement sample contains 8.95% of job short term unemployment (less than 30 days) job moves, 41.87% of job medium term unemployment (between 30 and 365 days) job moves and 17.62% job long term unemployment (more than 365 days) job moves.

Table 2 displays the summary statistics for the different types of displacement. There are $17,655$ individuals displaced due to a closure, where 27.53% have been displaced around Vienna, 21.13% in eastern Austria, 17.17% in southern Austria, 23.25% in northern Vienna and 10.8% in western Austria. Of the displaced individuals due to a closure 30.61% where working in manufacturing, 24.59% in sales and 9.97% in transportation. Of the $23,834$ mass laid off individuals, 46.54% have been displaced around Vienna, 13.52% in eastern Austria, 14.71% in southern Austria, 19.58% in northern Vienna and 25.08% in western Austria. 30.55% of these displaced indiviuals worked in manufacturing, 11.09% in sales and 11.79% in transport. The numbers for the $77,789$ individual layoffs are very similar; 20.39% have been displaced around Vienna, 20.46% in eastern Austria, 23.07% in southern Austria, 23.08% in

[13]These assumptions are standard in the literature, see e.g., Jacobson et al. (1993), Sullivan and von Wachter (2007), von Wachter et al. (2009) who restrict firms to have at least 50 employees and define mass layoff as an instance where the employment of a firm drops by at least 30%.

[14]Seemingly there is no layoff by seniority rule in place for Austria. https://www.help.gv.at/Portal.Node/hlpd/public/content/201/Seite.2010205.html - accessed 21.02.2014.

Table 1: Number of Individuals in the Different Categories

	All	Layoff	Mass Layoff	Closure
Job to Job	31202	0	18045	12998
Short Term Job	63	0	41	22
Medium Term Job	4918	0	2284	2634
Long Term Job	26221	0	15856	10365
Job Short Term Unemployment Job	12967	10972	841	1154
Short Term Job	101	90	9	2
Medium Term Job	4725	4129	223	373
Long Term Job	8141	6753	609	779
Job Medium Term Unemployment Job	60647	56015	2444	2188
Short Term Job	914	837	54	23
Medium Term Job	29545	27801	959	785
Long Term Job	30188	27377	1431	1380
Job Long Term Unemployment Job	25533	20112	3087	2334
Short Term Job	992	872	82	38
Medium Term Job	11886	9686	1287	913
Long Term Job	12655	9554	1718	1383
Job Unemployment	14503	11150	2044	1309

Source: ASSD, own calculations.

Notes: The term short term unemployment is used when an individual experiences an unemployment spell which lasts less than 30 days. Medium term unemployment is used when the spell lasts between 30 and 365 days, while long term unemployment is used if the spell lasts longer than 365 days. I defined short term job in a similar fashion, meaning that if it lasts for less than 30 days, while it is labelled as a medium term job if it lasts between 30 and 365 days. Jobs that last longer than 365 days are labelled long term jobs.

northern Vienna and 10.78% in western Austria. 34.77% of these displaced indiviuals worked in manufacturing, 23.09% in sales and 8.55% in transport.[15]

Table 2: Summary Stats by Type of Layoff

	Firm Closure		**Mass Layoff**		**Layoff**	
	mean	sd	mean	sd	mean	sd
# Displaced Workers	17655		23834		77789	
# Displaced Workers Region						
Vienna	4862		11093		15858	
East	3731		3223		15919	
South	3033		3507		17945	
North	4105		4668		19508	
West	1908		1329		8387	
# Displaced Workers Industry						
Manufacturing	5402		7278		27038	
Sales	4337		2650		17966	
Transport	1760		2819		6658	
Change in Wages	0.022	0.298	0.024	0.305	-0.002	0.358
Age at Displacement	36.57	9.19	36.65	9.23	34.48	9.14
Ratio of Blue Collar Workers	0.54	0.50	0.45	0.50	0.66	0.47
Tenure at Displacement	1939	1857	2671	2347	1511	1469
Average Firm Operation Duration	4076	3294	9095	4271	8420	4155
Person Effects	3.45	0.24	3.46	0.23	3.41	0.21
Firm Effects	0.05	0.26	0.09	0.24	0.05	0.23
Firm Effects new Firm	0.02	0.28	0.09	0.21	0.02	0.25
Unemployment Duration Since LFP	166	339	144	330	242	397
Age at First Employment	26.61	8.61	25.51	8.07	25.35	8.05
Days Since LFP	3736	2507	4160	2567	3534	2489
Number of Unemployment Spells	2.10	3.75	1.75	3.40	3.22	4.69
Firm Size (*)	15.00	39.22	398.00	5875.02	30.00	1885.23
Total Male Hires	2.57	6.38	78.94	196.33	12.74	69.84
Total Male Fires	5.17	10.93	114.08	221.29	19.14	86.01
Tenure at Disp. Blue Collar	1851	1796	2359	2121	1406	1335
Tenure at Disp. White Collar	1862	1750	2570	2227	1603	1569

Source: ASSD, own calculations.
Notes: (*) For firm size the median is depicted, not the mean. Tenure at displacement, average firm operation duration, unemployment duration since labor force participation (LFP), and days since LFP are measured in days.

A look at the change in wages reveals that it is largest for the mass layoff group 0.024, but very similar to the closure group 0.022. For the individual layoffs, this number differs at -0.002. Looking at age at displacement the average is about the same for the three groups, 36.6 for the closure group and 36.7 for the mass layoff group while only 34.5 for the individual layoffs. On average the individual layoffs are thus a bit younger than the firm closure or mass laid off sample. Looking at the ratio of

[15]These percentages do not add up to 100% as for some displaced workers the region is missing, and the percentages for the industry were only calculated for the industries named.

blue collar workers in the firm at the displacement date, we see that the share of blue collar workers is higher in firms where we observe more individual layoffs, 0.66, while in the firm closures we observe nearly as many blue collar as white collar workers with a share of 0.54. For the mass layoff firms we observe a share of 0.45 blue collar workers. Looking at the tenure at displacement, we can see that it is smallest for the individual layoffs around 1500 days, which nevertheless equals around 4 years, while for the closing individuals the average tenure at the displacement firm is 1900 days (about 5 years), and for the mass laid off individuals, we observe a longer tenure around 2600 days (about 7 years).

The average firm operating duration points into the direction that the individuals may work at different firm types. The closing firms have the shortest survival at around 4000 days (about 10 years), while individual layoff firms, have an operating duration of 8400 days (about 23 years), while the mass layoff firms have the longest survival at around 9000 days (about 24 years). Looking at the unemployment duration since labor force participation (LFP), we see that the individual layoffs have the highest number of days unemployed with an average of 242 days, whereas it is 166 days for the closure types and 144 days for the mass laid off individuals. The age at first employment is balanced at around 25 years for the three samples. The average days worked since LFP yields a similar picture to the unemployment days. On average the individual layoffs have the shortest days employed with an average of $3,534$ days (nearly 10 years) and around $3,736$ days for the closing sample (about 10 years) and $4,160$ days for the mass layoff sample (about 11 years). The number of unemployment spells is highest for the laid off individuals at 3.2, while it is only 2.1 for the closure types and 1.7 for the mass layoff individuals. In terms of firm size, the closing firms have a median of 15 employees, while the median for the individual layoff firms is 30 and 398 for the mass layoff firms. The total number of male hires and male fires goes along the lines of the firm size. It is highest in the year before displacement for the mass layoff firms, with an average of 78.9 hires and 114 fires, lowest for the closing firms, with an average of 2.5 hires and 5.2 fires, while the individual layoff firms are in the middle of this distribution with around 12.7 hires and 19.1 fires. For completeness the table also includes the means of the person and firm fixed effects, but I will return to these effects later when I discuss the heterogeneity.

4 Results

This section discusses the main results. Section 4.1 present the estimates of the person and firm fixed effects to test whether or not firm use leeway when deciding whom to lay off.[16] In other words, Section 4.1 tests whether the least able are laid off individually and whether individuals suffering from a closure are more heterogeneous. Section 4.2 addresses the "lemon" by replicating GK. GK is then taken a step further by differentiating between high ability individuals. Finally Section 4.2 addresses whether the "lemon" affects the resulting matching.

[16] The reader is referred to the Appendix A.1.2 where the validity of the AKM model is discussed. The validity is checked using an event study as in Card et al. (2012), which allows to show that the crucial assumptions are fulfilled.

4.1 Heterogeneity

Figure 3 plots the densities of the estimated person effect for the different layoff types. This graph gives us a first glance whether the underlying assumption, that firms have more leeway in determining whom to layoff in case of a mass layoff and an individual layoff than in a closure event, is true. If it is true that firms layoff the least able individually, we should observe a lower mean for the individual group compared to the closures, whereas the mean for the mass layoffs should be in between the individual layoffs and the closures. Therefore when comparing the mass layoffs with the individual layoffs, we should observe more low productivity individuals in the individual layoff group. Eyeballing, does not allow to conclude that the distribution of the closure and mass layoff types differ. Nevertheless, the individual layoff is always to the left of the closure and the mass layoff curve. This observation points into the right direction: on average the individually laid off seem to be less able and less heterogeneous than the other types. The Kolmogorov-Smirnov test rejects equality of the distributions.

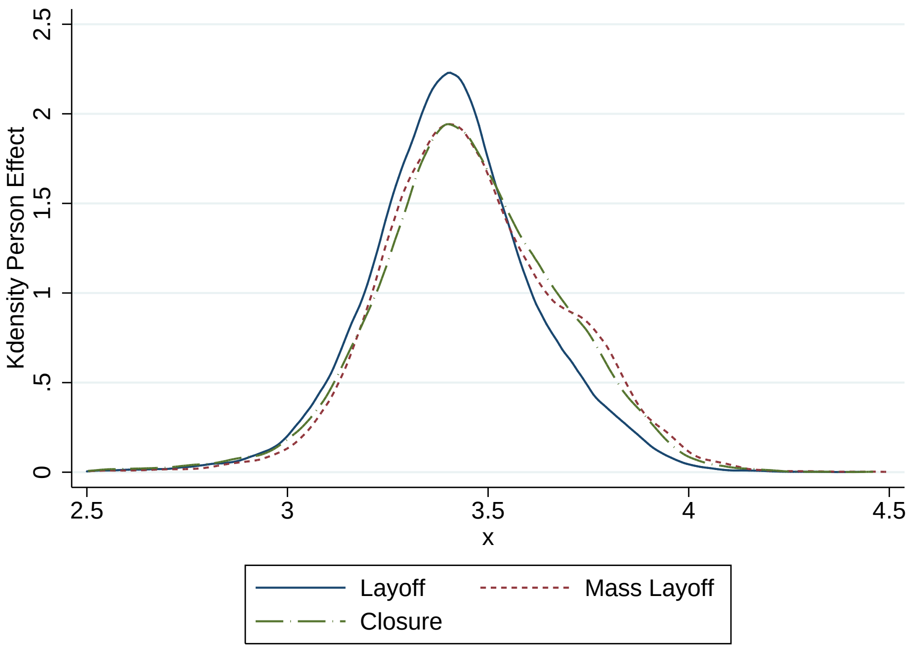


Figure 3: Person Effects by Type of Layoff

Table 3 takes a closer look at the means and the variances of the person effects across the different groups. The results from the whole AKM file are included in order to get a feeling where the displaced individuals stand compared to the individuals in the connected set. The following relationship between the means of the person effects is observed: mean(mass layoff) = 3.461 > mean(closure) = 3.448 > mean(layoff) = 3.410. These means are significantly different from each other, as the different p-values in Table 3 show. On average the individual layoffs are the least able, as expected, but unlike suggested, the mass layoff group seems to be more able than the closing types, at least in our sample. In terms of variance and therefore heterogeneity, the heterogeneity is expected to be highest among the closure types, and lowest among the individual layoffs. Looking at the data the following relationship holds:

Var(closure) = 0.058 > Var(mass layoff) = 0.53 > Var(layoff) = 0.046. The p-values reported in Table 3 are from a Levene Test of variance equality and they show that the variances are significantly different from each other.[17] This result supports the conjecture that firms use their knowledge about the workers ability when deciding whom to layoff.[18]

If the sample is split and only white collar workers are analyzed, the following holds: mean(mass layoff) = 3.557 ≈ mean(closure) = 3.556 > mean(layoff) = 3.503. The difference between the mass layoff and the closure group is not significant anymore, but still the individually laid off are on average the least able. For the variances the following holds: Var(closure) = 0.067 > Var(layoff) = 0.061 > Var(mass layoff) = 0.058. A little switch between the mass layoff and the individual layoff group can be observed, but nevertheless the heterogeneity is highest in the closing sample which is as theory would predict. Looking at the blue collar sample we have: mean(mass layoff) = 3.368 > mean(closure) = 3.362 ≈ mean(layoff) = 3.360. The difference between the closure and the individual layoff group is not significant, but the difference between the mass layoff and the individual layoffs is significant, thus on average the individually laid off are the least able type. In terms of the heterogeneity, I find: Var(closure) = 0.037 > Var(layoff) = 0.032 ≈ Var(mass layoff) = 0.033. Again the closing types are the most heterogeneous while the difference between the mass layoff and the individual layoffs is not significant. These results support the assumption usually made, that firms layoff the least able first.

Table 3: Heterogeneity in Layoff Decision? - Person Effect

	PERSON EFFECTS						
	AKM	**CL**	**ML**	**Lay.**	**Two Sided P-value**		
					CL-ML	Layoff-CL	Layoff-ML
Whole sample							
N	3703068	20006	26597	98249			
Mean	3.389	3.448	3.461	3.410	0.000	0.000	0.000
Variance	0.113	0.058	0.053	0.046	0.000	0.000	0.000
White Collar							
N	1692802	8228	12513	32667			
Mean	3.474	3.556	3.557	3.503	0.964	0.000	0.000
Variance	0.124	0.067	0.058	0.061	0.000	0.000	0.001
Blue Collar							
N	2785345	10851	12263	63117			
Mean	3.337	3.362	3.368	3.360	0.024	0.134	0.000
Variance	0.083	0.037	0.033	0.032	0.000	0.000	0.443

Source: ASSD, own calculations.

Notes: AKM stands for the whole AKM sample, CL = closing sample, ML = mass layoff sample, Lay. = individual layoff sample.

Figure 4 takes a different angle by looking at the differences between the firm fixed effects. This should help shed some light on whether really the worst firms shut down, and how different the firms are. The mass layoff curve is always to the right of the other two groups, meaning that on average the mass layoff firms are different from the closure or layoff firms. A finding, which is in line with the

[17]The relationship also holds, if a robust version of this test is used. This holds true for all the following Levene tests.

[18]Figure 12 in the appendix, shows the same graph as Figure 3 but including all individuals, also those that have not been laid off. This graph supports the idea, that the least able have been laid off.

summary statistics. On average the mass layoff firms are different from the closure or individual layoff firms. Looking at the closure and the individual layoff firms, the trend is not as clear. One could try to argue that the curve of the closure group is shifted slightly to the right compared to the mass layoff group which is confirmed by the Kolmogorov-Smirnov test (rejecting equality of the distributions).

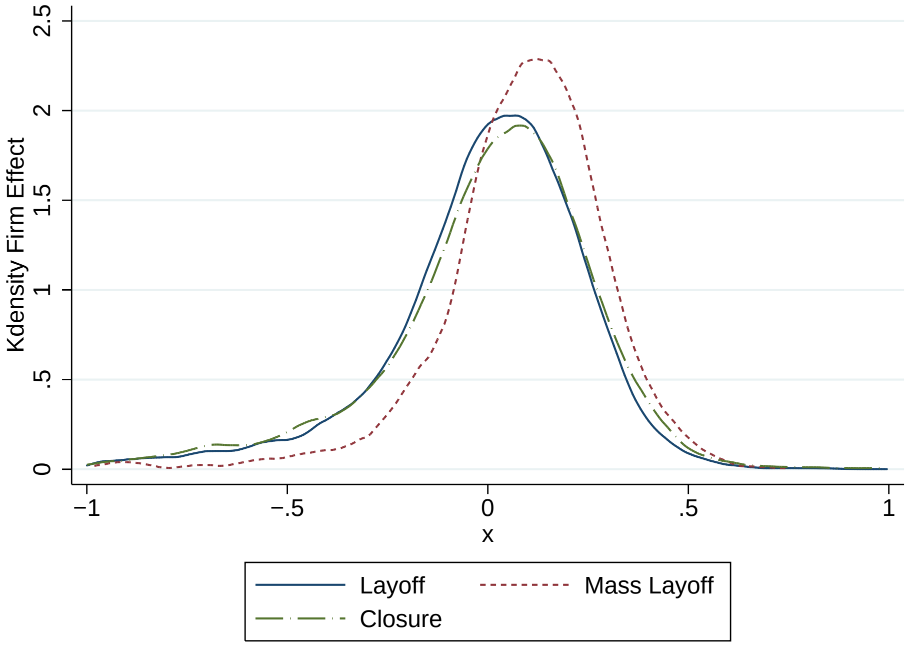


Figure 4: Firm Effects by Type of Layoff

Table 4 includes the different means and variances of the firm fixed effects. The first panel takes a look at these values at the displacement firm. For the means of the firm fixed effects, the following relationship holds; mean(closure) = 0.043 ≈ mean(layoff) = 0.046 < mean(mass layoff) = 0.098. The mass layoff firms have the highest fixed effect, while the closure firms the lowest - reflecting why they are closing. Mass layoff firms seem to be paying higher wages on average than individual layoff and closing firms. The Levene test concludes that: Var(closure) = 0.070 > Var(layoff) = 0.057 > Var(mass layoff) = 0.056. The closing firms are thus the most diverse, while mass layoff firms are the least variable. These results are confirmed in the first panel of Table 5, a sensitivity check, which uses the mean co-worker person effect at the layoff firm instead of using the firm fixed effect.

Figure 5 looks at the differences between the firm fixed effects at the receiving firm. They should capture where the individuals of the different types end up after displacement. If the layoff type did not matter, I would expect similar distributions. Comparing Figures 4 and 5 we see that the distribution changed, but the mass layoff individuals seem to end up at better firms (on average their curve is furthest to the right). The individual layoffs and the closure individuals seem to end up at a slightly better firms than before displacement. Hypothesizing that the closing curve is a bit more to the right than the layoff curve, should be confirmed by tests. The Kolmogorov-Smirnov test rejects equality of the distributions.

Table 4: Heterogeneity in Layoff Decision? - Firm Effects

	FIRM EFFECTS						
	AKM	**CL**	**ML**	**Lay.**	**Two Sided P-value**		
					CL-ML	Lay.-CL	Lay.-ML
		At the Displacement Firm					
Whole sample							
N	3703068	20006	26597	98249			
Mean	0.029	0.043	0.098	0.046	0.000	0.215	0.000
Variance	0.076	0.070	0.056	0.057	0.000	0.000	0.045
		At the Re-employment Firm					
Whole sample							
N		18697	24553	87099			
Mean		0.021	0.090	0.019	0.000	0.333	0.000
Variance		0.076	0.042	0.064	0.000	0.000	0.000

Source: ASSD, own calculations.

Notes: AKM stands for the whole AKM sample, CL = closing sample, ML = mass layoff sample, Lay. = individual layoff sample.

The second panel of Table 4 presents the means and variances at the re-employment firm, where the following relationship holds for the means: mean(mass layoff) = 0.090 > mean(closure) = 0.021 ≈ mean(layoff) = 0.019. The comparison to the means at displacement reveals that mass layoffs end up at firms which still have the highest mean and are thus still the highest paying firms. Things have changed quite considerably for the individual and closure layoffs; the means declined in both cases. Individual layoffs lose more than closures, even though on average they end up at the same firm type.[19] The variances reveal the following: Var(closure) = 0.076 > Var(layoff) = 0.064 > Var(mass layoff) = 0.042. Mass laid off individuals end up at the least diverse firm. Closure individuals end up at more heterogeneous firms compared to individual and mass layoffs. Again the sensitivity check with the mean co-worker person effect in Table 5 confirms these results.

4.2 Signaling versus Sorting?

4.2.1 Gibbons and Katz (1991) Replication

This section presents the replication of GK, thereby trying to find evidence of signaling for Austria. Table 6 replicates Table 3 of GK. Like GK, I find a significantly negative effect on the difference between pre and post layoff wages of an individual layoff compared to a closure (reference group). This result does not change when other covariates or number of displacement fixed effects or industry fixed effects are included.[20] Column (1) in Table 6 presents results for the change in wages, column (2) presents results for the pre-displacement wage and column (3) presents results for the post-displacement wage on a standard set of worker characteristics, year of displacement dummies, number of displacement

[19] I will come back to this result later as well, when sorting is addressed in Section 4.2.

[20] See Table 20 in the appendix, for the different specifications.

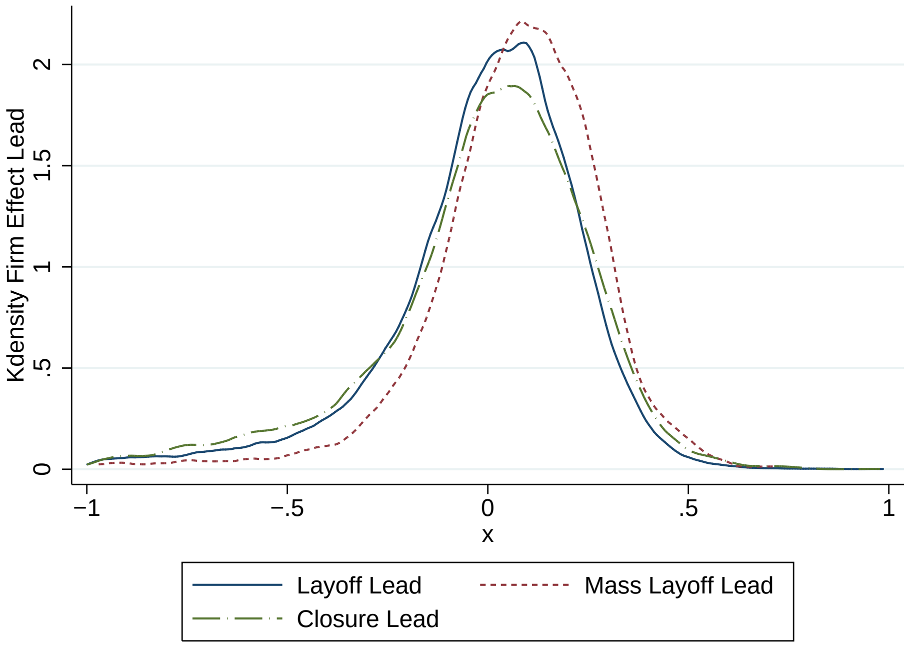


Figure 5: Firm Effects at Re-Employment Firm by Type of Layoff

Table 5: Heterogeneity in Layoff Decision? - Mean Coworker PE

	Mean Coworker Person Effect					
	Closure	**Mass Layoff**	**Layoff**	**Two Sided P-value**		
				CL-ML	Layoff-CL	Layoff-ML
			At the Displacement Firm			
Whole sample						
N	20006	26597	98249			
Mean	3.418	3.446	3.432	0.000	0.000	0.000
Variance	0.021	0.012	0.020	0.000	0.000	0.000
			At the Re-emp. Firm			
Whole sample						
N	18697	24553	87099			
Mean	3.434	3.457	3.426	0.000	0.000	0.000
Variance	0.027	0.015	0.018	0.000	0.000	0.000

Source: ASSD, own calculations.

Notes: AKM stands for the whole AKM sample, CL = closing sample, ML = mass layoff sample.

dummies, industry dummies and region dummies.[21]

Table 6: Coefficients on Layoff and Mass Layoff Dummy

		Dependent Variable*		
		Wage Change	Predisplacement	Postdisplacement
Sample	N	(1)	(2)	(3)
		Coefficient on Layoff Dummy		
Whole sample	125495	-0.049***	-0.019***	-0.068***
		0.003	0.003	0.003
White collar	45271	-0.091***	-0.028***	-0.119***
		0.006	0.005	0.006
Blue collar	75477	-0.017***	-0.003	-0.020***
		0.004	0.003	0.004
		Coefficient on Mass Layoff Dummy		
Whole sample	125495	0.007*	0.026***	0.033***
		0.004	0.004	0.004
White collar	45271	0.051***	-0.008	0.043***
		0.007	0.006	0.008
Blue collar	75477	-0.030***	0.075***	0.046***
		0.004	0.004	0.005

Source: ASSD, own calculations.
Notes: As reference group the individuals suffering from a firm closure are used. The reported regressions include a quadratic in age, age at first employment, firm size, firm operation duration, employment duration since LFP, unemployment duration since LFP, tenure at the closing firm, wage at first employment, number of employment spells, number of unemployment spells, year of displacement dummies, number of displacement dummies, industry dummies and region dummies.
* Dependent variable: Column 1: log(current wage)- log(previous wage). Column 2: log(previous wage). Column 3: log(current wage)

Individual layoffs have about 5% larger wage reductions than workers with the same predisplacement characteristics who were displaced due to a closure. Mass laid off individuals on the contrary seem to have slight wage gains of 0.7% compared to the closures. Column (2) and (3) reveal that the estimate in column (1) arises from both lower pre- and post-displacement wages for the individually laid off. Seperate regressions for the sample of white and blue collar workers show that the larger wage reductions seem to be driven by the white collar workers. Usually fewer white than blue collar jobs are covered by collective bargaining (or unions). White collar individual layoffs have 9% larger wage reductions than closure individuals, blue collar workers suffer from 1.7% wage reductions. This difference is along the lines of the findings in GK. This finding helps to presume that the degree of discretion over whom to layoff is larger in the white collar sample than in the blue collar sample. Furthermore there may be stricter layoff by seniority rules for blue collar workers than for white collar workers.[22] Overall

[21]The standard set of worker characteristics includes a quadratic in age, age at first employment, firm size, firm operation duration, employment duration since labor force participation (LFP), unemployment duration since LFP, tenure at displacement firm, wage at first employment, number of employment spells and number of unemployment spells.

[22]Table 2 shows that there is seemingly no difference between blue and white collar workers when a firm closes, but when we observe a mass layoff or an individual layoff, a longer tenure at displacements is observed for the white collar workers (with much higher standard deviations).

this evidence points into the direction that a "lemons" effect is in place.

The mass layoff dummy for these two samples shows an interesting feature, white collar individuals have wage increases of 5.1% compared to closures, while the blue collar workers suffer a 3% decrease in wages. Thus the close to zero overall effect is composed of a gain for the white collar workers and a loss for the blue collar workers. This could point into the direction that blue collar laid off workers are evaluated according to an individual layoff, but the signal for a mass layoff is not as strong as being individually laid off. The decomposition into pre- and post-displacement wages shows that at the re-employment firm, both blue and white collar workers earn more than a comparable individual who has suffered from a firm closure.

A further step in the replication of GK, is to check whether the information content of a layoff is higher if the individual had longer tenure at the pre-displacement firm. Arguing that the pre-displacement employer was able to evaluate the individual's ability. Therefore an individual layoff where the worker has a longer pre-displacement tenure contains more information. Table 7 replicates Table 4 in GK where the layoff dummy is now replaced by a layoff dummy interacted with high tenure and a layoff dummy interacted with low tenure. Here the exact definition of GK is followed where the low tenure dummy is one if an individual had less than 2 years tenure on the pre-displacement job.

Comparing the results (Austria vs. GK) there are a few differences which are probably due to the larger sample size, leading to lower standard errors and higher power. GK find a coefficient of -0.011 for the whole sample on the interaction of the layoff dummy with the low tenure dummy which is statistically insignificant and a significant coefficient of -0.054 on the interaction with high tenure. This leads to the claim that their findings are driven by the high tenure individuals. I find a 3.6% significant decrease for the low tenure individual layoffs and a significant 5.6% decrease for the high tenure layoffs. As pointed out, the significance may stem from the fact that my sample is larger including $125,495$ observations, while GK only have $3,427$. Nevertheless my results are in line with theirs in the sense that the "lemons" effect is much stronger for the high tenure individuals. Furthermore the effect is again driven by the significantly lower wages at post-displacement, even though the individual layoffs already have lower wages to begin with. This result is confirmed when looking at the white versus blue collar samples. In fact I find a 9.8% decrease for white collar workers with high tenure and a 2.3% decrease for the blue collar workers with longer tenure. A 7.9% decrease for the white collar workers with lower tenure, while there is no effect for the blue collar workers which have a low tenure. These findings are in line with firms having more discretion over whom to layoff in the white collar sample than in the blue collar sample.

When looking at the mass laid off individuals, I find similar results as before. There is no effect for those individuals who have high tenure, while a 1.6% increase is found for the low tenure individuals. This effect is driven by the significantly lower earnings at the pre-displacement firm, and not by the post-displacement earnings. Splitting the sample into blue and white collar workers, I observe a positive effect for white collar workers, no matter whether they work longer or shorter at the displacement firm. The effect ranges between 4.4 and 6.8%. While for blue collar workers the negative effect persists, and is stronger for the high tenured individuals. This effect ranges between 2.0 and 3.5% and is driven

Table 7: Coefficients on Interaction of Layoff and ML Dummy with Low- and High-Tenure Dummy

Sample	N	Wage Change (1)	Predisplacement (2)	Postdisplacement (3)
		Dependent Variable*		
		Coefficient on Layoff Dummy		
Whole sample				
Layoff x Low Tenure	125495	-0.036***	-0.035***	-0.071***
		0.003	0.003	0.004
Layoff x High Tenure		-0.056***	-0.010***	-0.067***
		0.003	0.003	0.003
White collar				
Layoff x Low Tenure	45271	-0.079***	-0.053***	-0.131***
		0.007	0.006	0.007
Layoff x High Tenure		-0.098***	-0.015***	-0.113***
		0.006	0.005	0.006
Blue collar				
Layoff x Low Tenure	75477	-0.006	-0.013***	-0.019***
		0.004	0.004	0.004
Layoff x High Tenure		-0.023***	0.002	-0.021***
		0.004	0.003	0.004
		Coefficient on Mass Layoff Dummy		
Whole sample				
ML x Low Tenure	125495	0.016***	-0.020***	-0.004
		0.006	0.005	0.006
ML x High Tenure		0.002	0.045***	0.047***
		0.004	0.004	0.004
White collar				
ML x Low Tenure	45271	0.068***	-0.063***	0.005
		0.010	0.009	0.011
ML x High Tenure		0.044***	0.014**	0.058***
		0.008	0.007	0.008
Blue collar				
ML x Low Tenure	75477	-0.020***	0.048***	0.028***
		0.006	0.006	0.007
ML x High Tenure		-0.035***	0.087***	0.053***
		0.005	0.005	0.005

Source: ASSD, own calculations.
Notes: Low Tenure is a dummy which equals one when there is less than 2 years of tenure on the predisplacement job. High Tenure is a dummy which equals one when the individual had at least 2 years of tenure on the predisplacement job.
The reported regressions include a quadratic in age, age at first employment, firm size, firm operation duration, employment duration since LFP, unemployment duration since LFP, tenure at the closing firm, wage at first employment, number of employment spells, number of unemployment spells, year of displacement dummies, number of displacement dummies, industry dummies and region dummies. ML = Mass Layoff
* Dependent variable: Column 1: log(current wage)- log(previous wage). Column 2: log(previous wage). Column 3: log(current wage)

by the significantly lower earnings at the post-displacement firm, even though at the post-displacement firm their earnings are on average still 3 to 5% larger than those of a comparable closure individual.

Table 8 investigates whether the sorting explanation can be dismissed for Austria as well. As explained in Section 2.1, I will need to find $\gamma_2 > 0$ in equation (2) to reject the sorting model. GK find a significant negative effect on γ_1 the switch industry dummy (large in absolute value), a not significant coefficient on the layoff dummy (δ_1) similar in magnitude to the results before. Furthermore they find a positive coefficient on γ_2, the interaction between the switch industry and layoff dummy.[23] The first column of Table 8 presents the baseline results of column (1) in Table 6. Column (2) adds the switch industry information, and unlike GK our significant negative coefficient on the layoff dummy (δ_1), as well as on the industry change dummy (γ_1) and on the interaction between industry change and layoff (γ_2) remains. This evidence does not yet exclude sorting as a possible explanation. The results for the mass layoff sample are similar to the previous findings. The coefficient on the mass layoff dummy stays positive and significant, while the interaction with the industry change is negative, and thus driven by the wage loss due to the industry switch.

Table 8: Industry Change, Postdisp. Wage

	(1)	(2)
Mass Layoff	0.0329***	0.0486***
	(0.00408)	(0.00575)
Layoff	-0.0678***	-0.0361***
	(0.00329)	(0.00434)
Industry Change		0.0148***
		(0.00547)
Industry Change * Layoff		-0.0633***
		(0.00606)
Industry Change * ML		-0.0322***
		(0.00746)
Observations	125495	124896
R^2	0.420	0.421
Adjusted R^2	0.419	0.420
Year FE	✓	✓
Number of Displacements	✓	✓
Industry FE	✓	✓
Region FE	✓	✓

Source: ASSD, own calculations.
Note: *,**,*** indicates significance at the 10%, 5%, and 1% level, respectively. Standard errors in parentheses. Furthermore I control for a quadratic in age, age at first employment, firm size, firm operation duration, unemployment duration since LFP, employment duration since LFP, tenure at the closing firm, wage at first job, number of employment spells and number of unemployment spells.

[23] Gibbons and Katz (1991) do not show these results in their paper and therefore I am unable to talk about magnitudes.

4.2.2 Gibbons and Katz (1991) taken a step further

As outlined in Section 2.1, I will take GK a step further, by including an indicator whether the person is of high ability or not. Figure 6 shows why this distinction may be the potentially more interesting result. Categorizing individuals as high ability if they fall into the highest quintile of the person effect, and as low if they fall into the lowest quintile, we observe that the high ability individual layoffs lose most in terms of their wages. Again year zero is the year of displacement, during the five years before displacement individual layoffs and closures of high ability had more or less the same wages, but when displacement happens, the individual layoff loses in terms of wages and does not catch up within the next five years. This kink in wages is not visible for the low ability individuals.

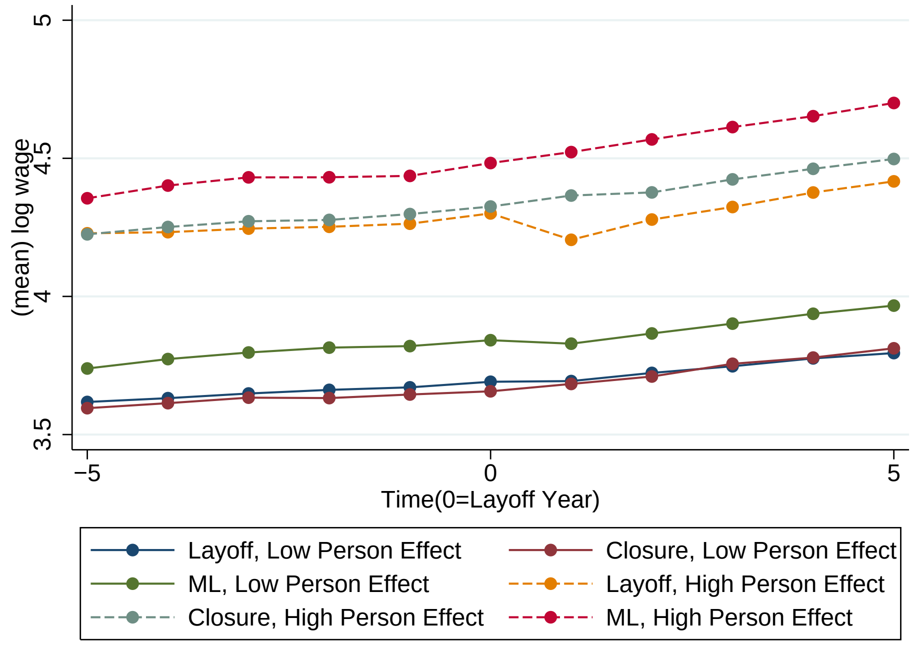


Figure 6: Mean Wages Re-employed Individuals by Layoff Type and Person Quintile

Table 9 takes GK a step further by including an indicator of the individual's ability, and an indicator if the layoff firm is a high wage firm (HWF) as outlined in equation (4).[24] This analysis extends GK analysis of the high versus low tenure analysis by trying to see if a high ability individual layoff is able to overcome the "lemon" stigma. Column (1) presents the baseline results from Table 6 while column (2) adds the high ability and HWF indicators. Column (3) includes the additional interaction terms. The coefficient on the individual layoff stays significantly negative. It seems that even controlling for whether or not the individual is of high ability does not suffice to overcome the negative stigma.

[24]The individual's ability is proxied by a dummy which equals one if her person effect falls into the highest quintile, while a HWF is proxied by a dummy equal to one if the firm's fixed effect falls into the highest quintile (similarly defined for the re-employment firm).

Table 9: Difference Between Wages High Type Person Effect

	(1)	(2)	(3)
Mass Layoff	0.00666*	0.0139***	0.0205***
	(0.00373)	(0.00366)	(0.00459)
Layoff	-0.0490***	-0.0426***	-0.0338***
	(0.00301)	(0.00294)	(0.00342)
High Person Effect		0.0174***	0.0471***
		(0.00333)	(0.00725)
High Firm Effect		-0.180***	-0.161***
		(0.00305)	(0.00716)
High PE * High FE		0.127***	0.0847***
		(0.00703)	(0.0165)
High Firm Effect at Reemp. Firm		0.208***	0.209***
		(0.00294)	(0.00294)
ML*High PE			-0.0129
			(0.00963)
ML*High FE			-0.0197**
			(0.00897)
ML * High PE * High FE			0.000218
			(0.0206)
Layoff*High PE			-0.0469***
			(0.00829)
Layoff*High FE			-0.0230***
			(0.00771)
Layoff * High PE * High FE			0.0815***
			(0.0193)
year FE	Yes	Yes	Yes
number of displacements	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Observations	125495	125495	125495
R^2	0.0613	0.1082	0.1086
Adjusted R^2	0.0602	0.1071	0.1075

Source: ASSD, own calculations.
Notes: Dependent variable: log(current wage) - log(previous wage). *,**,*** indicates significance at the 10%, 5%, and 1% level, respectively. Standard errors in parentheses.
Furthermore I control for a quadratic in age, age at first employment, firm size, firm operation duration, unemployment duration since LFP, employment duration since LFP, tenure at the closing firm, wage at first job, number of employment spells and number of unemployment spells.

Table 10 presents the different average effects based on column (3) in Table 9. A high ability mass laid off individual has a 5.5% increase in the difference in wages compared to a closure individual. A high ability individual layoff suffers a decrease in wages of about 3.4% compared to a closure individual.[25] Unlike expected, a high ability individual is not able to signal her high ability, and the "lemon" effect still dominates and therefore she still suffers from a wage decline ($\delta_1 + \delta_3 + \delta_4 < 0$). Coming from a HWF decreases the wage, for a mass layoff by about 16% and for an individual layoff by 22%.[26] This large decrease in wages may be due to the fact, that the pre-displacement firm was paying wages that were above the average productivity and this premia is now gone. Another interesting result is that a high ability individual from a HWF, suffers a decrease in wages. A high ability individual can thus not compensate for being previously employed at a HWF, in this case a mass laid off individual suffers a 4.1% decrease, while an individual layoff suffers from a 5.1% decrease.

Table 10: Expected Changes in Wages by type

t=	**Mass Layoff**		**Layoff**		
	$\delta_2 + \delta_3 + \delta_5$	P-val.	$\delta_1 + \delta_3 + \delta_4$	P-val.	P-val.
E[Δ W | T = t]	0.0205	0.0000	-0.0338	0.0000	0.0000
E[Δ W | T = t, high PE = 1]	0.0547	0.0000	-0.0336	0.0000	0.0000
E[Δ W | T = t, high FE = 1]	-0.1600	0.0000	-0.2177	0.0000	0.0000
E[Δ W | T = t, high PE = 1, high FE]	-0.0409	0.0001	-0.0512	0.0000	0.4381

Source: ASSD, own calculations.

Notes: These are the expectations calculated from a regression of the change in wages on a mass layoff dummy, a layoff dummy, a high PE dummy, a high FE dummy, the interaction of those two, a dummy for high FE at the reemployment firm, interactions of the high PE and FE with ML and layoff dummies. Furthermore I control for a quadratic in age, age at first employment, firm size, firm operation duration, employment duration since LFP, unemployment duration since LFP, tenure at the closing firm, wage at first job, number of employment spells, number of unemployment spells, year of displacement dummies, number of displacement dummies, industry dummies and region dummies.

The P-values on the different coefficients result from an F-test whether they are different from 0 or not. The P-value in the last column on the other hand, is a test of whether the coefficients for the mass layoff group are different from those of the layoff group.

This evidence reinforces the findings of a stigma being attached to an individual layoff. The question which is outside of the GK framework, but that is still interesting, is whether an individual layoff can end up at a high wage firm? Table 11 presents the results of a simple logit model (equation (5)) where the dependent variable is one if the individual ends up at a high wage firm.[27]

Table 12 presents the marginal effects for a mass layoff, or a layoff, compared to the baseline (closure). The standard errors are computed using the delta method and I find that if an individual was part of a mass layoff, she is nearly 5 percentage points more likely to end up at a high wage firm than a closure individual. This effect is negative but insignificant for an individual layoff. A high ability mass laid off individual is nearly 13 percentage points more likely to end up at a high wage firm, whereas an individual layoff is only 4 percentage points more likely. Thus being a high ability individual and having suffered from an individual layoff does not hamper employment at a HWF. This result may point

[25] These numbers are significantly different from each other, and also significantly different from 0. An F-Test on the linear combinations was used to test for significance.

[26] Again these numbers are significantly different from each other and from 0.

[27] I refer the reader for more information on the cell sizes for the different layoff categories to Table 19.

Table 11: Who Ends up at high type Firm?

	(1)	(2)	(3)	(4)
High Firm Effect at Reemp. Firm				
Mass Layoff	0.643***	0.227***	0.329***	0.339***
	(0.0272)	(0.0298)	(0.0472)	(0.0475)
Layoff	-0.0773***	-0.166***	-0.0865**	-0.0250
	(0.0243)	(0.0263)	(0.0375)	(0.0378)
Age	0.0906***	0.0480***	0.0459***	0.0374***
	(0.00761)	(0.00824)	(0.00836)	(0.00842)
Age^2	-0.000454***	-0.000138	-0.000176*	-0.000105
	(0.0000930)	(0.000101)	(0.000102)	(0.000103)
Total Unemployment Duration since LFP	-0.000185***	-0.0000443	-0.0000548	-0.0000778*
	(0.0000425)	(0.0000436)	(0.0000444)	(0.0000446)
Firm Size	-0.0000845***	-0.0000660***	-0.0000201***	-0.0000281***
	(0.00000446)	(0.00000460)	(0.00000550)	(0.00000565)
Firm Operation Duration	-0.000000312	0.0000141***	0.0000153***	0.0000139***
	(0.00000203)	(0.00000218)	(0.00000238)	(0.00000243)
Tenure at Closing Firm	0.0000408***	0.00000434	0.00000365	-0.00000198
	(0.00000545)	(0.00000599)	(0.00000612)	(0.00000618)
Total Employment Duration since LFP	-0.000328***	-0.000240***	-0.000224***	-0.000199***
	(0.0000183)	(0.0000200)	(0.0000207)	(0.0000208)
Wage at First Job	0.0265***	0.0132***	0.0115***	0.0111***
	(0.000637)	(0.000731)	(0.000742)	(0.000746)
Age at First Employment	-0.0705***	-0.0459***	-0.0407***	-0.0392***
	(0.00417)	(0.00458)	(0.00465)	(0.00468)
Number of Unemployment Spells	-0.0533***	-0.0379***	-0.0356***	-0.0288***
	(0.00384)	(0.00396)	(0.00405)	(0.00407)
Number of Employment Spells	0.0922***	0.0598***	0.0575***	0.0519***
	(0.00788)	(0.00856)	(0.00872)	(0.00877)
High Person Effect		0.372***	0.0149	-0.00355
		(0.0299)	(0.0746)	(0.0749)
High Firm Effect		2.222***	2.326***	2.263***
		(0.0189)	(0.0514)	(0.0519)
High PE * High FE		-0.587***	-0.161	-0.159
		(0.0465)	(0.116)	(0.117)
ML*High PE			0.288***	0.329***
			(0.0952)	(0.0956)
ML*High FE			-0.381***	-0.428***
			(0.0664)	(0.0673)
ML * High PE * High FE			-0.0908	-0.0893
			(0.146)	(0.147)
Layoff*High PE			0.300***	0.287***
			(0.0832)	(0.0834)
Layoff*High FE			-0.241***	-0.295***
			(0.0560)	(0.0565)
Layoff * High PE * High FE			-0.646***	-0.617***
			(0.134)	(0.135)
year FE	Yes	Yes	Yes	Yes
Region FE	No	No	No	Yes
Industry FE	No	No	Yes	Yes
Observations	139449	139449	139447	139445
Pseudo R^2	0.0543	0.1818	0.1958	0.2040

Source: ASSD, own calculations.
Note: *,**,*** indicates significance at the 10%, 5%, and 1% level, respectively. Standard errors in parentheses.

toward exploitation - individual layoffs are hired at HWF more often than closure individuals, but on average earn a lower wage after displacement. On the other hand coming from a HWF, decreases the likelihood of ending up at a high wage firm by 2 percentage points for a mass layoff and an individual layoff. A high ability mass layoff from a HWF is 3 percentage points more likely to end up at a HWF, while an individual HWF layoff is 16 percentage points less likely to end up at a HWF.[28]

Table 12: Marignal Effect of Being Employed in a HWF

t=	**Mass Layoff**		**Layoff**	
	ME	σ	ME	σ
P(Emp. HWF = 1 | T = t)	0.0537	0.0106	-0.0032	0.0048
P(Emp. HWF = 1 | T = t, high PE = 1)	0.1333	0.0228	0.0429	0.0138
P(Emp. HWF = 1 | T = t, high FE = 1)	-0.0210	0.0117	-0.0210	0.0112
P(Emp. HWF = 1 | T = t, high PE = 1, high FE)	0.0337	0.0227	-0.1621	0.0241

Source: ASSD, own calculations.
Notes: ME stands for the marginal effect, while σ stands for the standard error, calculated by the delta method. The marginal effects are calculated at the mean. I ran a logit regression of the probability to be re-employed at a high wage firm controlling for a mass layoff dummy, a layoff dummy, a high PE dummy, a high FE dummy, the interaction of those two, a dummy for high FE at the reemployment firm, interactions of the high PE and FE with ML and layoff dummies. Furthermore I control for a quadratic in age, age at first employment, wage at firt job, employment duration since LFP, unemployment duration since LFP, tenure at the closing firm, number of employment spells, number of unemployment spells, year of displacement dummies, number of displacement dummies, industry dummies and region dummies.

4.2.3 Does the "lemon" affect the resulting matching?

So far I replicated GK results, took them a step further and found slightly more evidence in favor of a signal, but cannot find evidence for rejecting the matching model. Therefore in this section I will investigate other sorting measures as discussed in Section 2.3, to see whether the "lemon" also affects the resulting matching.

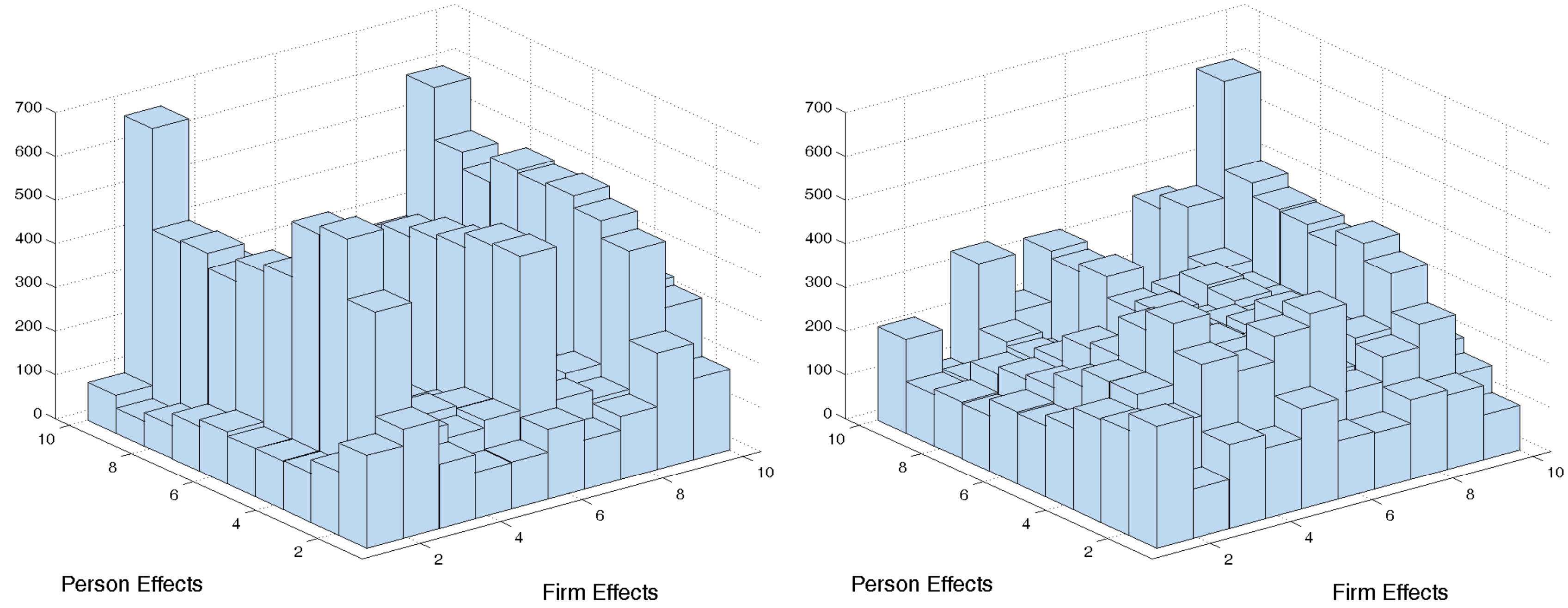
Figures 7a, 7b, 8a, 8b, 9a and 9b plot histograms of the firm and person effects, where the effects are grouped into their respective deciles. These graphs provide some information on who ends up where, and how the sorting in terms of the deciles was before and after displacement.[29] Taking a closer look at Figures 7a, 7b we see that the correlations of the person and firm effects, even though downward biased increased after the mass layoff. This may indicate sorting before and after the layoff event, as the correlation increases from -0.0023 to 0.1142. Individuals sorted into the second firm decile move, which "evens" the graph out at the re-employment firm. Furthermore there is more mass in the lowest firm decile after displacement, while higher firm deciles seem to remain stable.

[28] A related paper which focuses on unemployment durations is Böheim et al. (2011), who find that individuals laid off from a high wage firm take longer to find a job than those coming from a low wage firm (they only analyze the individuals behavior after a plant closure.) The main rationale behind their finding is that individuals coming from a high wage firm take longer to update their prior about the wage distribution.

[29] All these graphs use only re-employed individuals, excluding still unemployed individuals.

Figures 8a and 8b show the same correlation of the person and firm fixed effects for the closure individuals. The correlation between the deciles of the firm and person effects increases slightly at the new job from a correlation of 0.1046 to 0.1221. Most of the movements seemingly take place in the last firm decile, "evening" themselves out. Again there is sorting before and after displacement.

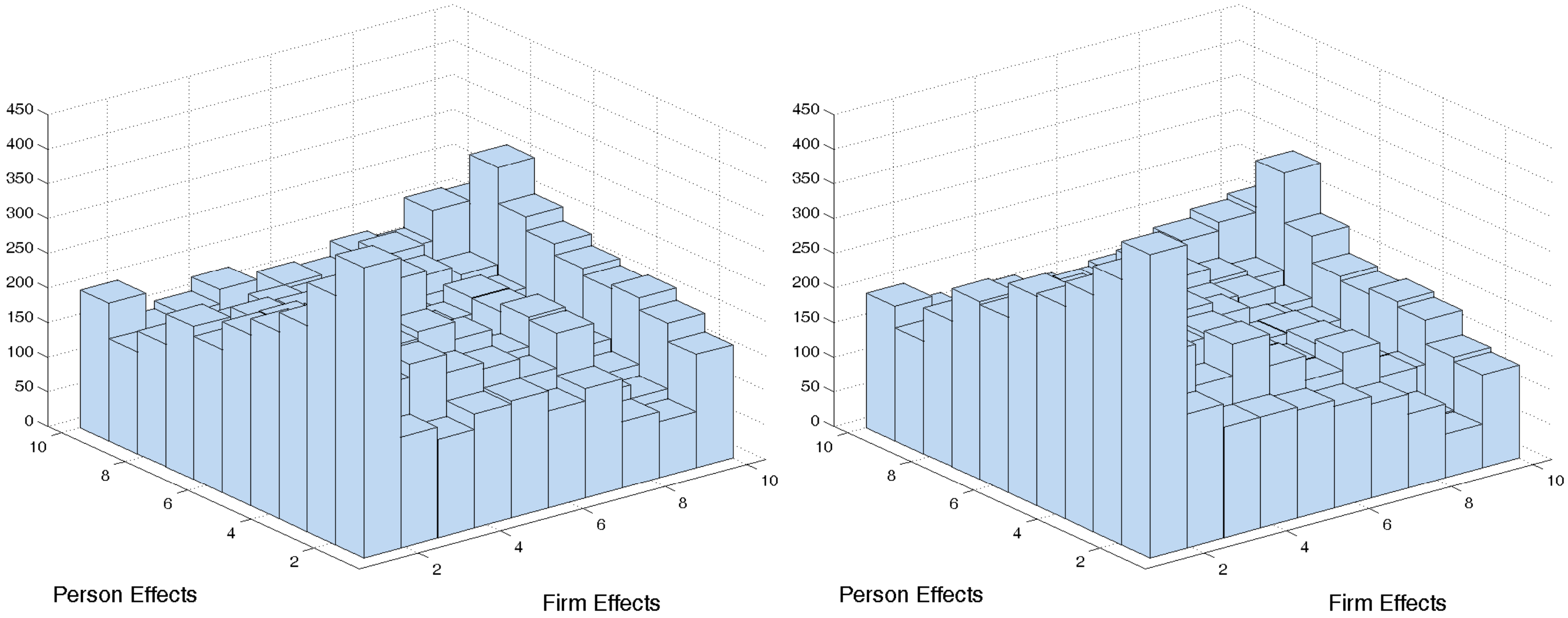
Figures 9a and 9b show that the correlation increases slightly after the displacement from 0.0217 to 0.0280 for individual layoffs. The visible movements take place in the first person decile, where individuals move from the lowest firm decile to the highest firm decile. In contrast to the highest person decile, where the opposite is happening. In these graphs individual movements cannot be observed, only mass changes, which excludes conclusions on which workers moves.



(a) At Layoff Firm Corr(PE,FE)=-0,0023

(b) At Re-Emp. Firm Corr(PE,FE)=0,1142

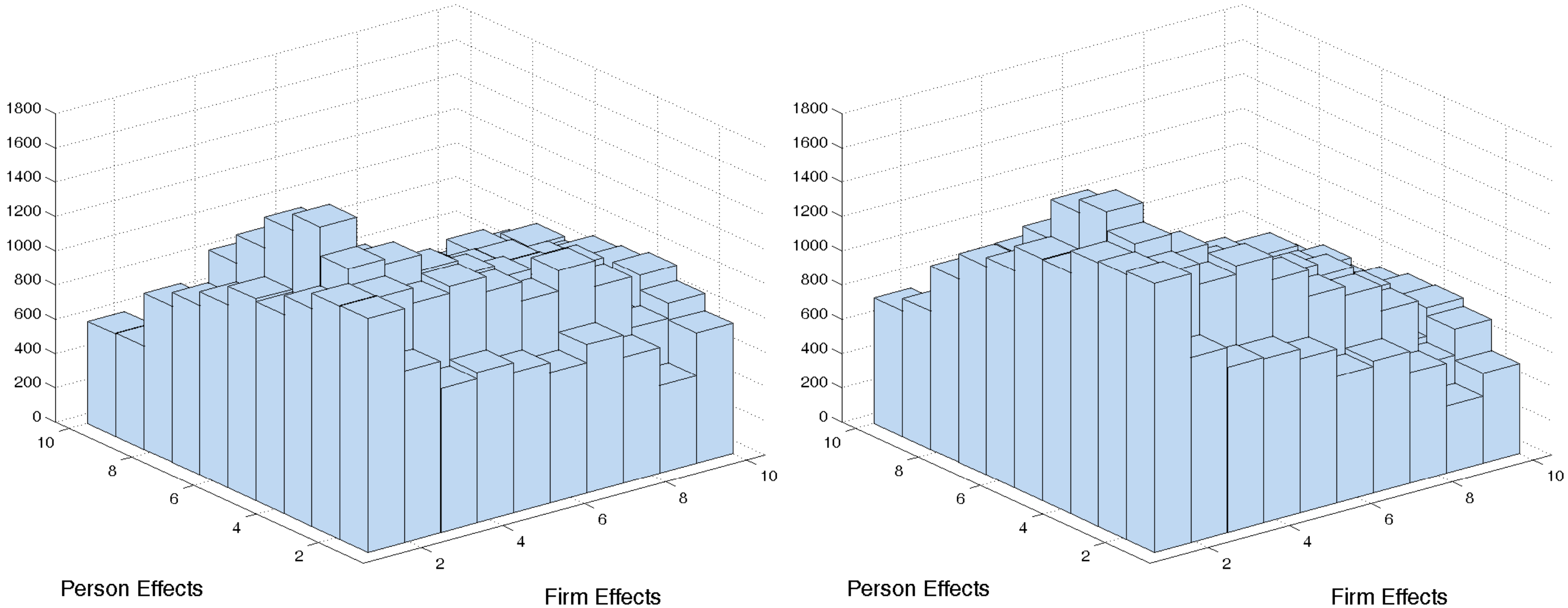
Figure 7: Mass Layoff Deciles



(a) CL Deciles at Layoff Firm Corr(PE,FE)=0,1046

(b) CL Deciles at Re-Emp. Firm Corr(PE,FE)=0,1221

Figure 8: Closure Deciles



(a) Layoff Deciles at Layoff Firm Corr(PE,FE)=0,0217

(b) Layoff Deciles at Re-Emp. Firm Corr(PE,FE)=0,0280

Figure 9: Involuntary Layoff Deciles

The first measure available to check whether the "lemon" affects the resulting matching is the firm fixed effects before and after displacement. Table 13 lists the average firm fixed effect for the layoffs at the pre- and post-displacement firm. For the closing individuals, we observe a clear decline of the average firm fixed effect from 0.042 at the pre-displacement firm to 0.021 at the post-displacement firm. Looking at the individual layoffs, the firm fixed effect decreases from 0.046 at the pre-displacement firm to 0.019 at the post-displacement firm. This decrease is larger than the one in the closing firms. This pattern suggests that both sorting and signaling may take place, since the sorting measure decreases more for the individual layoffs than for the closures. Sorting for the mass layoff types remains nearly the same; the average firm fixed effect is at 0.093 before the displacement and 0.090 after the displacement.

These differences remain more or less stable depending on the subsample. The firm fixed effect decreases after the layoff event for the closing and the individual layoffs, for the white collar sample, the high person effect sample, the low person effect sample, the high firm effect, the low firm effect the long firm operation duration and the small turnover sample. In these samples, the firm fixed effect decreases less for the closing types than for the individual layoffs. For the blue collar sample, the short firm operation sample and the high turnover sample the opposite is true. It grows stronger for the layoff sample than for the closing sample (or decreased by less). For the blue collar workers, that might be due to the fact that they are covered by more rigid rules in terms of layoff decisions.

Table 14 on the other hand as a sensitivity check, looks at a very similar measure, which focuses on the average co-worker person effect in the pre- and post-displacement firm. Contrary to the firm fixed effect, I find that the measure for the closing types always grows stronger (or declines less) than that of the individual layoff sample, only for the low person effect sample.[30]

For the question of whether or not there is sorting in the data the problems with the correlation between the firm and the person effect have been discussed and whether or not I should use Lopes de Melo (2013)'s measure, which can only identify the strength, but not the sign. Using this measure in Table 15, I find that there is significant sorting going on in the case of Austria. Table 15 analyzes $\mathrm{Corr}(\theta_i, \tilde{\theta}_{j(i,t)})$ and confirms the differential changes in the sorting measure for the three categories of job loss (mass layoff, individual layoff, and firm closure). This points into the direction that there is signaling and sorting happening on aggregate. A finding which should not surprise us, since the resulting outcome on the labor market usually is a combination of signaling and sorting. Future research should focus on developing a model that merges the asymmetric information literature with the sorting literature.

The question about expectations and priors concerning sorting, may be raised. To give probable priors for the change in the correlations, I would have to assume that the sorting at the displacement firm is not affected by the displacement. The first problem that needs to be addressed, in this case, is that especially the firm fixed effect of the closing firm, may be affected, since these firms are already the "worst" firms, otherwise they would not shut down. Furthermore, the sorting at the displacement firm may also be the result of signaling and sorting based on previous experiences of the firm and the

[30] In the firm fixed effect changes, the difference between the two has not been significant, so this does not challenge the result from before.

Table 13: Sorting measure: $\Psi_{j(i,t)}$

Sample	Closure Mean	Closure P.	Mass Layoff Mean	Mass Layoff P.	Layoff Mean	Layoff P.	Two-Sided P-value CL-ML	Two-Sided P-value Lay-CL	Two-Sided P-value Lay-ML
Whole sample									
N	18697		24553		87099				
Predisplacement	0.042	0.000	0.093	0.000	0.046	0.000			
Postdisplacement	0.021	0.000	0.090	0.000	0.019	0.000			
Δ	-0.021	0.000	-0.003	0.027	-0.026	0.000	0.000	0.007	0.000
White Collar									
N	7803		11739		27401				
Predisplacement	0.068	0.000	0.022	0.000	0.055	0.000			
Postdisplacement	0.058	0.000	0.066	0.000	0.011	0.000			
Δ	-0.010	0.000	0.044	0.000	-0.044	0.000	0.000	0.000	0.000
Blue Collar									
N	10018		11035		57494				
Predisplacement	0.018	0.000	0.165	0.000	0.039	0.000			
Postdisplacement	-0.011	0.000	0.114	0.000	0.023	0.000			
Δ	-0.029	0.000	-0.051	0.000	-0.016	0.000	0.000	0.000	0.000
High Person Effect									
N	3139		4610		8343				
Predisplacement	0.066	0.000	0.093	0.000	0.037	0.000			
Postdisplacement	0.054	0.000	0.111	0.000	-0.007	0.063			
Δ	-0.011	0.002	0.018	0.000	-0.044	0.000	0.000	0.000	0.000
Low Person Effect									
N	3689		4473		20037				
Predisplacement	-0.010	0.055	0.076	0.000	0.036	0.000			
Postdisplacement	-0.033	0.000	0.051	0.000	0.011	0.000			
Δ	-0.023	0.000	-0.025	0.000	-0.025	0.000	0.694	0.657	0.983
High Firm Effect									
N	3337		7259		13463				
Predisplacement	0.342	0.000	0.301	0.000	0.321	0.000			
Postdisplacement	0.225	0.000	0.206	0.000	0.158	0.000			
Δ	-0.117	0.000	-0.095	0.000	-0.163	0.000	0.000	0.000	0.000
Low Firm Effect									
N	4496		6014		21560				
Predisplacement	-0.300	0.000	-0.183	0.000	-0.246	0.000			
Postdisplacement	-0.223	0.000	-0.063	0.000	-0.148	0.000			
Δ	0.077	0.000	0.120	0.000	0.098	0.000	0.000	0.000	0.000
Long Firm Operation									
N	199		8465		22522				
Predisplacement	0.038	0.001	0.043	0.000	0.082	0.000			
Postdisplacement	0.009	0.612	0.081	0.000	0.037	0.000			
Δ	-0.029	0.029	0.038	0.000	-0.045	0.000	0.000	0.318	0.000
Short Firm Operation									
N	14750		8139		34133				
Predisplacement	0.037	0.000	0.135	0.000	0.008	0.000			
Postdisplacement	0.018	0.000	0.088	0.000	-0.002	0.135			
Δ	-0.019	0.000	-0.046	0.000	-0.010	0.000	0.000	0.000	0.000
High Turnover									
N	10624		7447		31312				
Predisplacement	0.016	0.000	0.069	0.000	0.024	0.000			
Postdisplacement	-0.003	0.284	0.068	0.000	0.019	0.000			
Δ	-0.019	0.000	-0.000	0.917	-0.005	0.000	0.000	0.000	0.113
Small Turnover									
N	3058		7814		24869				
Predisplacement	0.072	0.000	0.071	0.000	0.051	0.000			
Postdisplacement	0.041	0.000	0.062	0.000	0.009	0.000			
Δ	-0.031	0.000	-0.009	0.000	-0.042	0.000	0.000	0.032	0.000

Source: ASSD, own calculations.

Notes: P. designates the two sided P-value of a t-test whether the mean is equal to zero at the 95 percent level.

Δ, denotes the change in the correlations at the postdisplacement firm and the predisplacement firm. High person effect designates the highest quintile, while low person effect designates the lowest quintile. The same logic holds for the high and low firm effects. Large firm size refers to a firm size which falls into the highest tertile, small firm size refers to a firm size which falls into the lowest tertile. The same logic holds for turnover. Long firm operation refers to a firm, who's operation duration falls in the highest tertile, while it is short if it falls in the smallest tertile.

Table 14: Sorting measure: $\tilde{\theta}_{j(i,t)}$

Sample	Closure Mean	Closure P.	Mass Layoff Mean	Mass Layoff P.	Layoff Mean	Layoff P.	Two Sided P-value CL-ML	Two Sided P-value Lay-CL	Two Sided P-value Lay-ML
Whole sample									
N	18697		24553		87099				
Predisplacement	3.417	0.000	3.448	0.000	3.432	0.000			
Postdisplacement	3.432	0.000	3.457	0.000	3.426	0.000			
Δ	0.015	0.000	0.009	0.000	-0.006	0.000	0.000	0.000	0.000
White Collar									
N	7803		11739		27401				
Predisplacement	3.468	0.000	3.479	0.000	3.492	0.000			
Postdisplacement	3.484	0.000	3.486	0.000	3.476	0.000			
Δ	0.015	0.000	0.007	0.000	-0.015	0.000	0.000	0.000	0.000
Blue Collar									
N	10018		11035		57494				
Predisplacement	3.376	0.000	3.417	0.000	3.403	0.000			
Postdisplacement	3.391	0.000	3.429	0.000	3.402	0.000			
Δ	0.016	0.000	0.013	0.000	-0.001	0.014	0.037	0.000	0.000
High Person Effect									
N	3139		4610		8343				
Predisplacement	3.534	0.000	3.537	0.000	3.575	0.000			
Postdisplacement	3.577	0.000	3.558	0.000	3.576	0.000			
Δ	0.042	0.000	0.022	0.000	0.001	0.633	0.000	0.000	0.000
Low Person Effect									
N	3689		4473		20037				
Predisplacement	3.309	0.000	3.382	0.000	3.341	0.000			
Postdisplacement	3.297	0.000	3.378	0.000	3.337	0.000			
Δ	-0.013	0.000	-0.004	0.009	-0.004	0.001	0.007	0.001	0.735
High Firm Effect									
N	3337		7259		13463				
Predisplacement	3.440	0.000	3.445	0.000	3.444	0.000			
Postdisplacement	3.454	0.000	3.462	0.000	3.434	0.000			
Δ	0.014	0.000	0.017	0.000	-0.010	0.000	0.100	0.000	0.000
Low Firm Effect									
N	4496		6014		21560				
Predisplacement	3.384	0.000	3.459	0.000	3.416	0.000			
Postdisplacement	3.400	0.000	3.462	0.000	3.419	0.000			
Δ	0.015	0.000	0.003	0.057	0.003	0.002	0.000	0.000	0.494
Long Firm Operation									
N	199		8465		22522				
Predisplacement	3.442	0.000	3.488	0.000	3.446	0.000			
Postdisplacement	3.449	0.000	3.483	0.000	3.434	0.000			
Δ	0.007	0.357	-0.005	0.000	-0.012	0.000	0.051	0.018	0.000
Short Firm Operation									
N	14750		8139		34133				
Predisplacement	3.416	0.000	3.424	0.000	3.417	0.000			
Postdisplacement	3.431	0.000	3.444	0.000	3.418	0.000			
Δ	0.015	0.000	0.020	0.000	0.001	0.271	0.010	0.000	0.000
High Turnover									
N	10624		7447		31312				
Predisplacement	3.395	0.000	3.405	0.000	3.403	0.000			
Postdisplacement	3.415	0.000	3.433	0.000	3.412	0.000			
Δ	0.020	0.000	0.028	0.000	0.009	0.000	0.000	0.000	0.000
Small Turnover									
N	3058		7814		24869				
Predisplacement	3.456	0.000	3.476	0.000	3.453	0.000			
Postdisplacement	3.460	0.000	3.470	0.000	3.435	0.000			
Δ	0.004	0.140	-0.005	0.000	-0.019	0.000	0.000	0.000	0.000

Source: ASSD, own calculations.

Notes: Δ, denotes the change in the correlations at the postdisplacement firm and the predisplacement firm. High person effect designates the highest quintile, while low person effect designates the lowest quintile. The same logic holds for the high and low firm effects. Large firm size refers to a firm size which falls into the highest tertile, small firm size refers to a firm size which falls into the lowest tertile. The same logic holds for turnover. Long firm operation refers to a firm, who's operation duration falls in the highest tertile, while it is short if it falls in the smallest tertile.

Table 15: Sorting measure: Corr($\theta_i, \tilde{\theta}_{j(i,t)}$)

Sample	Closure N	Closure Corr	Mass Layoff N	Mass Layoff Corr	Layoff N	Layoff Corr
Whole sample						
Predisplacement	18697	0.684	24553	0.491	87099	0.646
Postdisplacement	18697	0.725	24553	0.553	87099	0.648
Δ		0.041		0.061		0.002
White Collar						
Predisplacement	7803	0.655	11739	0.382	27401	0.612
Postdisplacement	7803	0.714	11739	0.490	27401	0.630
Δ		0.059		0.107		0.018
Blue Collar						
Predisplacement	10018	0.620	11035	0.501	57494	0.613
Postdisplacement	10018	0.668	11035	0.541	57494	0.608
Δ		0.048		0.040		-0.005
Only ML, Closure Firms						
Predisplacement	18697	0.684	24553	0.491	4103	0.470
Postdisplacement	18697	0.725	24553	0.553	4103	0.564
Δ		0.041		0.061		0.094
High Person Effect						
Predisplacement	3139	0.408	4610	0.112	8343	0.440
Postdisplacement	3139	0.430	4610	0.181	8343	0.451
Δ		0.023		0.069		0.011
Low Person Effect						
Predisplacement	3689	0.524	4473	0.131	20037	0.468
Postdisplacement	3689	0.626	4473	0.192	20037	0.447
Δ		0.103		0.061		-0.021
High Firm Effect						
Predisplacement	3337	0.693	7259	0.513	13463	0.648
Postdisplacement	3337	0.723	7259	0.549	13463	0.630
Δ		0.030		0.037		-0.017
Low Firm Effect						
Predisplacement	4496	0.751	6014	0.359	21560	0.777
Postdisplacement	4496	0.792	6014	0.461	21560	0.730
Δ		0.041		0.102		-0.047
High Firm and Person Effect						
Predisplacement	602	0.139	1104	0.007	1423	0.119
Postdisplacement	602	0.117	1104	0.149	1423	0.134
Δ		-0.022		0.141		0.015
Low Firm and Person Effect						
Predisplacement	1151	0.527	1091	0.165	5068	0.544
Postdisplacement	1151	0.643	1091	0.157	5068	0.486
Δ		0.116		-0.008		-0.058
Long Firm Operation						
Predisplacement	199	0.714	8465	0.433	22522	0.497
Postdisplacement	199	0.777	8465	0.497	22522	0.582
Δ		0.062		0.064		0.085
Short Firm Operation						
Predisplacement	14750	0.691	8139	0.515	34133	0.740
Postdisplacement	14750	0.734	8139	0.584	34133	0.686
Δ		0.043		0.068		-0.053
High Turnover						
Predisplacement	10624	0.669	7447	0.484	31312	0.629
Postdisplacement	10624	0.725	7447	0.561	31312	0.635
Δ		0.057		0.077		0.007
Small Turnover						
Predisplacement	3058	0.761	7814	0.355	24869	0.714
Postdisplacement	3058	0.751	7814	0.456	24869	0.678
Δ		-0.010		0.102		-0.036

Source: ASSD, own calculations.

Notes: Δ, denotes the change in the correlations at the postdisplacement firm and the predisplacement firm. High person effect designates the highest quintile, while low person effect designates the lowest quintile. The same logic holds for the high and low firm effects. Large firm size refers to a firm size which falls into the highest tertile, small firm size refers to a firm size which falls into the lowest tertile. The same logic holds for turnover. Long firm operation refers to a firm, who's operation duration falls in the highest tertile, while it is short if it falls in the smallest tertile.

workers. Nevertheless, I may assume at first that the sorting at the displacement is not affected by the displacement type. Since the question I am trying to answer is whether or not the "lemon" affects the resulting matching, the sorting at the re-employment firm may be affected by the layoff. This leaves two possibilities;

1. the sorting at the re-employment firm is not affected by the displacement type. This gives the prediction that I should observe no change in sorting or a trend in sorting.
2. The sorting at the re-employment firm is affected by the displacement type, then it depends on what type (high or low ability) individual is trying to sort herself. Still assuming that the closing types are the ones that do not suffer from a stigma, we get the following predictions, (see Table 16);

Table 16: Priors on sorting

Displacement	**Low Ability**	**High Ability**
Closure	No change in sorting	No change in sorting
Layoff	"better" match	even more distorted
	↑ in "better" matching	↓ "better" in matching

For the closing individuals, we should observe no change in the sorting measure, or a trend. For the individual layoffs who are affected by the stigma, we should observe a "better" matching since the low ability individuals will now clearly be seen as low ability and should thus find their match. A high ability individual layoff on the other hand will be seen as low ability, and her match will be distorted, we should thus observe a decrease in efficient matching. Talking about efficiency raises another problem; I know how the sorting changes, but I do not know how good or efficient the sorting was before the displacement, so saying that it should become better is not a precise statement. The problem arises that to the best of my knowledge there is no efficiency measure available for sorting, so future research will need to investigate how to measure efficient matching.

5 Conclusion

This paper answered three related questions in the displacement literature of the labor market and combined two strands of the literature, namely sorting (Becker, 1973) and signaling (Gibbons and Katz, 1991). Analyzing individuals laid off due to a firm closure, a mass layoff or an individual layoff, I first test one of the assumptions usually made in the literature, namely that firms have leeway in determining whom to layoff and thus layoff the least able. Comparing individuals laid off due to plant closures, mass layoffs and individual layoffs, using as an ability proxy the person fixed effect from an Abowd et al. (1999) estimation, I confirm that firms layoff the least able individuals, while individuals laid off due to a plant closure are more heterogeneous than the individual layoffs. Individuals laid off due to a mass layoff are also strategically laid off; in terms of the variance of their ability, they are always in between the individuals suffering from a closure and those suffering from an individual layoff. Standard tests for the validity of the AKM estimation are performed, and I am able to confirm the validity of a linear model in the case of wages, which allowed me to use the person and firm fixed effects to determine whether there is sorting or signaling.

To determine whether a so called "lemons" effect from being individually laid off exists, I replicate Gibbons and Katz (1991). I am not able to reject the hypothesis that individual layoffs contain information about the individual's type, since I confirm GK results on signaling (in line with their asymmetric information model). I even take GK a step further and show that the high ability individual layoffs lose the most in terms of wages. A different result which is also important for future research, is that high ability individual layoffs get hired at high wage firms, but on average suffer from a wage loss. This result may be evidence of exploitation of the workers type.

The results cannot reject the asymmetric information model but I can also not reject the assortative matching model (Becker (1973)). I am not able to confirm the robustness check done in Gibbons and Katz (1991) to exclude the sorting explanation. Therefore I have to go one step further an analyze the sorting before and after displacement. This leads to a tentative reconciliation of the signaling literature with the sorting literature. I find sorting before the layoff event, as well as sorting after the layoff event (measured by the correlation between the worker and firm fixed effect, the correlation between the worker fixed effect and the mean of the co-workers person effect or by the average firm fixed effect, before and after displacement). I observe a differential change in the sorting measure for the three types of layoffs (closures, individual layoffs and mass layoffs). This leads to the conclusion that there is sorting as well as signaling.

As this paper brings together two strands of the literature, it highlights the fact that in future research we need to model the labor market as a combination of search and signals. The asymmetric information model of GK is a right start of modeling the signal. The question remains how to include it into a search framework of the Becker type and how to measure sorting efficiently.

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A AKM Appendix

A.1 Measure of Productivity according to Abowd et al. (1999) (AKM)

In order to capture unobserved heterogeneity on the individual and the firm level, I follow the formulation of Abowd et al. (1999), where the log daily wage ω_{it} of individual i in year t can be written as;

$$\begin{aligned}\omega_{it} &= \underbrace{\alpha_i + \Psi_{J(i,t)}}_{\text{Fixed Effects}} + x_{it}^{'}\beta + \underbrace{\eta_{iJ(i,t)} + \varsigma_{it} + \epsilon_{it}}_{\text{Random Effects}} \\ &= \alpha_i + \Psi_{J(i,t)} + x_{it}^{'}\beta + r_{it}\end{aligned} \tag{7}$$

the sum of a time-invariant worker component α_i, a time-variant establishment component $\Psi_{J(i,t)}$, a linear index of time-varying observable characteristics $x_{it}^{'}\beta$, a mean zero random match component $\eta_{J(i,t)}$, a unit root component of individual wage ς_{it} and a mean zero transitory error ϵ_{it}. All the error terms go into the same random effects component, r_{it}.[31] Following Card et al. (2013b), α_i can be interpreted as the portion of the individual's earnings power that is fully portable across employers. It is a combination of skills and other factors that are rewarded equally across employers. $\Psi_{J(i,t)}$ captures the proportional pay premium that is common to all employees at workplace j (i.e. all individuals for whom $J(i,t) = j$). This could be rent sharing, efficiency wage premium or strategic wage posting behavior. x_{it} captures changes in the portable component of an individuals earnings power. It includes an unrestricted set of year dummies, quadratic and cubic terms in age. The match effect η_{ij} allows for time-invariant wage premium (or discounts) for individual i at establishment j, relative to the baseline level $\alpha_i + \Psi_j$. This can also be interpreted as an idiosyncratic wage premium. It is the complementarity between the skills of the worker and the needs of the firm. These complementarities arise in models where idiosyncratic productivity components are associated with each potential job match and workers receive some share of the rents from a successful match. It is assumed that the match effect has mean 0. ς_{it} captures the drift in the portable component of the individual's earnings power. It can represent employer learning (about the productivity), unobserved human capital accumulation, health shocks or the arrival of outside offers. The drift component is assumed to have mean 0 but contains a unit root. ϵ_{it} presents any left out mean reverting factors, it is also assumed to have mean 0 for each person in the sample.

Following Abowd et al. (2002) a linear restriction is used on the firm effects within each "connected" set of firms for the estimation.[32] I refer the reader to Card et al. (2012) for a closer description of the estimation procedure and the discussion of the threats to validity. We will briefly mention the crucial assumptions here. First there is the standard orthogonality condition between the composite error r_{it} and the time-varying covariates X_{it}. Secondly, the crucial assumption is that, the composite error has to be orthogonal to the matrix of establishment identifiers. It is important to notice, that this does not preclude systematic patterns of job mobility related to α_i and or $\{\Psi_1, \ldots, \Psi_J\}$. Following the argument in Card et al. (2012), for example, a comparison of the number of job movers in the various cells of Tables 17 and 18, suggests that workers are more likely to move from low to high wage establishments than to move in the opposite direction. This does not represent a violation of the orthogonality condi-

[31]For completeness, when estimating this equation, I have N^* person-year observations with N workers and J establishments.

[32]The "connected" set of firms is the set of all firms which are linked to each other by moves of individuals between these firms. The direction of the move does not matter in order to identify the "connected" set.

tion between the error and the fixed effects because our fixed effects estimator conditions on the actual sequence of establishments at which each employee is observed. Similarly, higher (or lower) turnover rates among lower productivity workers is fully consistent with this condition, as is the possibility that high skilled workers are more (or less) likely to transition to workplaces with higher wage premiums. Mobility may be related to fixed or time-varying non-wage characteristics of establishments, such as location or recruiting effort. Such mobility helps the identification by expanding the connected set of establishments.

Other threats to the validity of the estimation are first sorting based on η_{ij}. The standard Roy (1951) model sorting changes the interpretation of Ψ_j, depending on the match component, different workers may have different wage premia at any given establishment. If job selection takes place based on the match component, we would expect wage gains for individuals who move from one establishment to another to be different from the wage losses for the individuals who make the opposite transition.[33] Furthermore if the match component is the relevant selection criterium, then a fully saturated model with a dummy for each job should fit the data much better than the additively separate baseline model.

Secondly, if abilities are valued differently at different firms, productive workers will experience a wage growth at their initial employer and are then also more likely to move to higher-wage firms (and vice-versa for less productive workers). This basically means that the drift in the expected wage predicts firm-to-firm transitions. This will lead to an overstatement of the firm effects.[34]

Thirdly, if fluctuations in the transitory error ϵ_{it} are associated with systematic movements between higher- and lower-wage workplaces. The example given in Card et al. (2012) is; if ϵ_{it} contains an industry by year component and workers tend to cycle between jobs at higher-wage employers that are relatively sensitive to industry conditions, and jobs at low-wage employers that are more stable. (As noted in discussion of Figures 10 and 11, there is little evidence that mobility patterns are related to transitory wage fluctuations, suggesting that any correlation between mobility patterns and the ϵ_{it}'s are small.)

In Section A.1.2, I will show that the identification criteria are met, and therefore I may use the firm fixed effects and the person fixed effects to test for heterogeneity, signaling and sorting. The person effects (which can be interpreted as ability) are then used to determine whether individuals laid off due to a plant closure are more heterogeneous than those laid off individually. The firm fixed effect will allow us to analyze the unobservables on the firm levels between the different groups of the layoff firm, as well as of the receiving firm.

A.1.1 AKM Sample

The AKM sample considers the Austrian universe of male blue and white collar workers from 1980 onwards. I select one main job per year per individual, with a wage and a firm number. If there are

[33] I will show in Section A.1.2, that the gains associated with transitioning from a low to high co-worker-wage firm is roughly equal to the losses associated with moving in the opposite direction. Moreover, the mean wage differentials for workers who move between firms in the same coworker wage quartile are close to zero in the time frame from 2002-2009, suggesting that there is no general mobility premium for movers.

[34] This will also be addressed in Section A.1.2.

overlapping spells, I select the longest spell as a main spell. This sample is used to estimate the person and firm fixed effects, but as outlined above, the effects are only identified within the connected set, which is the set of firms that are linked to each other due to the movement of workers between the firms. It does not matter in which direction the link goes. No further restrictions are put on this sample.[35]

A.1.2 Validity of the AKM Model

To show that the AKM model actually fits the data and that the orthogonality conditions do not seem to be violated, I follow closely Card et al. (2012).

To address the first threat to the validity concerning the sorting, or as Card et al. (2012) put it: "people who change workplaces will not necessarily experience systematic wage changes. If, on the other hand, different establishments pay different average wage premiums, then individuals who join a workplace where other workers are highly paid will on average experience a wage gain, while those who join a workplace where others are poorly paid will experience a wage loss", I replicate their event study.

To see whether sorting on wage premia happens in the Austrian Data I ran the event study, where I look at job movers and their co-workers wages at the job before and after the job movement. Figures 10 and 11 classify the movers according to the quartile of their mean co-worker wage. For clarification, the figures only show the wage profiles for workers leaving quartile 1 and quartile 4 jobs. Tables 17 and 18 provide a complete listing of mean wages before and after the job change event for each of the 16 cells in the two different time intervals (1990-1997 and 2002-2009). These figures look very similar to Figures 6a and 6b in Card et al. (2012).

The figures suggest that different mobility groups have different wage levels before and after a move. For example, average wages prior to a move for workers who switch from quartile 4 to quartile 1 jobs are lower than for those who move from quartile 4 to quartile 2 jobs, with similar patterns for the other mobility groups. Within mobility groups there is also strong evidence that moving to a job with higher-paid co-workers raises the own wage. People who start in quartile 1 jobs and move to quartile 1 jobs have relatively constant wages, while those who move to higher quartile jobs experience wage increases. Likewise for people who start in quartile 4 jobs.

An interesting feature of Figures 10 and 11, is the almost symmetry of the wage losses and gains for those who move between quartile 1 and quartile 4 firms. As shown in Tables 17 and 18, the gains and losses for other mover categories exhibit a similar degree of symmetry, particularly after adjusting for trend growth in wages. This symmetry suggests that a simple model with additive worker and firm effects may provide a reasonable characterization of the mean wages resulting from different pairings of workers to firms.

[35] To estimate AKM, I use Card et al. (2012)'s Matlab code. Originally I have $46,492,753$ person year observations, including $3,732,947$ workers at $624,055$ firms with a mean wage of 3.99 and a variance of 0.2846. When I restrict estimation to the largest connected set, I am left with $46,263,319$ person year observations, representing $3,690,879$ workers at $586,600$ firms with a mean wage of 4.001 and a variance of 0.28095. If we estimate the match effects model of AKM I have a root mean squared error of 0.1579 an R^2 of 0.9336 and an adjusted R^2 of 0.9112.

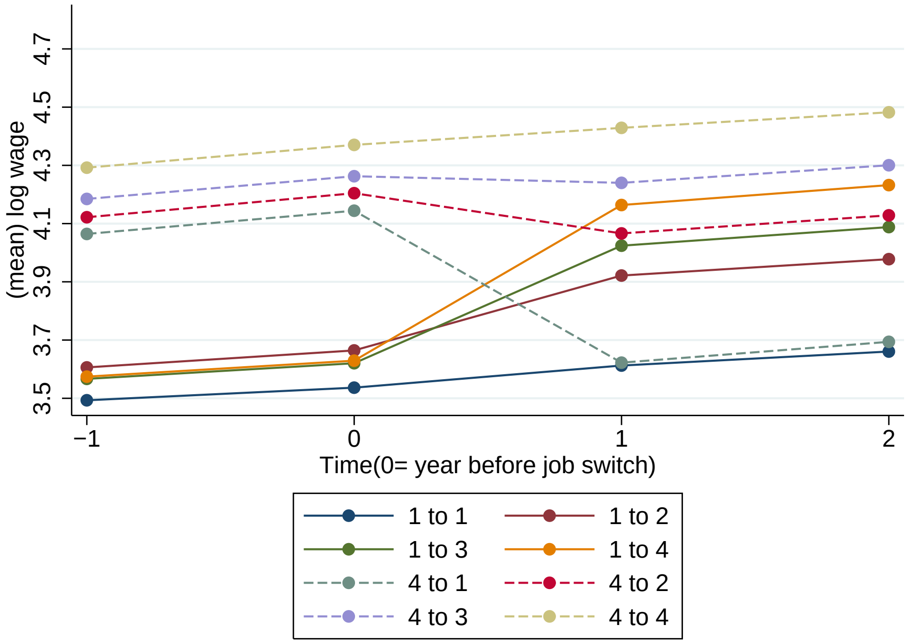

Figure 10: Mean Wages of Job Changers, Classified by Quartile of Mean Wage of Co-Workers at Origin and Destination Firm, 1990-97

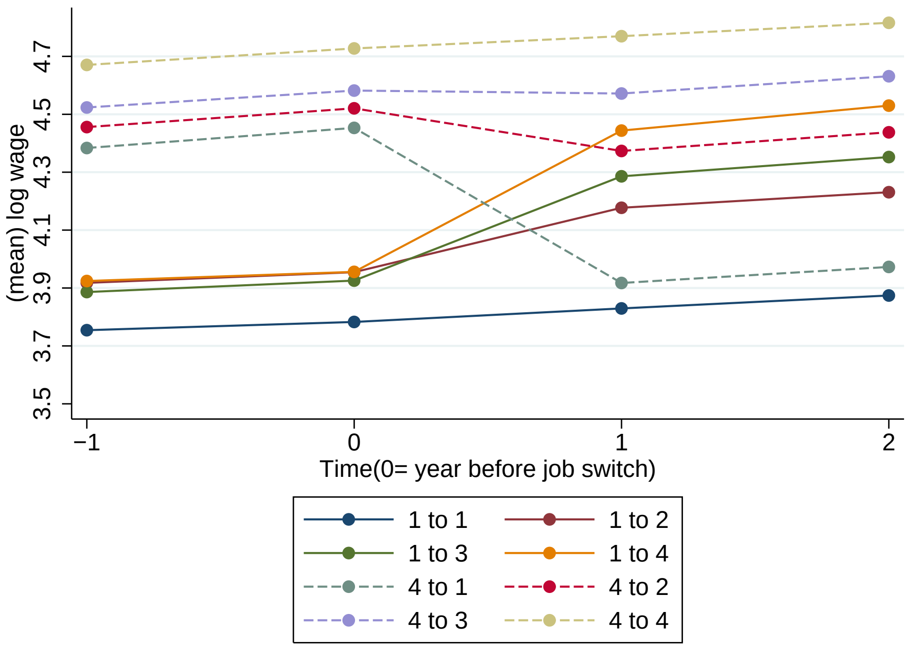

Figure 11: Mean Wages of Job Changers, Classified by Quartile of Mean Wage of Co-Workers at Origin and Destination Firm, 2002-2009

Table 17: **Mean Log Wages Before and After Job Change by Quartile of Mean Co-Workers' Wages at Origin and Destination Firms**

		Mean Log Wages of Movers				Change from 2 Years Before to 2 Years After	
Origin/Destination Quartile*	Number of Observations (1)	2 Years Before (2)	1 Year Before (3)	1 Year After (4)	2 Years After (5)	Raw (6)	Adjusted** (7)
Years: 2002 - 2009							
1 to 1	63083	3.75	3.78	3.87	3.94	0.19	0.00
1 to 2	30388	3.92	3.96	4.23	4.25	0.33	0.14
1 to 3	16526	3.89	3.93	4.35	4.38	0.49	0.30
1 to 4	9042	3.92	3.96	4.53	4.56	0.63	0.44
2 to 1	27355	4.12	4.17	4.06	4.13	0.01	-0.13
2 to 2	56903	4.22	4.25	4.33	4.36	0.14	0.00
2 to 3	31970	4.24	4.29	4.44	4.47	0.23	0.09
2 to 4	12823	4.24	4.32	4.60	4.63	0.39	0.25
3 to 1	13618	4.24	4.29	4.04	4.13	-0.10	-0.25
3 to 2	23460	4.32	4.36	4.36	4.40	0.08	-0.07
3 to 3	54814	4.40	4.44	4.53	4.55	0.15	0.00
3 to 4	23365	4.46	4.51	4.68	4.71	0.25	0.10
4 to 1	6728	4.38	4.45	3.97	4.07	-0.31	-0.47
4 to 2	8867	4.45	4.52	4.44	4.48	0.03	-0.14
4 to 3	19646	4.52	4.58	4.63	4.67	0.14	-0.02
4 to 4	70615	4.67	4.73	4.82	4.83	0.16	0.00

Source: ASSD, own calculations.
Notes: Entries are mean log real daily wages for job changers who are observed with at least two years of data prior to a job change, and two years after. Sample exlcudes mover to/from firms with 1 worker.
* Quartiles are based on mean wages of co-workers at old job in year prior to move, and in new job in year after move.
** Trend-adjusted mean wage change, calculated as mean wage change for origin-destination group, minus mean change for job movers from the same origin quartile who remain in same quartile.

Table 18: **Mean Log Wages Before and After Job Change by Quartile of Mean Co-Workers' Wages at Origin and Destination Firms**

		Mean Log Wages of Movers				Change from 2 Years Before to 2 Years After	
Origin/Destination Quartile*	Number of Observations (1)	2 Years Before (2)	1 Year Before (3)	1 Year After (4)	2 Years After (5)	Raw (6)	Adjusted** (7)
Years: 1990 - 1997							
1 to 1	65459	3.49	3.54	3.66	3.73	0.23	0.00
1 to 2	40251	3.61	3.66	3.98	4.00	0.40	0.16
1 to 3	25297	3.57	3.62	4.09	4.10	0.54	0.30
1 to 4	12528	3.57	3.63	4.23	4.25	0.68	0.44
2 to 1	31417	3.80	3.86	3.77	3.84	0.04	-0.16
2 to 2	44245	3.88	3.94	4.05	4.07	0.20	0.00
2 to 3	33316	3.90	3.96	4.15	4.17	0.27	0.07
2 to 4	15450	3.94	4.02	4.31	4.33	0.39	0.20
3 to 1	18854	3.93	3.98	3.74	3.82	-0.10	-0.28
3 to 2	28421	3.99	4.05	4.07	4.10	0.11	-0.07
3 to 3	47908	4.07	4.13	4.23	4.25	0.18	0.00
3 to 4	29010	4.13	4.19	4.36	4.37	0.25	0.07
4 to 1	10459	4.06	4.14	3.70	3.81	-0.26	-0.47
4 to 2	13368	4.12	4.21	4.13	4.17	0.04	-0.17
4 to 3	23319	4.18	4.26	4.30	4.32	0.14	-0.07
4 to 4	60835	4.29	4.37	4.48	4.50	0.21	0.00

Source: ASSD, own calculations.
Notes: Entries are mean log real daily wages for job changers who are observed with at least two years of data prior to a job change, and two years after. Sample exlcudes mover to/from firms with 1 worker.
* Quartiles are based on mean wages of co-workers at old job in year prior to move, and in new job in year after move.
** Trend-adjusted mean wage change, calculated as mean wage change for origin-destination group, minus mean change for job movers from the same origin quartile who remain in same quartile.

A final important characteristic of the wage profiles in Figures 10 and 11 is the absence of any Ashenfelter (1978) style transitory dip (or rise) in the wages of movers in the year before moving. The profiles of average daily wages are remarkably flat in the years before and after a move. Taken together with the approximate symmetry of the wage transitions, these flat profiles suggest that the wages of movers may be well-approximated by the combination of a permanent worker component and a firm component, and a time varying residual component that is uncorrelated with mobility.

B Figures

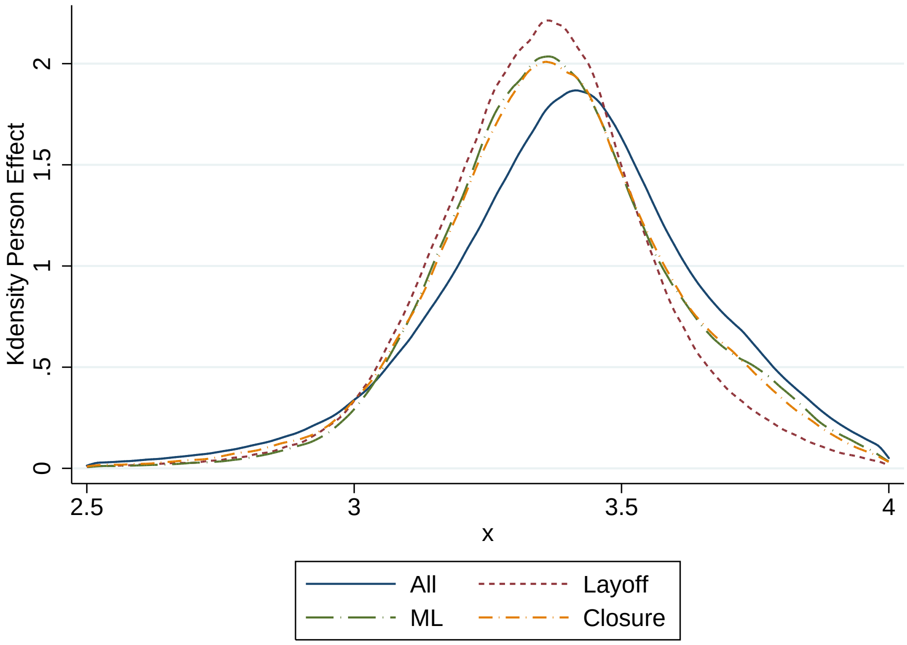

Figure 12: Person Effects by Type of Layoff

C Tables

Table 19: Number of Individuals in the Different PE/FE Categories

	All	Layoff	Mass Layoff	Closure
High Person Effect	18467	10189	4919	3359
High Firm Effect	27240	15775	7916	3549
High Person and Firm Effect	3613	1761	1201	651
Re-emp. at High Firm	19659	11056	5669	2934
Re-emp. at High Firm & High PE	3105	1293	1247	565
Re-emp. at High Firm & High FE	12144	6317	4021	1806
Re-emp. at High Firm & High FE & PE	1588	568	688	332

Source: ASSD, own calculations.

Notes: High person effect if the individual falls into the highest quintile. High firm effect, if the individuals firm falls into the highest quintile of the distribution.

Table 20: Difference Between Pre and Post Layoff Wages

	(1)	(2)	(3)	(4)
Mass Layoff	0.00799**	0.00814**	0.00543	0.00666*
	(0.00365)	(0.00365)	(0.00371)	(0.00373)
Layoff	-0.0453***	-0.0460***	-0.0471***	-0.0490***
	(0.00301)	(0.00302)	(0.00300)	(0.00301)
Age	-0.0145***	-0.0146***	-0.0149***	-0.0142***
	(0.000945)	(0.000945)	(0.000941)	(0.000942)
Age^2	0.000134***	0.000136***	0.000133***	0.000127***
	(0.0000116)	(0.0000116)	(0.0000115)	(0.0000115)
Age at First Employment	0.00363***	0.00354***	0.00362***	0.00362***
	(0.000524)	(0.000524)	(0.000521)	(0.000522)
Firm Size	0.00000194***	0.00000198***	-0.00000135***	-0.000000543
	(0.000000376)	(0.000000376)	(0.000000474)	(0.000000485)
Firm Operation Duration	4.37e-08	-6.25e-09	0.000000722***	0.000000282
	(0.000000253)	(0.000000253)	(0.000000268)	(0.000000271)
Total Unemployment Duration since LFP	-0.000000445	-9.00e-08	-0.00000148	-0.000000883
	(0.00000456)	(0.00000456)	(0.00000454)	(0.00000455)
Total Employment Duration since LFP	-0.0000108***	-0.0000118***	-0.00000468*	-0.00000766***
	(0.00000239)	(0.00000239)	(0.00000240)	(0.00000241)
Tenure at Closing Firm	-0.0000107***	-0.0000103***	-0.00000908***	-0.00000888***
	(0.000000715)	(0.000000717)	(0.000000717)	(0.000000717)
Wage at First Job	-0.00260***	-0.00259***	-0.00236***	-0.00229***
	(0.0000825)	(0.0000826)	(0.0000830)	(0.0000832)
Number of Unemployment Spells	0.00158***	0.00144***	0.00133***	0.000844**
	(0.000401)	(0.000401)	(0.000402)	(0.000405)
Number of Employment Spells	0.000541	0.000691	-0.000798	0.000109
	(0.00100)	(0.00100)	(0.001000)	(0.00100)
Observations	125497	125497	125495	125495
R^2	0.040	0.040	0.059	0.061
Adjusted R^2	0.040	0.040	0.058	0.060
Year FE	✓	✓	✓	✓
Number of Displacements	✗	✓	✓	✓
Industry FE	✗	✗	✓	✓
Region FE	✗	✗	✗	✓

Source: ASSD, own calculations.
Note: *,**,*** indicates significance at the 10%, 5%, and 1% level, respectively. Standard errors in parentheses.