ONLINE APPENDIX FOR "MANDATORY NOTICE OF LAYOFF, JOB SEARCH AND EFFICIENCY"

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A THEORETICAL SECTION

This section provides a more detailed description of the model in Section II. It also contains some analysis that we omitted from the main text for the purpose of brevity. Throughout, we consider a case where it is efficient for the firm to layoff the worker: $U^u > (1-z)y$ (the notation is the same as in the main text). For the sake of simplicity, the model assumes no discounting over time.

I.A MN effect on target wages, job finding rates, & earnings

In general, let $\lambda^{j} = \phi^{j}(w)$ denote the job-finding rate for an unemployed $(j = u)$ or an employed worker $(j = e)$. The job-finding rate is decreasing in the target wage (w) . We define the η as the efficiency of employed search relative to unemployed search. With this definition, we parameterize the difference in the job-finding rate across an unemployed and an employed worker as $\phi^u = \phi(w, 0)$ and $\phi^e = \phi(w, \eta)$, respectively.

The optimal choice of the target wage for an unemployed individual is given by

$$
U^{u} = \max_{w} \phi(w, 0) w + (1 - \phi(w, 0)) b
$$

The first order condition is

(OA1)
$$
\phi(w^u, 0) + \frac{\partial \phi(w^u, 0)}{\partial w}(w^u - b) = 0
$$

and the second order condition:

$$
-\xi \equiv \frac{\partial \phi}{\partial w} + \frac{\partial^2 \phi}{\partial w^2} (w - b) < 0
$$

We evaluate how the choice of the target wage of the unemployed agent responds to exogenous changes. To do so, we look at the comparative statics of the target wage with respect to η and *b*. We have:

(OA2)
$$
\frac{\partial w}{\partial \eta} = \frac{1}{\xi} \left[\frac{\partial \phi}{\partial \eta} + \frac{\partial^2 \phi}{\partial \eta \partial w} (w - b) \right]
$$

and

$$
\frac{\partial w}{\partial b} = -\frac{1}{\xi} \frac{\partial \phi}{\partial w}
$$

The optimal choice of the target wage for an employed individual on notice is defined by

$$
U^{n} = \max_{w} \phi(w, \eta) w + (1 - \phi(w, \eta)) U^{u}
$$

The first order condition is

(OA4)
$$
\phi(w^e, \eta) + \frac{\partial \phi(w^e, \eta)}{\partial w}(w^e - U^u) = 0
$$

The two first order conditions, equations [\(OA1\)](#page-1-2) and [\(OA4\)](#page-2-0), implicitly define a wage function, which we with slight abuse of notation denote by *w*. Thus, $w^e = w(\eta, U^u)$ and $w^u = w(0, b)$.

Using linear approximation as well as equations [\(OA2\)](#page-1-3) and [\(OA3\)](#page-1-4), the difference between two wages can be written as

(OA5)
$$
w^{e} - w^{u} \simeq \eta \frac{\partial w}{\partial \eta} + (U^{u} - b) \frac{\partial w}{\partial b} = \frac{1}{\xi} \left[\eta \frac{\partial \phi}{\partial \eta} - (U^{u} - b) \frac{\partial \phi}{\partial w} \right]
$$

The expected wage for a notified worker is:

(OA6)
$$
w^{n} = \frac{\lambda^{e} w^{e} + (\lambda^{n} - \lambda^{e}) w^{u}}{\lambda^{n}}.
$$

Using equations [\(OA5\)](#page-2-1) and [\(OA6\)](#page-2-2), we can write the wage change due to notice as

$$
\Delta w = w^n - w^u
$$

= $\frac{\lambda^e}{\lambda^n} (w^e - w^u)$

$$
\simeq \frac{1}{\xi} \frac{\lambda^e}{\lambda^n} \left[\eta \frac{\partial \phi}{\partial \eta} - (U^u - b) \frac{\partial \phi}{\partial w} \right]
$$

The change in the employment rate in the second period due to notice is

$$
\Delta \lambda = \lambda^e + (1 - \lambda^e) \lambda^u - \lambda^u
$$

= $\lambda^e (1 - \lambda^u)$

which can be rewritten as a decomposition to two parts: One component is due to an to extended period of search that is $\lambda^u(1-\lambda^u)$. The other component is due to the relative effectiveness of employed job search, $\lambda^e - \lambda^u$. That is

$$
\Delta \lambda = \lambda^u (1 - \lambda^u) + (\lambda^e - \lambda^u) (1 - \lambda^u)
$$

and using linear approximation

$$
\Delta \lambda \simeq \underbrace{\lambda^u (1 - \lambda^u)}_{\text{Extended search}} + \underbrace{\left[\eta \frac{\partial \phi}{\partial \eta} + (w^e - w^u) \frac{\partial \phi}{\partial w}\right]}_{\text{Relative effectiveness}} (1 - \lambda^u)
$$

We can replace $w^e - w^u$ with its linear approximation, as in [\(OA5\)](#page-2-1), but this does not add intuition.

Now, let us turn to the change in earnings due to MN. MN affects earnings by increasing the income of those who receive notice, by severance payments, and by changing the income of workers with delayed separation, that is

$$
\Delta Y = \left[\lambda^n w^n P^N + (\lambda^u w^u + \sigma) P^S + w^D P^D \right] - \lambda^u w^u
$$

= $(\lambda^n w^n - \lambda^u w^u) P^N + (w^D - \lambda^u w^u) P^D + \sigma P^S$

Using the following two equalities:

$$
\lambda^n w^n - \lambda^u w^u = w^u \Delta \lambda + \lambda^n \Delta w = w^N \Delta \lambda + (w^u - w^N) \Delta \lambda + \lambda^n \Delta w
$$

$$
w^D - \lambda^u w^u = w^D (1 - \lambda^u) - (w^u - w^D) \lambda^u
$$

we can rewrite the MN effect on earnings as

$$
\Delta Y = \left[w^N P^N \Delta \lambda + w^D P^D (1 - \lambda^u) \right] + \left[\left(w^u - w^N \right) P^N \Delta \lambda - \left(w^u - w^D \right) P^D \lambda^u \right] + \lambda^n \Delta w P^N + \sigma P^S
$$

Normalizing by w^N , we get

$$
\frac{\Delta Y}{w^N} = \left[P^N \Delta \lambda + \frac{w^D}{w^N} P^D (1 - \lambda^u) \right] - \frac{w^N - w^u}{w^N} \left[P^N \Delta \lambda - \frac{w^D - w^u}{w^N - w^u} P^D \lambda^u \right] + \lambda^n \frac{\Delta w}{w^N} P^N + \frac{\sigma}{w^N} P^S
$$

Assuming $w^D \simeq w^N$, we get

$$
\frac{\Delta Y}{w^N} = -\Delta NE - \left(\frac{w^N - w^u}{w^N}\right)\Delta L + \lambda^n \frac{\Delta w}{w^N} P^N + \frac{\sigma}{w^N} P^S
$$

where $\Delta NE = -\left(P^N\Delta\lambda + P^D(1-\lambda^u)\right)$ denotes the change in non-employment duration and $\Delta L =$ $P^N \Delta \lambda - P^D \lambda^u$ the change in the duration of the new job (which yields an earnings loss since $w^u < w^N$ due to the job displacement effect).

To implement this decomposition in practice, we use the fact that this decomposition applies to

each type of jobs separately. For all jobs in Ω^D , for example, we have

$$
\frac{\Delta Y}{w^D} = \underbrace{(1 - \lambda^u)}_{\text{non-emptyment dur. effect}} - \underbrace{w^D - w^u}_{\text{new job dur. effect}} [-\lambda^u]
$$

And for all jobs in Ω*^N*

$$
\frac{\Delta Y}{w^N} = \underbrace{\Delta \lambda}_{\text{non-emptyment dur. effect}} - \underbrace{w^N - w^u}_{w^N} \Delta \lambda + \underbrace{\lambda^n \frac{\Delta w}{w^N} P^N}_{\text{wave effect}}
$$

I.B Equilibrium profits, wages, and the choice of layoff policy

Without a mandate, the expected profit over both periods for the employer is

$$
\underbrace{y-w}_{1\text{st period profit}} + \underbrace{(1-\theta)(y-w)}_{2\text{nd period profit}} = (2-\theta)(y-w)
$$

since with probability θ productivity drops in the second period, which implies that separation occurs.

Under the mandate, the expected profit under each layoff policy – Notice (*N*), Severance (*S*), and Delay (D) – can be written as

(OA7)
\n
$$
\pi^{N}(w) = (2 - \theta)(y - w) - \theta \alpha y
$$
\n
$$
\pi^{S}(w) = (2 - \theta)(y - w) - \theta \sigma
$$
\n
$$
\pi^{D}(w) = (2 - \theta)(y - w) + \theta [(1 - z)y - w]
$$

For simplicity, we assume that delayed layoff does not require notice, so productivity does not fall due to notice in the second period. All our results are robust to this assumption, but the expressions would be more complex.³⁹

 39 This simplifying assumption is consistent with the two period set up, since firms cannot be compelled to provide notice at the start of the 2nd period if it is optimal to delay layoff.

Equilibrium wages are determined by zero-profit conditions, $\pi^i\left(w^i_0\right)$ $\binom{i}{0} = 0$. They are given by

$$
w_0^N = y - \frac{\theta}{2 - \theta} \alpha y
$$

$$
w_0^S = y - \frac{\theta}{2 - \theta} \sigma
$$

$$
w_0^D = y - \frac{\theta}{2} z y
$$

The utility associated with each layoff policy is:

$$
U^{N}(w) = (2 - \theta) w + \theta U^{n}
$$

$$
U^{S}(w) = (2 - \theta) w + \theta (U^{u} + \sigma)
$$

$$
U^{D}(w) = 2w
$$

Evaluated at equilibrium wages, the utilities are given by:

$$
U^N (w_0^N) = (2 - \theta)y + \theta (U^n - \alpha y)
$$

$$
U^S (w_0^S) = (2 - \theta)y + \theta U^u
$$

$$
U^D (w_0^D) = (2 - \theta)y + \theta (1 - z)y
$$

With very low wages, delay is the only credible layoff policy as the intercepts of the profit functions is always larger for the policy of delaying notice, i.e., $\pi^D(0) > \max(\pi^N(0), \pi^S(0))$. In addition, if $w_0^D = \max(w_0^N)$ $_0^N, w_0^S$ $\frac{S}{0}, \omega_0^D$ $_0^D$, then delay is the only incentive compatible policy independently of the wage level. This condition is equivalent to $\left(1-\frac{\theta}{2}\right)$ $\frac{\theta}{2}$) *zy* \leq min($\alpha y, \sigma$). By defining $\kappa^N = \alpha y$, $\kappa^S = \sigma$, and $\kappa^D = \left(1 - \frac{\theta}{2}\right)$ $\frac{\partial}{\partial z}$) zy, we can write this condition as min $(\kappa^N, \kappa^S, \kappa^D) = \kappa^D$.

Another way of showing this, which is also helpful to characterize other equilibria, is as follows. Delay is optimal for firms if $\pi^{D}(w) \ge \max(\pi^{N}(w), \pi^{S}(w))$. The highest wage that is incentive compatible with delay is given by:

$$
w_1^D = (1 - z)y + \min(\alpha y, \sigma)
$$

Delay is thus incentive compatible in equilibrium if $w_0^D \leq w_1^D$ $_1^D$. Inserting the expressions for the wages, we see that this condition can again be written as $\left(1-\frac{\theta}{2}\right)$ $\frac{\theta}{2}$) zy \leq min($\alpha y, \sigma$).

Giving notice is incentive compatible in equilibrium if two conditions hold. First, the firm can afford to pay higher wages under notice than under the other two options: $w_0^N = \max\left(w_0^N\right)$ $_0^N, w_0^S$ $\frac{S}{0}, w_0^D$ $\left(\begin{smallmatrix} D \ 0 \end{smallmatrix} \right)$. This condition is equivalent to $\alpha y \le \min\left(\left(1 - \frac{\theta}{2}\right)\right)$ $\left(\frac{\theta}{2}\right)$ zy, σ) or min $(\kappa^N, \kappa^S, \kappa^D) = \kappa^N$. Second, the equilibrium wage with notice should provide higher utility than w_1^D $\frac{D}{1}$: $U^N\left(w_0^N\right)$ $\binom{N}{0}$ > U^D $\left(w_1^D\right)$ $_1^D$). Here we

used the fact that the worker prefers a higher wage for given layoff policy and the profit functions of *N* and *S* have the same slopes with respect to the wage, see equations [\(OA7\)](#page-4-1). We can also verify that the second condition is implied by the first, given the efficient separation condition $(1-z)y < U^u$.

In the same vein, there are two conditions guaranteeing that severance is incentive compatible in equilibrium. First, there exist a wage level where severance is incentive compatible for the employer, that is, $w_0^S = \max(w_0^N)$ $_0^N, w_0^S$ $^S_0, w^D_0$ \mathcal{L}_{0}^{D}), or equivalently min $(\kappa^{N}, \kappa^{S}, \kappa^{D}) = \kappa^{S}$. Second, w_{0}^{S} 0 should provide higher utility than w_1^D $\frac{D}{1}$: U^{S} $\left(w_{0}^{S}\right)$ $\binom{S}{0}$ > U^D (w_1^D $_1^D$). Again, the second condition is implied by the first, given the efficient separation condition $(1-z)y < U^u$.

To summarize, the equilibrium choice of layoff policy can be characterized by choosing the minimum cost among: $\kappa^N = \alpha y$, $\kappa^S = \sigma$, and $\kappa^D = \left(1 - \frac{\theta}{2}\right)$ $\frac{\theta}{2}$) *zy*.In partial equilibrium with exogenous wages, on the other hand, the last cutoff is different: $\kappa^D = w - (1 - z)y$, see equations $(OA7).^{40}$ $(OA7).^{40}$

I.C The optimal mandate

To study the optimal duration of the mandate, we extend our model by introducing a mixed strategy for the firm's information sharing decision. Rather than making a binary choice, the firm now determines the probability of sharing information, denoted *p*. The mandate imposes a minimum requirement for the probability of information sharing, denoted by *m*. Probabilistic MN duration is a convenience assumption that allows us to abstract from the complications arising because of fixed duration; see Pissarides (2001) for a similar approach.

In cases where the notice period is shorter than the mandate, severance pay is given by $S(p,m)$ = $(m-p)\sigma$; severance thus compensates for the deviation from the mandate, and captures the value for workers of receiving notification.

The zero-profit condition when adhering to the mandate is

$$
(2 - \theta) (y - w_0^N(m)) = \theta m \alpha y
$$

and if the firm is paying severance

$$
(2 - \theta) \left(y - w_0^S(m) \right) = \theta S(0, m)
$$

⁴⁰If we factor in the productivity loss of notice, this would be $\kappa^D = w - (1 - \alpha)(1 - z)y$.

The wages consistent with zero-profits are determined by π^{i} (w_{0}^{i} $\binom{i}{0}(m) = 0$. Thus

$$
w_0^N(m) = y - \frac{\theta}{2 - \theta} m\alpha y
$$

$$
w_0^S(m) = y - \frac{\theta}{2 - \theta} m\sigma
$$

$$
w_0^D(m) = y - \frac{\theta}{2} zy
$$

Thus, the firm's decision rules remain largely unchanged, with the only difference being that compliance with the law entails giving notice in accordance with *m*. Severance compensation and the productivity loss are thus proportional to the mandate, implying $\kappa^N = m\alpha y$, $\kappa^S = m\sigma$, and κ^D is unchanged.

We denote worker utility in equilibrium as V^i for $i \in \{N, S, D\}$. These represent the expected utilities for each match at the beginning of two periods, in contrast to U^i for $i \in \{n, u\}$ used previously, which denote the utility after notification or layoff.

For *N* we have $p = m$, and

$$
V^N = (2 - \theta) w_0^N(m) + \theta [mU^n + (1 - m)U^u]
$$

= (2 - \theta)y + \theta [m(\sigma - \alpha y) + U^u]

This has two implications. First,

$$
\frac{\partial V^N}{\partial m} = \theta \left(\sigma - \alpha y \right)
$$

Second,

$$
V^{D} - V^{N} = \theta \left[\left\{ (1-z)y - U^{u} \right\} - m \left\{ \sigma - \alpha y \right\} \right] < 0
$$

$$
V^{D} - V^{S} = \theta \left[(1-z)y - U^{u} - m\sigma \right] < 0
$$

At the boundary, i.e., for the marginal cases,

$$
V^{D} - V^{N} = \theta \left[w_{0}^{D} - U^{u} - m\sigma \right]
$$

$$
V^{D} - V^{S} = \theta \left[w_{0}^{D} - U^{u} \right]
$$

Given that profits are zero in equilibrium, social welfare is

$$
V = \sum \int_{\Omega^i} V^i d\mu
$$

To determine the properties of the optimal mandate in the most general terms, we write the first

order condition with the respect to mandate duration using the multi-dimensional version of the Leibniz rule (Flanders, 1973):

(OA8)
$$
\int_{\Omega^N} \frac{\partial V^N}{\partial m} = \int_{\partial \Omega^D \cap \Omega^N} \iota \left(V^N - V^D \right) + \int_{\partial \Omega^D \cap \Omega^S} \iota \left(V^S - V^D \right)
$$

where ∂ boundary operator and *t* denotes, with slight abuse of notation, the interior product with the vector field of the velocity.

Consider a marginal extension of MN. Such a change has two effects. First, it extends notice for the sub-set of the population already receiving notice (infra-marginal effect). Second, the cost of providing notice increases, and marginal cases are moved between states, *N*, *S*, and *D*. Moves from notification to severance are, in general, not relevant for welfare as severance exactly compensates the marginal worker for not receiving the mandated amount of advance notice.⁴¹ The same is not true for the marginal cases pushed from notice or severance to delay, where there is a discontinuous reduction in utility. In other words, delays are inefficient.

In its most general form, the first order condition that characterizes the optimal duration of MN is:

$$
P^N\,\mathbb{E}\left(\frac{\partial V^N}{\partial m}|\Omega^N\right)=\frac{\partial P^D}{\partial m}\,\mathbb{E}\left(V^o-V^D|\partial\Omega^D\right)
$$

where ∂ denotes the boundary operator and V^o is the alternative utility, being V^N or V^S depending on on the location on the boundary of D: either boundary between N and D or the boundary between S and D. The left-hand side represents the net gain of extending MN among those who receive longer notice due to the extension. The right-hand side represents the cost of extending MN among those whose separation is delayed due to the extension.

In our setting, this simplifies to

$$
\underbrace{P^N \mathbb{E} (\sigma - \alpha y | \Omega^N)}_{\text{Net Production gain of info sharing}} = \underbrace{\frac{\partial P^D}{\partial m} \mathbb{E} (\widetilde{w} - w^D | \partial \Omega^D)}_{\text{Net Production loss of delaying}}.
$$

where \widetilde{w} \widetilde{w} denotes expected post-displacement production (including home production) for marginal workers. Ignoring home production, the left-hand-side measures the increase in aggregate market

 41 In our probabilistic two-period model, the boundary between *N* and *S* does not shift, which is an artifact of the model rather than a general result.

production due to MN. Alternatively, we can write

I.D The delay caused by MN

To study delay, we consider a continuous-time model with an exogenous wage. Productivity, *y*(*t*), is differentiable and decreasing over time: $\frac{\partial y}{\partial t} < 0$. Firms face a mandate of *m* periods and a severance-pay function of $\sigma(n)$, which captures workers' willingness to pay for notice. Our setting is illustrated in Figure [1.](#page-9-1) Among other things, this figure shows that in the absence of a mandate, layoff occurs at t_0 where worker productivity is equal to wage, $y(t_0) = w$.

> ONLINE APPENDIX FIGURE 1 Timing of notification and delay

Notes: This figure shows the optimal timing of notification and delay chosen by the firm facing exogenous fixed wage and falling productivity.

First, we consider the problem of choosing the timing of notification and layoff – t_N and t_L

respectively – for a firm that wants to give *n* periods of notice:

$$
\max_{t_N,t_L} \int\limits_0^{t_N} y(t) - w dt + \int\limits_{t_N}^{t_L} (1 - \alpha) y(t) - w dt
$$

under the constraint

$$
t_L = t_N + n
$$

The optimal timing of notification is defined by equalizing net marginal profits at the time of notification and layoff

$$
[y(t_N) - w] - [(1 - \alpha)y(t_N) - w] + [(1 - \alpha)y(t_L) - w] = 0
$$

which is illustrated by the two red-lines in Figure [1.](#page-9-1) Substituting the constraint into the first order condition, we find that optimal notification time is given by

$$
\alpha y(t_N(n)) + (1 - \alpha) y(t_N(n)) + n) = w
$$

The weighted average of marginal productivity at the time of notification and at the time of layoff must equal the wage, with the weighting factor being the productivity loss of notice. To see the connection to our framework in the main text, the counterpart of equation [\(OA9\)](#page-10-0) is the comparison between the cost of notice and the cost of delay, that is, αy and $w-(1-\alpha)(1-z)y$, or equivalently comparing the wage with the weighted average of productivities, $\alpha y + (1 - \alpha)(1 - z)y$.

From equation [\(OA9\)](#page-10-0) it follows that t_N is increasing in α . Therefore, delay is increasing in the productivity loss of notice. To see this, note that the left hand side of equation [\(OA9\)](#page-10-0) is increasing in α and decreasing in t_N .

Comparative Statics We can evaluate the change in delay with respect to the notice period, *n*, by taking the derivative of equation [\(OA9\)](#page-10-0) with respect to *n*:

(OA10)
$$
\frac{\partial t_N(n)}{\partial n} = -\frac{(1-\alpha)\frac{\partial y(t_N(n))}{\partial t}}{\alpha \frac{\partial y(t_N(n))}{\partial t} + (1-\alpha)\frac{\partial y(t_N(n))}{\partial t}}
$$

In the case of a linear production decline, we get $\frac{\partial t_N(n)}{\partial n} = -(1-\alpha)$. This implies $\frac{\partial t_L(n)}{\partial n} = \alpha$. An increase in the notification period, advances notification by $1-\alpha$ period and postpones layoff by α period. In other words, delay is proportional to α ,

$$
t_L(n)-t_0=\alpha n
$$

The relative slope of the productivity function at the notification point and the lay-off point also matters. In particular, if $\frac{\partial y(t_N(n))}{\partial t}$ is much smaller than $\frac{\partial y(t_L(n))}{\partial t}$, then a one-period increase in the notification period, advances notification by one period and does not affect the timing of layoff. Conversely, if the opposite is true, a one-period increase in the notification period, does not change the timing of notification and causes a one-period increase in delay.

Denote by $\sigma(n)$ the willingness to pay of the worker for *n* period of notice. We can microfound $\sigma(n) = U^n(w, n) - U^u$

$$
rU^{n} + \frac{\partial U^{n}}{\partial t} = \max_{x} w + \lambda (x) (x - U^{n})
$$

where *x* denotes the target wage and $U^n(w,t_L) = U^u$.

First-best notice equates the marginal gain and loss of notice. That is,

$$
\sigma\left(n^{FB}\right) = w - (1 - \alpha) y \left(t_L \left(n^{FB}\right)\right)
$$

So the first-best layoff time is decreasing in α .

Now, consider the problem for the firm choosing the notice period, when it has the option of paying severance. This second-best notice policy given a mandate of *m* is as follows. Either the firm obeys, $n^{SB} = m$, or the firm provides the first best notice, $n^{SB} = n^{FB}$, and tops it off with severance.

(OA12)
$$
n^{SB} = \begin{cases} m & \text{if } m < n^{FB} \\ n^{FB} & \text{if } m \ge n^{FB} \end{cases}
$$

Consider an increase in MN, $\Delta m > 0$. Firms with $m \ge n^{FB}$ just pay more severance and continue to give first-best notice, $n = n^{FB}$. Others, increase their notice period by Δm . This increase involves more rapid information sharing – ∆*t^N* < 0 – which is efficient, but also a delay in separation – $\Delta t_L > 0$ – which is inefficient.

Consider the extreme case where there is no production loss due to notice, i.e., $\alpha = 0$. In this scenario we have $\frac{\partial t_N(n)}{\partial n} = -1$, according to equation [\(OA10\)](#page-10-1), indicating that the timing of notification changes one-for-one with the duration of notice.⁴² A marginal extension of MN then leads to a corresponding one-to-one increase in the actual notice when $m < n^{FB}$. Since the timing of notification completely offsets the increase in notice duration, the timing of separation remains unchanged. In other words, there is no delay when $\alpha = 0$.

⁴²If $\alpha = 0$, the duration of notice in the first best is at its maximum, that is, $y(t_L(n^{FB})) = w - \sigma(n^{FB})$ using equation [\(OA11\)](#page-11-0). This condition implies that the notice period given the mandate is also at its maximum, see [\(OA12\)](#page-11-1).

B ROBUSTNESS OF THE INDIVIDUAL-LEVEL ANALYSES

II.A RD validity tests

A possible concern is that firms try to selectively displace low-cost workers, along the lines of the insider-outsider theory (see Lindbeck and Snower, 1989). In our setting, this would manifest itself through more laid-off workers just to the left of the age-55 threshold. Figure [2](#page-13-0) examines whether there is manipulation around the age-55 threshold by comparing the number of observations in the vicinity of the threshold. There is no evidence of suspect bunching on either side of the threshold.

Table [1](#page-14-0) investigates whether baseline covariates are evenly distributed across the age-55 threshold. Columns (1)-(4) examine overall balancing. We regress an indicator for being above the age-55 threshold on all baseline characteristics and polynomial control functions in age. We are mainly interested in the *F*-statistics, reported at the bottom end of the table, which test the null hypotheses that all coefficients on individual (and firm) characteristics are jointly zero. As indicated by the *p*-values of the *F*-tests we cannot reject these hypotheses. Also, the individual coefficients are typically small.

Columns (6) and (7) report bivariate tests of equality of baseline covariates above and below the threshold. These tests reinforce the view that the coefficients are generally small: those just above the threshold earned 0.85% less than those just below the threshold according to the estimates in Column (6), for instance.

Notes: The figure shows the distribution of displaced individuals by age at notification (measured in months). The regression lines come from estimating a regression corresponding to equation (6) with the fraction of observations at each age bin as the outcome variable. The regression includes a linear age polynomial interacted with the threshold dummy. The estimated jump at the threshold is 0.0005 (standard error = 0.0006 , p-value = 0.435).

ONLINE APPENDIX TABLE 1 BALANCING OF PRE-DETERMINED COVARIATES

Notes: The table shows balancing of covariates at the age-55 threshold for notified white-collar workers aged 52-58 at the time of notification. Columns (1)-(5) show the results of regressing an indicator for being above the age–55 threshold on baseline covariates and polynomial control functions in age. The bottom part of the table reports the *F*-statistic and the associated *p*-value from testing the null hypothesis that all coefficients on (individual and firm) baseline covariates are jointly zero. Firm characteristics included in Columns (3) and (5) are workforce characteristics – average earnings, share of females, share of immigrants, average age, share of college-educated, and number of employed. All firm characteristics are balanced, except average age in Column (3), which is 0.0014 years higher for individuals above the age-55 threshold. Column (6) and (7) report the results of bivariate balancing tests where each covariate listed in the left-hand column is regressed on the treatment indicator and an interacted first and second order polynomial control function in age at notification, respectively. Standard errors are clustered on notification event. [∗] *p* < 0.1, ∗∗ *p* < 0.05, ∗∗∗ *p* < 0.01.

II.B Optimal bandwidth

Figure [3](#page-15-1) show the dynamic effects of MN on Employment using the default bandwidth of \pm 3years. Figure [4](#page-16-0) reproduces Figure [3](#page-15-1) but with the optimal bandwidth selector of Calonico, Cattaneo and Titiunik (2014). The figure is built from 48-60 separate RD-regressions, and, consequently, there are 48-60 optimal bandwidths. In general, optimal bandwidths are in between 2.0 and 4.0 years, and our default bandwidth of 3 is thus well in-line with the optimal ones. There are instances when bandwidth-selector picks 1.8 or 4.5 years as the optimal ones, but these are rare occasions.

The most important message from [4,](#page-16-0) however, is that none of our results change when we use this approach rather than the one we opt for in the main text. Conceptually, since age is discrete in our data, we prefer the parametric approach of the main text. Moreover, Appendix [C](#page-41-0) illustrates that the optimal bandwidth selector is sensitive to measurement error in the assignment variable. Our default approach also avoids the slightly cumbersome exercise of using potentially different data sets for each single point estimate.

Notes: The figures show employment outcomes by month relative to notification. A new firm is defined as a new employer-employee spell that i) pays more than 10 kSEK per month; and ii) the worker has not derived any income from during the 12 months preceding notification. We set the indicator of working at the notifying firm to zero in case of a new job (so that the two employment markers are mutually exclusive). At any given point in time, we plot estimates of the constant (hollow circles) and the constant+ β (black circles) from a regression corresponding to equation (6) where the outcome is one of the employment outcomes. Dashed vertical lines indicate that the estimate of β is significant at the 5% level. These regressions include a linear age polynomial interacted with the threshold indicator, individual-level baseline covariates (earnings in the year prior to notification, gender, immigrant status, tenure, educational attainment FEs), and month-by-year FE:s. The analysis includes individuals aged 52-58 at the time of notification. Standard errors are clustered on notification event.

ONLINE APPENDIX FIGURE 4 Employment by month relative to notification (optimal bandwidth)

Notes: The figure shows the probability of working at the notifying firm (panel a) and at a new firm (panel b) by month relative to notification. At any given time point, we plot estimates of the constant (hollow circles) and the constant+ β (black circles) from a local linear regression corresponding to (6) with an optimal bandwidth according to Calonico et al. (2014), which is indicated by the number next to each point in the graph. Dashed lines indicate that the estimate of β is significant at the 5%-level. The regressions include baseline covariates (earnings in the year prior to notification, gender, immigrant status, tenure, educational attainment FEs) and month-by-year FE:s. Standard errors are clustered on notification event.

SENSITIVITY OF RD-DESIGN TO BANDWIDTH AND FUNCTIONAL FORM SENSITIVITY OF RD-DESIGN TO BANDWIDTH AND FUNCTIONAL FORM **ONLINE APPENDIX TABLE 2** ONLINE APPENDIX TABLE 2

specification (6) but apply the optimal bandwidth suggested by Calonico, Cattaneo and Tinunk (2014). Columnic (2014). Columnical diss-corrected estimates using the optimal bandwidth selector of Calonico, Cattaneo and Titiu

II.C MN wage effect

Additional evidence on MN effect on wages

ONLINE APPENDIX FIGURE 5 Effect of MN on re-employment wage

Notes: Panel (a) shows the log of the wage from the first new job after notification by age at notification relative to the 55-threshold, corresponding to the estimate in Table III Column 1. In contrast to Figure IIIa, the first new job is defined via the monthly markers as the first employer the worker is observed working for after notification for whom she has not worked for at least one year prior to notification. The wage refers to full-time equivalent monthly wage reported in the Wage Survey by this particular employer within two years after notification. Sample size is 2,752. Panel (b) shows results from a permutation test where we vary the threshold between the ages 30-60 (at the monthly level), keeping a fixed bandwidth of +/- 3 years. The figure plots the distribution of the 360 placebo estimates from fictitious discontinuities including the true estimate (shown in panel a), indicted by the red dashed vertical line. Panel c) and d) show the probability of the wage at the first new job being either 5 percent lower or higher, respectively, compared to the worker's wage at the notifying firm. All estimates are based on equation (6) controlling for age linearly interacted with the threshold indicator for individuals aged 52-58 (except panel (b) where we vary the threshold) at the time of notification. The estimated jump at the threshold and its standard error are displayed in the figures. The regressions include individual-level baseline covariates (earnings in the year prior to notification, gender, immigrant status, tenure, educational attainment FEs) and month-by-year FE:s. Standard errors are clustered by notification event

Notes: The figure plots the MN effect on the PDF of wage growth distribution on the left y-axis (marked solid line) and surrounding 95%-confidence intervals (dashed vertical lines). The PDF itself is on the right y-axis. The regression estimates come from estimating equation (6) with a linear age polynomial interacted with the threshold indicator. The regressions also include baseline covariates (earnings in the year prior to notification, gender, immigrant status, tenure, educational attainment FEs) and month-by-year FE:s. The analysis only includes individuals aged 52-58 at the time of notification. Standard errors are clustered on notification event.

ONLINE APPENDIX TABLE 3 EFFECT OF MN ON WAGE DYNAMICS

Notes: This table shows regression estimates of equation (6) where the outcome is wage growth. We examine notified workers who find a new job at some point after notification. For those workers, we measure wage growth relative to the wage in the new job. In Column (1), for example, we show the difference between the log wage one year after re-employment and the log wage in the year of re-employment. We include a linear age polynomial interacted with the threshold indicator for individuals aged 52-58 at the time of notification as controls. The regressions also include individual-level baseline covariates (earnings in the year prior to notification, gender, immigrant status, tenure, educational attainment FEs) and month-by-year FE:s. Standard errors are clustered on notification event. \dot{p} < 0.1, ∗∗ *p* < 0.05, ∗∗∗ *p* < 0.01.

Role of sorting in the MN wage effect

Higher firm quality partly explains our positive wage effects. Table [4](#page-22-0) presents estimates of the effect of longer MN on characteristics of the new firm. We measure all outcomes in the year prior to notification, and thus before the worker joins the firm, so that the firm outcomes are not affected by the worker. With varying statistical significance, longer notification is associated with higher wages,, older workers, and larger firms. Estimates of the effects on firm productivity and profits per worker are positive but imprecise.

regressions include a linear age polynomial interacted with the threshold indicator, baseline covariates (earnings in the year prior to notification, gender, immigrant

status, tenure, educational attainment FEs), and month-by-year FE:s. Standard errors are clustered by notification event. ∗ *p* < 0.1, ∗∗ *p* < 0.05, ∗∗∗ *p* < 0.01.

status, tenure, educational attainment FEs), and month-by-year FE:s. Standard errors are clustered by notification event. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

MANDATORY NOTICE (MN) EFFECT ON FIRM SORTING MANDATORY NOTICE (MN) EFFECT ON FIRM SORTING ONLINE APPENDIX TABLE 4 ONLINE APPENDIX TABLE 4

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ONLINE APPENDIX TABLE 5 EFFECT OF MN ON NEW JOB CHARACTERISTICS

Notes: The table show the estimated effect of longer mandated notice on the characteristics of the new job. Regressions include individuals aged 52-58 at the time of notification and comes from estimating equation (6) with a linear age polynomial interacted with the threshold indicator. The regression also includes baseline covariates (earnings in the year prior to notification, gender, immigrant status, tenure, educational attainment FE:s) as well as month-by-year FE:s. Standard errors are clustered by notification event. $p < 0.1$, $\epsilon^* p < 0.05$, $\epsilon^{**} p < 0.01$.

ONLINE APPENDIX FIGURE 7

Notes: The figure plots the log of firm size (measured as the number of employees) of the first new job against age at notification relative to the 55-threshold in 2 months bins. The estimated jump at the threshold along with its standard error is depicted in the figure. The regression lines come from estimating equation (6) with a linear age polynomial interacted with the threshold indicator for individuals aged 52-58 at the time of notification and corresponds to the estimate found in Column (5) of Table [4.](#page-22-0) The regression includes individual-level baseline covariates (earnings in the year prior to notification, gender, immigrant status, tenure at notification, educational attainment FE:s), and month-byyear FE:s. Standard errors are clustered on notification event. [∗] *p* < 0.1, ∗∗ *p* < 0.05, ∗∗∗ *p* < 0.01.

II.D Severance pay and cash-constrained firms

A key message of our theory in Section II is that the efficiency case for MN relies on firms being able to pay severance in the instances where giving advance notice would be inefficient. If some firms that lay off workers are credit constrained, it is possible that inefficient MN cannot be undone by such monetary side-payments.

To shed light on this issue, we examine whether the usage of severance payments is lower among cash-constrained firms. Empirically, we define a firm as cash-constrained if the share of liquid assets over total assets is below the mean. The information on the asset position of firms comes from balance sheets. Figure [8a](#page-26-0) shows severance pay for workers in unconstrained firms. Unconstrained firms pay about one additional month worth of severance to workers eligible for long notification. Figure [8b](#page-26-1) examines constrained firms. There is little indication of additional severance to workers eligible for longer notice. We interpret this as evidence suggesting that MN is associated with some efficiency loss for cash-constrained firms. Note, however, that our estimates of the gains and losses associated with MN already reflect that some firms are unable to pay severance. For instance, the inability to pay severance most likely inflates the estimate of α from Section VI.A relative to a scenario where all firms could undo inefficient notice.

ONLINE APPENDIX FIGURE 8 Effects of MN on severance by cash constraints

Notes: The figure shows severance pay and notification time by age at notification relative to the 55-threshold in 2 month-bins for cash-unconstrained firms and cash-constrained firms. Cash-unconstrained firms are defined as firms with the share of liquid assets over total assets (measured in the year before notification) above the mean (the share constrained firms is 0.65). Severance pay is measured as excess earnings in the year of displacement (detailed in Section IV.A). The estimated jump at the threshold along with its standard error is depicted in the figure. The regression lines come from estimating equation (6) with a linear age polynomial interacted with the threshold indicator for individuals aged 52-58 at the time of notification. The regressions include baseline covariates earnings in the year prior to notification, gender, immigrant status, tenure, educational attainment FE:s) and month-by-year FE:s. Standard errors are clustered by notification event. $p < 0.1$, $\binom{p}{k} < 0.05$, $\binom{p}{k} < 0.01$.

II.E Additional results

Impact of MN on advance notice

	(1)	(2)	(3)	(4)	(5)	(6)
Above 55	$2.415***$	$2.593***$	$2.623***$	1.298***	$1.561***$	1.499***
	(0.215)	(0.203)	(0.198)	(0.388)	(0.347)	(0.379)
Control mean	$6.832***$	$6.723***$	$6.916***$	$7.697***$	7.498***	7.680***
	(0.213)	(0.171)	(0.171)	(0.349)	(0.277)	(0.309)
Polynomial order						
1st degree		✓				
2nd degree				\checkmark		
Interacted w. threshold		✓				
Baseline covariates		✓				
Month/Year FEs		\checkmark			✓	
Displacement FEs			✓			✓
F-stat	125.97	162.43	176.25	11.18	20.22	15.66
R^2	0.085	0.178	0.231	0.087	0.180	0.235
Number of clusters	4,158	4,158	4,158	4,158	4,158	4,158
Number of observations	10,275	10,275	10,275	10,275	10,275	10,275

ONLINE APPENDIX TABLE 6 EFFECTS OF MN ON ADVANCE NOTICE DURATION, SPECIFICATION ANALYSIS

Notes: The table investigates the sensitivity of the first-stage with the outcome being notification time in days. The regression come from estimating equation (6) with a linear or quadratic age polynomial interacted with the threshold indicator for individuals aged 52-58 at the time of notification. Where indicated regressions also. baseline covariates consisting of earnings in the year prior to notification, gender, immigrant status, tenure, educational attainment FE:s. Standard errors are clustered on notification event $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Earnings decomposition

The earnings decomposition features two sources of approximation: (i) earnings and wage effects are estimated on two *calendar* year horizon; (ii) the wage effects are estimated on a subsample of the baseline population. Despite the approximations involved in the decomposition, the estimated and imputed severance pay effect line up fairly well, leading to the following decomposition:

(OA13)

ONLINE APPENDIX TABLE 7 DECOMPOSITION OF 2-YEAR CUMULATIVE EARNINGS EFFECT

Notes: The table shows a decomposition of the 2-year cumulated earnings effect estimated at the age-55 threshold. Estimated earnings effect $=\Delta y/w_0^L$. Employment effects: non-employment $=-\Delta NE$; new job $=-\left[(w_0^L-w_1^L)\Delta l_1\right]/w_0^L$. Wage effects: wage at new job $=\left[l_1^Sw_1^S\Delta\ln w_1\right]/w_0^L$; imbalance in initial wage = $[\ell_0^S w_0^S \Delta \ln w_0] / w_0^L$. Estimated severance pay effect = $\Delta SP/w_0^L$. The index L (S) denotes eligibility for long (short) notification. The employment effects come from Table II, the wage estimate from Column (2) of Table III, the severance pay from Figure Ib.

Measurement of severance pay

ONLINE APPENDIX FIGURE 9 Earnings for workers for whom January is the last month with the notifying firm

Notes: The figure shows average monthly earnings (in 1,000 SEK) for workers whose last recorded month with the notifying firm is January in the year of separation. The sample includes individuals aged 52-58 at the time of notification. Earnings in t≤0 come from the notifying firm whereas earnings in t>0 are summed over all employers and include zero earnings.

ONLINE APPENDIX FIGURE 10 Firm-level correlation between imputed and actual severance payments

Notes: The figure probes our imputation of severance payments. For each worker who separates from her employer, we calculate the severance payment as the difference between total earnings from the separating employer in the year of separation and imputed annual earnings. The latter is defined as the CPI-adjusted monthly earnings from the separating employer in the year prior to separation times the number of months worked for that employer in the separation year. We censor severance payments from below at zero. We then sum the severance payments to the firm- and yearlevel. From Statistics Sweden we retrieve a supplemental dataset to the Balance Sheet and Income Statements. This supplement, available to a random sample (stratified by size) of around 14,000 firms annually, specifies firm-level costs in a more detailed manner than the income statements. Importantly, it includes total severance payments during the year. The plot is a binscatter of our imputed severance payments against the reported severance payments in the data. The slope coefficient is reported in the graph. Number of observations: 183,848. We illustrate our measurement strategy for severance in Online Appendix Figure [9.](#page-29-0)

Employment outcomes

ONLINE APPENDIX FIGURE 11 Employment outcomes 12 months after notification by age

Notes: The figure shows employment outcomes 12 months after notification by age at notification (2-month-bins). The regression lines come from estimating equation (6) with a linear age polynomial interacted with the threshold indicator. The estimated jump at the threshold is depicted in the figure along with its standard error. The regressions include baseline covariates (earnings in the year prior to notification, gender, immigrant status, tenure, educational attainment FEs) and month-by-year FE:s. The analysis only includes individuals aged 52-58 at the time of notification.

Notes: The figure shows employment outcomes cumulated over 2 years post notification by age at notification relative to the 55-threshold in 2month bins. These figures correspond to the estimates displayed in Table II. The regression lines come from estimating equation (6) with a linear age polynomial interacted with the threshold indicator for individuals aged 52-58 at the time of notification. The regressions also include individuallevel baseline covariates (earnings in the year prior to notification, gender, immigrant status, tenure at notification, educational attainment FEs), and month-by-year FE:s. Estimated jumps at the threshold along with standard errors are depicted in the figures. Standard errors are clustered by notification event. $*$ $p < 0.1$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Permutation test of the MN severance pay effect

ONLINE APPENDIX FIGURE 13 Permutation test of the MN severance pay effect

Notes: The figure shows results from a permutation test where we vary the threshold between the ages 30-60 (at the monthly level), keeping a fixed bandwidth of +/- 3 years. The figure plots the distribution of the 360 placebo estimates from fictitious discontinuities including the true severance estimate, indicted by the red dashed vertical line.

where a white-collar worker aged 52-58 was notified. ∗ *p* < 0.1, ∗∗ *p* < 0.05, ∗∗∗ *p* < 0.01.

where a white-collar worker aged 52-58 was notified. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

FIRST STAGE ESTIMATES OF ADVANCE NOTICE AND SEVERANCE PAY FIRST STAGE ESTIMATES OF ADVANCE NOTICE AND SEVERANCE PAY ONLINE APPENDIX TABLE 8 ONLINE APPENDIX TABLE 8

Supporting material, 2-IV analysis

ONLINE APPENDIX FIGURE 14 Spillover of the share coworkers aged 55 and above on severance pay

Notes: Panel (a) shows the relationship between severance pay and the instrument, i.e., the share of coworkers aged 55 and above, for workers who themselves are below age 55. Panel (b) shows the corresponding relationship for those above age 55. The plots show residualized relationships where we control for a linear age polynomial interacted with age bracket FEs (in 6 year bins), individual-level baseline covariates (earnings in the year prior to notification, gender, immigrant status, tenure, educational attainment FEs), month-by-year FEs. Individual covariates are interacted with a dummy for being close to the threshold (age 52-58). We also control for firm covariates consisting of average age of workers, average age squared, average earnings of workers, share female workers, share college educated, firm size and layoff characteristics that include size of layoff and flexible controls for average tenure within layoff. Regression estimates are depicted in the figure along with its standard error clustered by notification event. $p < 0.1$, ** $p < 0.05$, ∗∗∗ *p* < 0.01.

ONLINE APPENDIX TABLE 9 BALANCING TESTS WITH RESPECT TO SHARE COWORKERS ABOVE AGE-55

Notes: The table examine whether the earnings a year prior to notification are balanced with respect to the (individual) age-55 indicator and the share coworkers who are above age-55. The sample includes all white-collar workers in notification events where a white-collar worker aged 52-58 was notified. Sample size varies marginally across columns since we do not observe firm covariates for all observations. The regression specifications are such that the effect of the Above 55 indicator is identified within the sample of white-collar workers aged 52-58, while share coworkers above 55 is identified across all white-collar workers. All regressions include a linear age-polynomial interacted with age-bracket FEs (in 6 year bins), individual-level baseline covariates (earnings in the year prior to notification, gender, immigrant status, tenure, educational attainment FEs), month-by-year FEs. Individual covariates are interacted with a dummy of being close to the threshold (age 52-58). Where indicated we control for firm covariates consisting of average age of workers, average age squared, average earnings of workers, share female workers, share college educated and firm size. Layoff characteristics include size of layoff and flexible controls for average tenure within layoff.. Standard errors are clustered by notification events. $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

ONLINE APPENDIX FIGURE 15 Search by month relative to notification

Notes: The figure shows the evolution of job search around notification during 2005-2016 for four measures of search. We do this separately for workers with short and long notification time defined as below or above median (90 days) in panel (a) and (b), respectively. The solid and hollow black series correspond to self-reported search in the Labor Force Survey (LFS). The former shows the probability of search (extensive margin) whereas the latter show the intensity of search, defined as the inverse hyperbolic sine function (arcsinh) of the number of channels used to look for a job. The channels are: visiting the Public Employment Service (PES), using a PES job coach, searching jobs databases, searching via recruitment firms, searching by directly approaching firms, applying to posted ads, reading ads, asking friends for job tips. The red solid and hollow squared series use administrative data from PES. The former shows the probability of being registered at the PES (extensive search) and the latter search intensity defined as the inverse hyperbolic sine function (arcsinh) of the number of interactions with a PES caseworker within a month. The dashdotted line between t-3 and t-2 indicates when on average the firm reports the notice to the PES, relative to a workers individual notice at t=0.

ONLINE APPENDIX FIGURE 16 The effect of MN on cumulated search and hazard to new job

Notes: This figure plots the dynamic effects of being above the age-55 threshold on cumulative search until a new job (circles) and the hazard to a new job (triangles), both relative to month of notification. The sample comprises all white-collar workers in notification events where a white-collar worker aged 52-58 was notified. Search is defined as inverse hyperbolic sine function (arcsinh) of the number of interactions with the PES, cumulated over time until the workers finds a new job. All regressions include (i) a linear age-polynomial interacted with age-bracket (in 6 years width) indicators, individual-level baseline covariates (earnings in the year prior to notification, gender, immigrant status, tenure, educational attainment FEs), month-by-year FE:s. Individual covariates are interacted with a dummy for being close to the threshold (age 52-58). (ii) Firm covariates: average age of workers, average age squared, average earnings of workers, share female workers, share college educated and firm size. (iii) Layoff characteristics include size of layoff and flexible controls for average tenure within layoff. (iv) 2-digit industry FEs. Dashed lines surrounding the estimates indicate 95% confidence intervals with standard errors clustered by notification events.

ONLINE APPENDIX FIGURE 17 Effects of the kink in the UI-schedule on search and the job finding rate for the unemployed

Notes: The figure shows the workings of our RKD-design to estimate the effect of job search on the hazard among unemployed. Panel (a) makes the research design visible by plotting the replacement rate as a function of the daily wage prior to becoming unemployed. Panel (b) plots the likelihood of searching for a job and panel (c) the likelihood of finding a new job in the subsequent month. The search measure is retrieved from the Labor Force Survey (LFS). Finding a job is defined as no longer being registered with the PES and having positive monthly wage earnings. The plots are shown for unemployed individuals eligible for UI during the years 2005-2015. The search graph is estimated using 32,138 observations while the hazard is estimated based on 9,988,274 observations. Standard errors are clustered at the individual level.

ONLINE APPENDIX FIGURE 18 Cumulative Earnings Loss of Delay

Notes: These results are based on 862 establishments with two consecutive layoffs within 4-6 months (1,724 layoff events, involving 12,646 individuals). The y-axis shows cumulative earnings from the new job during the first year following the initial layoff report (of the first event). Cumulative earnings are normalized by monthly earnings in the pre-notification job. The x-axis orders workers by their seniority within layoff event. The two dots closest to the threshold thus compare the most senior worker in the first layoff (normalized seniority $= 0$) to the least senior worker in the second layoff (normalized seniority $= 1$). The regression lines come from estimating an equation containing a linear seniority polynomial interacted with the threshold indicator. The regressions also include individual-level baseline covariates: age, age squared, tenure and gender, all interacted with an indicator for white-collar status. The estimated jumps at the threshold along with standard errors are depicted in each panel. Standard errors are clustered by notification event[∗] *p* < 0.1, ∗∗ *p* < 0.05, ∗∗∗ *p* < 0.01.

C MEASUREMENT ERROR IN THE ASSIGNMENT VARIABLE

III.A Illustration of measurement error

Summary

Measurement error in the assignment variable is a potential problem for RD settings as it causes some individuals to be placed on the wrong side of the threshold. In our case, the measurement error stems from misreporting of notification dates, which translates into a measurement error in age at notification – our assignment variable. If the measurement error is sufficiently large, a true discontinuity looks like a non-linearity; see Davezies and Barbanchon (2017) for example.

Measurement error in the assignment variable severely complicates non-parametric RD-analyses. Intuitively, as the measurement error grows, a greater fraction of individuals are misplaced relative to the threshold and the discontinuity at the cutoff increasingly looks like a non-linearity. Optimal bandwidths then fall. Non-parametric RD thus places larger weight on the portion of the data that is most affected by the measurement error. A parametric RD approach, on the other hand, is less susceptible to the severity of the problem, since the bandwidth is fixed a priori.

Figure [19](#page-42-0) illustrates this intuition. It is based on a simulation that mimics the data configuration that we observe. The effect of interest is the impact on notification times when an individual surpasses the age threshold. Individuals are uniformly distributed over age at notification. The true effect is 90 days. Along the horizontal axis, we vary the share of the observations which is potentially misplaced. The left-hand panel shows the outcome of the non-parametric RD approach devised by Calonico, Cattaneo and Titiunik (2014). Their approach features a local linear regression using data on an optimally chosen bandwidth around the age threshold. When there is no measurement error it recovers the true treatment effect, i.e., 90 days. The estimated impact then falls linearly with the amount of measurement error in the data; when 50% of the data is affected by the measurement error, the estimated impact is reduced to 60 days for example.

The right-hand panel shows that our baseline parametric approach is essentially immune to the measurement error problem. This approach features a linear interacted control function on data within \pm 3 years of the age threshold. By estimating the linear control function, it puts equal weight on all data points belonging to the analysis window. Consequently, the fact that individuals closest to the threshold are misplaced has little impact for the estimate of interest.

The details: measurement error in our setting

Our data contain information on all firms intending to lay off at least five workers simultaneously. A firm must submit a list containing the identities of laid-off workers and the displacement

ONLINE APPENDIX FIGURE 19 RD Estimates using different approaches

Notes: Panel (a) shows the results from the non-parametric (local linear) RD approach following Calonico et al. (2014). At each level of measurement error, the local linear regressions using a triangular Kernel are fit to data determined by an optimally chosen bandwidth. Each point in the graph has a different bandwidth as illustrated by panel (b) of Figure [22.](#page-46-0) Panel (b) mimics our baseline approach where we use data on ± 3 years around the threshold. In the analysis, we include a linear control function which is allowed to have different slopes above/below the age threshold. Both panels are based on simulated data where individuals are uniformly distributed on age a notification. Conditional on the total amount of measurement error, reported on the x-axis, the age of individuals is reported ± 2 months erroneously with 50% probability; \pm 3 months erroneously with 30% probability; and \pm 4 months erroneously with 20% probability. The simulation is based on 100,000 observations, the true age distribution is uniform and the true discontinuity is 90 days.

dates to the Public Employment Service (PES). The list also contains information on individual notification dates (which in 84% of the cases is the same as the arrival date of the list to the PES). Our running variable is age at individual notification date.

A concern is that individual notification date may contain some measurement error. Such errors imply that age at notification is measured with error. Measurement error in the assignment variable is potentially destructive for RD-analysis, since individuals may be placed on the wrong side of the threshold. As illustrated by Davezies and Barbanchon (2017), for example, a true discontinuity looks like a non-linearity when the measurement error is sufficiently large.⁴³

Figure [20a](#page-43-0) illustrates the presence of measurement error and its likely form. The left-hand panel shows the cumulative distributions functions (CDF:s) of the notice period in the vicinity of the age-55 threshold. The lines labeled -4 and +4, for example, display the CDF:s for individuals

⁴³It is possible that measurement error in notification dates translates to measurement error in the notification period (depending in part on whether the measurement error translates into displacement dates or not). This is not a concern as it will only reduce the precision of the first-stage estimates.

who are notified 4 months before and after the age-55 threshold, respectively. These two cumulative distributions have mass points roughly where one would expect them to be, i.e., at 180 and 360 days, consistent with workers above age 55 receiving an additional 180 days of notice if they have more than 10 years of tenure. Workers with less than 10 years of tenure, receive less than 180 days, no matter their age, which explains why 35% of workers above age 55 have less than 180 days of notice; moreover, workers may bargain for additional notice, which explains why some 40% of workers below age 55 have more than 180 days of notice.

The nature of the measurement error (A) Cumulative distribution functions \circ $\frac{a}{b}$
 $\frac{a}{c}$
 0 100 200 300 400 500 Notification time -4 -1 1 4 Normalized age (months) (B) Notice periods by age, donut RD $\beta = 97.021$ *** (7.763) 50 $\frac{300}{100}$
 $\frac{300}{$ -36 -24 -12 0 12 24 36

ONLINE APPENDIX FIGURE 20

Notes: Left-hand panel: Cumulative distributions of notification periods in the data for individuals whose recorded age at notice is 4 months below (-4), 1 month below (-1), 1 month above (1), and 4 months above (4) the age 55 threshold, respectively. Dashed vertical lines at 180 and 360 days. Right-hand panel: Notice time by age (1-month bins). Data within \pm 3 months of the discontinuity are excluded.

Matters are different for the data just above (+1 month) and below (-1 month) the threshold. These two distributions are indistinguishable from one another, suggesting a good deal of measurement error in the notification date; it would take a measurement error of at least 2-months to move an individual from above to below the threshold, or vice versa. The CDF:s for those reported to be 2 and 3 months above (below) the threshold lie in between CDF:s at 1 and 4 (-1 and -4), suggesting some measurement error at these horizons as well.

Figure [20b](#page-43-1) pursues the same theme by showing notice times by normalized age, excluding data +/-3 months relative to the threshold. There is a trend in notice periods below the threshold, which largely has to do with age being positively correlated with tenure. But importantly, there is no trend in mean notice periods above the threshold. This is as it should be, because (i) tenure does not matter above the threshold, and (ii) there is no reason to expect spillover from workers below to workers above the threshold. The fact that there is some curvature in Figure Ia above the threshold is entirely due to measurement error.⁴⁴ The "donut RD" shown in Figure [20b](#page-43-1) suggests that notification jumps by 97 days – from 189 days to 286 days – at the threshold.

The presence of measurement errors poses problems for all non-parametric RD approaches. Since they are designed to pick up non-linearities in the conditional mean function at the threshold, the local linear regression will focus on a smaller and smaller portion of the data when the measurement error increases.

Simulation To illustrate this problem, we have simulated data containing measurement error. We generate a data set containing 100,000 observations, where individuals are uniformly distributed on (true) age at notification. Individuals just below the threshold are assumed to have 180 days of advance notice. Among individuals below the age threshold, average days of notice are assumed to increase linearly with age as in Figure [20b.](#page-43-1) Individuals just above the threshold have an additional 180 days of notice with 50% probability. This yields an increase in advance notice of 90 days as in Figure [20b.](#page-43-1)

We follow Battistin et al. (2009) and assume that notification dates are measured with error for a subset of workers. Conditional on the overall amount of measurement error, the error is ± 2 months with 50% probability, \pm 3 months with 30% probability, \pm 4 months with 20% probability.⁴⁵

Figure [21](#page-45-0) illustrates the consequences of different amounts of measurement error. In panel (a) there is no measurement error. We fit a 4th order polynomial control function separately on each side of the threshold. The estimated jump at the threshold is 90 days. In panel (b), the measurement error affects 25% of the observations; the estimated jump at the threshold equals 70 days. In panels (c) and (d), we increase the proportion of the data containing a measurement error to 50 and 75%, respectively. The figure shows that the estimated conditional mean functions becomes more nonlinear around the threshold when the amount of measurement error increases. Consequently, the estimated "treatment effects" decrease in magnitude with the amount of measurement error. In panel (a) the estimate is 90 days (as it should be); in panel (c), for example, the estimate drops to 50 days.

⁴⁴For workers below the threshold, on the other hand, spillover could cause a non-linearity.

⁴⁵Since we observe birth month rather than birth dates we exclude individuals exactly at the threshold. To be moved across the threshold, the measurement error must thus be at least two months.

ONLINE APPENDIX FIGURE 21 Simulated data, by amount of measurement error

Notes: The scatter plots show notice time by age in 1-month bins. The lines show estimates from a 4th order control function fitted separately to data on each side of the threshold. In panel (a) there is no measurement error; in panel (b) 25% of the data is affected by the measurement error; in panel (c) 50% of data contain a measurement error; in panel (d) 75% of data contain measurement error. Conditional on the overall amount of measurement error (0, 25%, 50% or 75%), the error is ± 2 months with 50% probability, ± 3 months with 30% probability, and ± 4 months with 20% probability.

Figure [22](#page-46-0) illustrates what different amounts of measurement error does to non-parametric regression discontinuity estimates. We use the Calonico, Cattaneo and Titiunik (2014) approach. We thus fit a local linear regression on a portion of the data determined by selecting the optimal bandwidth and weighing the data by the default triangular kernel.⁴⁶ The left-hand panel reproduces

⁴⁶When we use a uniform Kernel, the problem caused by the measurement error is not as severe as in Figure

ONLINE APPENDIX FIGURE 22 Simulated data with measurement error: Non-parametric RD estimates

Notes: Panel (a) show the results from the non-parametric (local linear) RD approach due to Calonico et al. (2014). This approach features a local linear regression fit to a portion of the data determined by an optimally chosen bandwidth using a triangular Kernel. Each point in the graph has a different bandwidth as illustrated by panel (b). Both panels are based on simulated data where individuals are uniformly distributed on age at notification. Conditional on the total amount of measurement error, the individual is reported: ± 2 months erroneously with 50% probability; ± 3 months erroneously with 30% probability; and \pm 4 months erroneously with 20% probability. The simulation is based on 100,000 observations, and the true treatment effect is assumed to be 90 days. In each panel, the solid line depicts the median across 100 simulations, while the dashed lines correspond to the 90th/10th percentile.

Figure [19a,](#page-42-1) while the right-hand panel illustrates the reduction in the bandwidth that comes along with an increase in the share of the data that is measured with error.

In the context of our simulation, a parametric approach which uses all data \pm 3 years of the threshold is more or less immune to the measurement error. Since it places equal weight on all observations used in estimation, it is less sensitive to the measurement error in notification date; see [19b.](#page-42-2)

[^{22.}](#page-46-0) Yet, the downward bias is still substantial. The first-stage estimate is 70 when 50% of the data is plagued by measurement error, for example.

III.B Additional donut RD-graphs

Figure [23](#page-48-0) and [24](#page-49-0) show RD-graphs for various outcomes where we exclude data +/-3 months relative to the age-55 threshold.

ONLINE APPENDIX FIGURE 23 Donut RD-graphs for earnings, severance and wages

Notes: The figure plots (a) annual earnings, (b) severance, (c) and (d) re-employment wages, all by age at notification relative to the 55-threshold in 1-month bins where we have excluded observations +/- 3 months away from the threshold. Severance pay is measured as excess earnings in the year of displacement (see Section IV.A). Re-employment wage refers to full-time equivalent monthly wage reported in the Wage Survey by an employer other than the notifying firm for whom the worker have have not worked for at least one year prior to notification. In panel c) we let the Wage Survey determine the first new job whereas in panel d) the first new job is determined by the monthly employment markers. The regression lines come from estimating equation (6) with a linear age polynomial interacted with the threshold indicator for individuals aged 52-58 at the time of notification. The regressions also include individual-level baseline covariates (earnings in the year prior to notification, gender, immigrant status, tenure at notification, educational attainment FEs), and month-by-year FE:s. The estimated jump at the threshold along with its standard error is depicted in the figures. Standard errors are clustered by notification event. $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

ONLINE APPENDIX FIGURE 24 Donut RD-graphs for employment outcomes

 β =-0.363* \bullet (0.295) 4 $\frac{4}{3}$ ທ $\sum_{\substack{S \text{intra} \\ S \text{in terms of } \mathcal{S} \\ \text{in terms$

 $\overline{12}$ 0 $\overline{12}$ 24 $\overline{36}$
Normalized age (months)

3.5

-36 -24 -12 0 12 24 36

Notes: The figure shows employment outcomes cumulated over 2 years post notification by age at notification relative to the 55-threshold in 1-month bins, where we have excluded observations +/- 3 months away from the threshold. The regression lines come from estimating equation (6) with a linear age polynomial interacted with the threshold indicator for individuals aged 52-58 at the time of notification. The regressions also include individual-level baseline covariates (earnings in the year prior to notification, gender, immigrant status, tenure at notification, educational attainment FEs), and month-by-year FE:s. The estimated jump at the threshold along with its standard error is depicted in the figures. Standard errors are clustered by notification event. $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

D FIRM-LEVEL ANALYSIS

IV.A Construction of the notification event panel

This appendix describes the construction of the data for the firm analysis. We start with the notification data. These data cover all notified workers during 2005-2018 and their employer-IDs. In constructing the analysis data set, we face two challenges. First, there is likely measurement error in the timing of the notification event. Second, we want to relate the productivity change to a particular layoff event. To achieve the second objective, we focus on firms that had no layoff events in the two years preceding a particular event.

To deal with measurement errors, we clean the data as follows. We first compute the firm-level share of workers with erroneously reported notification times. A displaced individual's notification time is erroneously reported if it is negative or zero (7% of all notified workers) or larger than 18 months (0.9% of notified workers). We drop firms from the notification data if the share of displaced workers with erroneous notice times exceeds 10%. The reason for dropping the firm, rather than just the particular event, is that we want to be sure that included firms does not have prior layoff during the two years prior to layoff. Dropping firms with erroneous layoff events, eliminates 25% of the notification events.

Next, we match the employer-employee data with the cleaned notification data. In doing so, we define an indicator for whether a notified worker is recorded at the displacing firm in the year and month of the notification event. We compute the firm-level share of such workers and retain firms with a share above 95%. The reason for this is that we want to make sure that the notified workers were employed at the firm at the time of the event. This restriction drops 40 percent of the cleaned notification data.

The implementation of the LIFO-rules depends on plant and year, plus whether the worker belongs to a blue-collar or a white-collar wage agreement. The combination of these three factors (plant/year/type-of-agreement) defines a so-called order-circuit. Within each circuit, we take the number of displaced workers as given, and rank workers by their tenure. We then compute the *de-jure* notification time for individuals with a tenure rank lower than or equal to the number of displaced workers within that circuit. If the de-jure notification time is longer than the remaining calendar months of the year, we assign the remaining notification time to the next calendar year, irrespective of whether and when the worker leaves.

We then create a panel for firms that notify workers by adding firm-level outcomes. We use both the SCB database FEK and the database Serrano (maintained by the Swedish House of Finance). Sales or revenue is our key variable. We focus on incorporated firms. Since balance sheet data are noisy, we make sure that these two sources of information are consistent with one another. We define an observation as inconsistent if the difference in sales between the two sources exceeds

10%. We remove firms, where more than 10% of the observations over time is labeled as inconsistent. This drops 32 percent of the remaining notification data. The outcome variable of interest, the differences in log revenue over two time-periods minus the corresponding difference in the log of employees, is winsorized at the 5th and 95th percentile, within displacement year.

IV.B Precision of the first-stage

Figure [25](#page-53-1) illustrates the first stage relationship between χ – the share of months worked by individuals on notice – and the instrument – the share of months predicted by the *de-jure* rules. The circles illustrate the relationship between these two variables over the percentiles of the instrument. The dashed line represents the linear relationship, while the solid line shows the fitted values when we fit a second-order polynomial to the data. As illustrated by Figure [25,](#page-53-1) the second-order polynomial fits the data much better. Indeed the first-stage F-value increase from 79.4, in the linear specification, to 222 in the quadratic specification. This also matters for the 2SLS estimates of α , which becomes unreasonably large with a linear first stage. Adding additional higher-order terms neither improves the first-stage nor changes the 2SLS estimate of α .

ONLINE APPENDIX FIGURE 25 The first-stage relationship

Notes: The figure plots the firm-level relationship between χ – the actual share of working time provided by workers on notice – and the instrument. The latter is the share of working time provided by workers under notice in case the firm had followed the last-in-first-out (LIFO) rule in the selection of who to lay off and the law as well as the CBAs for how long advance notice these workers would have received. Each circle represents a percentile of the distribution of the instrument. The location in x- and y-space is determined by the mean χ and the mean instrument within each percentile. The dashed, straight line corresponds to the line of best fit while the solid, curved line represents the quadratic best fit.

IV.C Graphical illustration of the IV estimates

Figure [26](#page-54-1) illustrates the IV estimates graphically.

ONLINE APPENDIX FIGURE 26 IV estimates

Notes: This figure plots the relationship between the outcome and the fitted values from the first-stage regression. In panel (a) the outcome is change in productivity, defined as $log(y_i) - log(y_{i-1})$ whereas panel (b) focuses on $log(y_i) -$ (log(*yit*−1) + log(*yit*−2) + log(*yit*−3))/3. The fitted values are estimated as explained in Section VI.A according to equation 9. We divide firms in 50 equal-sized bins according to the fitted values and show the average outcome against the average fitted value within each bin, including control variables as explained in the text. The line represents the coefficient on the predicted share of months on notice. We report the slope of the line along with standard errors in parenthesis that are clustered at the firm-level. We also report the corresponding estimate of α as well as its standard error.

E ADDITIONAL REFERENCES

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