Firms and Unemployment Insurance Take-Up

Marta Lachowska Isaac Sorkin Stephen A. Woodbury*

October 2021

Abstract

This paper uses administrative data from Washington State to quantify the role of employers in the incomplete take-up of unemployment insurance (UI). Consistent with previous literature, nearly half of the workers who appear to be UI-eligible do not claim UI. Moreover, there is a steep income gradient in claiming. Distinctively, we find substantial dispersion in both firm-level UI claim rates and appeals (of UI claims) rates. Firm-level claim and appeals rates are negatively correlated, which is consistent with a deterrent effect of firms' appeals on workers' claiming. Claims and appeals rates are tightly related to workers' pre-separation wage rates, and firm fixed effects explain a large share of the income gradient in take-up and appeals. We show that if firms with below-median firm effects in claims rates had the median claims rate, then take-up would increase by about six percentage points. Finally, we estimate a simple model of experience rating and claims and use it to assess the targeting properties of UI and how experience rating affects targeting and take-up. The main source of targeting error in the system arises through incomplete take-up and decreasing experience rating reduces targeting errors. We also solve for the changes in experience rating that would achieve similar increases in take-up as compressing the firm effects distribution.

*Lachowska: W.E. Upjohn Institute for Employment Research, marta@upjohn.org. Sorkin: Stanford University and NBER, sorkin@stanford.edu. Woodbury: Michigan State University and W.E. Upjohn Institute, woodbur2@msu.edu.
Thanks to Sarah Bana, Patrick Kline, Lee Lockwood, Ioana Marinescu, Raffaele Saggio, Maya Rossin-Slater, and Heidi Williams for helpful conversations. We are grateful to the Employment Security Department (ESD) of Washington State for allowing access to the Washington wage records, and especially to Jeff Robinson of ESD, whose help was essential to understanding the data. Sorkin thanks Stanford's Institute for Research in the Social Sciences for support while working on this project. All errors are our own.

Some members of the Council are concerned [that]...under a system of experience rating, some employers might make excessive use of the appeals system...[1]

Many employers have found Unemployment Insurance cost management companies to be a cost-effective "best practice," in terms of administering UI claims and managing UI tax liabilities. Professional service organizations ... can help you minimize your unemployment insurance taxes and exposure .... [2]

Unemployment insurance (UI) has the dual goals of smoothing the consumption of job losers and acting as an automatic stabilizer in an economic downturn.[3] But worker take-up of UI is incomplete, compromising both goals. The first quote above (from the Advisory Council on Unemployment Compensation) reflects a longstanding concern among policymakers that experience rating of the UI payroll tax—whereby firms effectively pay for some of the UI benefits their workers collect—creates an incentive for employers to appeal or challenge the UI claims of workers they have laid off, so as to avoid higher payroll tax rates. The second quote offers support for this concern: it comes from the website of the Association of Unemployment Tax Organizations, which includes about 25 companies that refer to themselves as UI "cost management" companies.

Much of the literature on UI take-up has taken the perspective of the worker, linking low take-up to reduced UI benefit generosity (Anderson and Meyer, 1997), limited information about the program (Vroman, 2009), and the hassle of claiming UI (Ebenstein and Stange, 2010).[4] Fewer papers have addressed the possible role of employers in discouraging UI claims, but those that have suggest a link.[5]

In this paper, we use linked employer-employee data from Washington State to quantify the extent of firm heterogeneity in UI take-up and to understand the mechanism underling the effect. We develop three key findings. First, there is substantial heterogeneity in the employer-specific UI take-up rates—the proportion of workers laid off by an employer who claim and receive UI. The mean employer-level take-up rate is 0.46, with a standard deviation 0.20. Second, there is also substantial heterogeneity in employer-specific appeals rate, defined as the proportion of UI claims filed by an employer's laid off workers that are challenged through the appeals process.

Third, we estimate firm fixed effects in both UI take-up and appeals, defined as the firm-specific take-

[1]U.S. Advisory Council on Unemployment Compensation (1996, pg. 19)).

[2]Association of Unemployment Tax Organizations `https://www.autax.org/employers.html`. Last accessed July 8, 2021)

[3]See Baicker, Goldin, and Katz (1998) for an interesting historical perspective on how the U.S. ended up with an unemployment insurance system that combines federalism, experience rating and limited duration of benefits. Interestingly, the paper does not mention take-up as being a factor in these historical debates. See Ganong and Noel (2019) and Gerard and Naritomi (2021) for recent analyses of consumption and unemployment insurance in the U.S. and Brazil. See Johnston (2021) for a recent analysis of the effects of experience rating on hiring.

[4]Blank and Card (1991) find that a shift in the share of unemployment to states with low UI take-up rates explains at least half the decline. See more generally Currie (2006) for a discussion of take-up in social insurance programs.

[5]Anderson and Meyer (2000) find that, when the payroll taxes paid by employers to finance UI became experience-rated in Washington in 1985, UI claims fell, and denials of claims increased. The link between experience rating and and claims suggests that employers may try to reduce UI receipt by challenging claims. Based on interviews with job losers, Gould-Werth (2016) finds that some firms actively help workers in claiming UI, whereas others are indifferent, and still others actively impede claims. Auray, Fuller, and Lkhagvasuren (2019) and Auray and Fuller (2020) use state-by-time variation in unclaimed benefits to study the effect of denied claims on UI take-up and link their results to experience rating.

up rate and appeals rate, *adjusted for worker characteristics*. The composition-adjusted rates are almost as dispersed as the raw rates. Finally, these two rates are negatively correlated, consistent with a deterrent effect of appeals—i.e., some UI-eligible job losers may be deterred from claiming UI by the possibility that their claim will be appealed by an employer who is known to dispute UI claims.

We first introduce the institutional setting and data in section 1. We have the population of UI administrative wage and claims records from Washington State during 2005-2013.

Then in section 2 we develop a theoretical framework that emphasizes the link between experience rating and heterogeneity among firms in UI take-up. The model highlights some benefits and costs of experience rating the UI payroll tax. On the benefits side, the model shows that experience rating creates incentives for firms to screen workers: In general, ineligible workers are less likely to apply than eligible workers, but in the absence of experience rating all workers would apply. In addition, experience rating acts as a layoff tax, so it reduces layoffs. On the costs side, experience rating reduces UI take-up among eligible workers because they are deterred by the possibility that the firm will appeal and they will not receive UI. In addition, the fact that not all workers apply for UI undoes some of the layoff-tax properties of experience rating, weakening one of its benefits.

In section 3, we discuss how we estimate the percentage of UI-eligible job losers who claim benefits—the UI take-up rate—and show that it is incomplete. We estimate that about 45 percent of UI eligible workers in Washington during 2005–2013 claimed and received UI benefits, consistent with Anderson and Meyer (1997) which uses samples of UI administrative records from six states in 1979–1983. We also find striking income gradients. The UI take-up rate increases from the first to fifth decile of pre-separation wage rates by almost 20 percentage points, and the appeals rate falls in half. The higher probability of appeal facing lower-wage claimants is a possible deterrent to claiming for these workers.

In section 4, we quantify the the role of firms in explaining incomplete take-up. We begin by presenting a "switchers" design, which compares the UI claiming behavior of the same worker when she separates from two different firms. This allows us to net out worker effects in UI claiming and shows that firms play a large role in explaining take-up: A 10 percentage point increase in the firm-specific claims rate leads to a 8 percentage point increase in the probability of claiming UI. Moreover, this design allows a simple visual inspection of the functional form and other assumptions underlying the additively separable variance decomposition we then turn.[6]

We then use a two-way fixed effect regression (e.g., Abowd, Kramarz, and Margolis (1999) and Card, Heining, and Kline (2013)) to estimate firm effects in take-up, while controlling for unobserved worker heterogeneity. We address limited mobility bias by estimating Kline, Saggio, and Sølvsten (2020) (KSS) bias-corrected estimates of variance components. These components allows us to directly assess the contribution of worker effects, firm effects, and sorting of workers to firms with respect to UI claiming. We find substantial firm heterogeneity in UI take-up: the standard deviation of firm effects equals 0.15, or about

[6] We present evidence that the switchers design satisfies the exogenous mobility assumption. First, moves between firms are separated by a spell of unemployment, so there is little scope for workers to select their subsequent employer. Second, the moves are symmetric around zero changes in the firm claims rate. That is, the moves do not appear directed. Third, we show that the firm effects satisfy a symmetry property: workers who move from lower- to higher-claims firms experience a change in their claims rate equal and opposite of those moving in the other direction.

a third of the sample mean of UI take-up. Put differently, giving firms with below-median firm effects in claiming the median claims rate would increase the claims rate by about six percentage points (or 12 percent). Finally, we find that about 60 percent of the positive relationship between the pre-separation wage rate and the UI take-up rate can be explained by firm effects.

In section 5, we conduct a parallel analysis of the role of firms in appeals and again find substantial firm heterogeneity. The standard deviation of firm effects in appeals is close to 0.03, or almost three-quarters of the mean. We also find that about 80 percent of the relationship between pre-separation wages and appeals can be explained by firm effects. We then relate the firm effects for claiming to firm effects for appeals and find these to be negatively related, with an elasticity equal to -0.16. For both claims and appeals, we find that the relative variance of firm effects to person effects is larger than typically found for wages. This finding emphasize that the study of UI take-up should embrace the central role of firms, just as the study of wage setting has increasingly come to focus on firms (Card, Heining, and Kline, 2013).

In section 6, we use the empirical findings to quantify section 2's theoretical framework, which allows us to quantify the targeting properties of UI, as well as to conduct counterfactuals. To do this, we observe how average take-up rates, appeals rates, and receipt rates vary as firms contract. We make two assumptions: first, that job losers separating from firms that have stable employment are a mix of UI-eligibles and UI-ineligibles; and second, that job losers who separate from massively contracting firms are all UI-eligible. These assumptions allow us to back out take-up rates, appeals rates, and receipt rates by UI-eligibility.

We use these estimates to assess the targeting errors in the UI system. Following the typology of Kleven and Kopczuk (2011), we find that the dominant source of targeting errors are type IA errors, where eligible workers do not apply. In fact, these type of errors are five times as prevalent as type II errors where ineligible workers collect.

We study a counterfactual where we decrease experience rating by 10 percent. This change decreases appeals by about 20 percent, and increases UI take-up by about four percent (hence, to achieve increases in take-up similar to what we find for replacing below median firms with median firms in take-up, we would need to decrease experience rating by 30 percent). By implication, the layoff tax implied by experience rating only falls by about six percent. Strikingly, we also find that decreasing experience rating decreases the targeting errors: the increase in applications from eligible workers exceeds that from ineligible workers. We conclude that variation in experience rating generates meaningful changes in UI take-up, and would be desirable from the perspective a social welfare function that equally weighted errors of inclusion and exclusion.

We also use the model estimates to ask how far experience rating can go in explaining the firm-level dispersion in UI take-up rates. We find that about 10-30 percent of the dispersion of firm effects for UI take-up is directly explained by the inter-firm dispersion in *appeals* rates, though plausible perturbations in parameters generate much larger values. It follows that experience rating (through its effect on firm appeals) is likely not the only source of inter-firm heterogeneity in UI take-up rates, although it is important.

Finally, we show that high take-up firms are, on average, more desirable firms. A higher probability of receiving UI is an amenity, and so in a competitive labor market, firms would be expected to compensate for this amenity by offering lower pay (Abowd and Ashenfelter, 1981 and Anderson, 1994). In contrast, we find that workers' pay increases when they move to firms with higher UI take-up rates. Similarly, when workers move to firms with higher take-up rates, they also move to firms with lower separation rates, suggesting that these are on the whole more desirable employers. Jointly, these findings are more consistent with a model of imperfect competition explaining the firm effects in UI take-up, where firms that are higher on the job ladder choose to treat workers better, rather than a model of perfect competition.

1 Institutional environment and data

We begin by describing how workers collect UI, which explains some of the strengths of our data. We then describe how experience rating works in Washington state which explains why it is plausible that firms would want to affect UI take-up.

1.1 How workers claim UI benefits

To be eligible for UI benefits, a claimant initially needs an adequate work history (that is, be "monetarily" eligible) and must have lost her job through lack of work and no fault of her own (that is, be non-monetarily eligible). In addition, to remain eligible, the claimant must be "able, available, and searching" for work—that is, she must satisfy the work test. Below, we describe each basic step of the claiming process.

Step 1. Monetary eligibility: To be monetarily eligible for UI in Washington, a claimant must have worked at least 680 hours in the so-called base period, which can be defined in one of two ways.[7] The regular base period is the first four of the last five completed quarters before the quarter in which a claim is filed.[8]

For claimants who do not meet the 680-hour requirement in the regular base period, an alternative base period can be applied—the last four completed calendar quarters before the quarter of filing.

Step 2. Conditions of job separation: In general, to be eligible a worker needs to have separated due to lack of work and for no fault of her own. Workers who are discharged for work-related misconduct or who quit voluntarily are in general disqualified from receiving benefits. However, conditions of separation are not always clearcut. For example, a worker who was discharged simply because he or she was unable to perform the work would be eligible for UI benefits. Similarly, a claimant who quit her job for "good cause"—that is, for a work-related reason such as hazardous working conditions or being reassigned to different shift—would still be eligible. (Washington also considers illness of the claimant and quitting to accept another job that subsequently does not materialize to be good causes.)[9]

[7] All states except Washington use some measure of base-period earnings to gauge work history; hence "monetary" eligibility. But the term is misnomer for Washington because of its hours requirement. Nevertheless, we use the more conventional terminology.

[8] See `https://esd.wa.gov/unemployment/calculate-your-benefit`, last accessed January 29, 2021.

[9] U.S. Department of Labor, 2015. Comparison of State Unemployment Insurance Laws 2015. Employment and Training Administration, Office of Unemployment Insurance (http://www.unemploymentinsurance.doleta.gov/unemploy/comparison2015.asp (last accessed 17 February 2016)).

Conditions of separation are clearly more difficult to determine than monetary eligibly. For this reason, UI agencies routinely inform each UI claimant's previous employers about the UI claim, and give employers the opportunity to indicate the conditions of separation. On the one hand, this employer role is important to maintain the integrity of the UI system—for example, a worker discharged for misconduct has an incentive to tell the UI agency that the separation was for lack of work. On the other hand, an employer has an incentive to give a reason for separation that will make a claimant ineligible so the employer will not be charged for benefits paid to the worker. (See the next subsection.) As a result, conditions of separation are often contentious and subject to appeal by either the claimant or the employer. We discuss this further in section 3.1. In practice, compared to monetary eligibility, this requirement is much fuzzier.

Step 3. Filing a claim: UI benefits are not paid automatically to laid off workers—the worker needs to act. This is the central UI take-up problem that has been a concern to policymakers. Most states accept UI claims by telephone and online, although a surprisingly large percentage of claims are still filed in person.[10] The Washington Employment Security Department (ESD) has an extensive "Unemployed Worker Handbook" describing the process, as well as a website where a claim can be filed.[11]

Step 4. Determination of eligibility: The ESD uses administration wage records (the quarterly employer reports of work hours and earnings on which our analysis is based) to determine monetary eligibility, and uses information provided by the UI claimant and his or her previous employers to determine conditions of separation. If the claimant and the employer disagree about the conditions of separation, an appeal by the employer may result; however, an initial determination is usually made using the information provided by the claimant. If the determination results in eligibility, benefits are paid. If an appeal reverses the initial eligibility determination, the claimant is liable for repaying the benefits than had been paid.

Step 5. Continuing eligibility: To continue receiving benefits, the claimants need to be "able, available, and searching" for work. Typically, the claimants needs to keep a record of employer contacts and the job search activities, and be prepared review these with ESD.[12] A claimant may also be required to attend job search workshops and receive other employment services, including job referrals by the agency. If a claimant refuses an agent referral to a suitable job (a job that is consistent with his or her training and experience), the claimant will be disqualified from receiving further benefits.

[10]Ebenstein and Stange (2010) do not find that accepting telephone or online claims has led to an increase in UI claiming rates.
[11]`https://esd.wa.gov/unemployment/how-to-file-a-weekly-claim`, last accessed January 29, 2021.
[12]On the effects of work search requirements, see Lachowska, Meral, and Woodbury (2016) and Toohey (2017).

1.2 Experience rating and the employer

In the US, each state finances regular UI benefits using an experience-rated payroll tax,[13] which is collected entirely from employers in all but three states.[14]

In Washington, the payroll tax rate paid by an employer increases with the UI benefits that have been "charged" to that employer in the previous four years. Specifically, benefits paid to each UI recipient are traced to the recipient's former employer(s), then each employer's benefit charges are used to calculate a measure of layoff experience that can be mapped into a tax rate.[15]

To calculate each employer's payroll tax rate, Washington uses a benefit ratio formula, which can be written:

$$\text{Benefit ratio in year } t = \frac{\text{Sum of benefits charged over last 4 years}}{\text{Sum of taxable wages over last 4 years}}, \tag{1}$$

where "taxable wages" is the base to which the tax rate is applied. Washington's tax base was $30,500 in 2005 (the earliest year we examine), and because the base is indexed to the state's average weekly wage, it increased to $39,800 in 2013 (the most recent year we examine).[16]

An employer's benefit ratio then maps to a UI tax rate. The tax schedule varies over time. In Washington, the tax rate is capped at 5.4%, so experience rating is incomplete—in the simplest case, when an employer's benefit ratio reaches 0.054, the tax rate cannot go higher. Although the tax schedule is not linear (in fact, it is in 40 discrete bins), the slope of the tax rate in the benefit ratio is usually close to 1. The slope of 1 means that if a firm is on the "sloped" part of the schedule (has a benefit ratio below 0.054) and permanently has $1 more in UI benefits charged to it each year, then up to the discrete bins the firm's annual taxes will go up by about $1.

1.3 Data

The data consist of wage records and unemployment insurance (UI) claims records from 2005 to 2013, provided by the Washington State Employment Security Department (ESD) The wage records consist of the quarterly earnings and work hours of each worker along with an identifier of the associated employer.[17]

[13]Experience rating a unique feature of the US system, and it was originally advanced as a way to distribute the cost of UI equitably among employers and to discourage employers from laying off workers (Blaustein (1993)). It has been shown repeatedly to reduce temporary layoff unemployment (for example, Topel (1983) and Card and Levine (1994)), but it also creates an incentive for an employer to challenge or appeal UI claims so as to avoid benefit changes and prevent an increase in the payroll tax rate. In particular, an employer might appeal the conditions of separation associated with a UI claim so that a UI claimant does not receive benefits—for example, attesting that a separation was a voluntary quit or a discharge for misconduct. See Guo and Johnston (2020) for a recent review of the literature.

[14]Alaska, New Jersey, and Pennsylvania collect part of the tax from covered workers.

[15]Not all benefits received by workers are chargeable—for example, those paid to workers who have quit with good cause Vroman (2009) and Vroman and Woodbury (2014). To cover these benefits, every state's UI payroll tax has a relatively small flat-rate component that is not experience rated and applies to all employers.

[16]See Miller and Pavosevich (2019) and Lachowska, Vroman, and Woodbury (2020) for further discussion and analysis of experience rating methods.

[17]The employer is the entity from which UI payroll taxes are collected and is the unit of observation in the wage records. Although we often use the term "firm" to refer to an employer, the two are not necessarily the same. For firms with a single establishment, and for firms with multiple establishments all located in Washington, the employer is also the firm (although in some cases, a multi-establishment firm may be divided into more than one employer for UI payroll tax purposes). For firms with

Washington is unusual in requiring employers to report quarterly work hours, and it is unique in using that information to determine eligibility fo UI. The wage records allow us to infer whether a worker would satisfy the monetary eligibility criteria for UI in any given quarter, if he or she had separated in that quarter.

The claims records contain a worker identifier and information on the date the worker claimed UI, the weekly benefit amount, and the benefits paid to the claimant. They also include information on the reasons for separation given by the worker and by the employer. When the reasons given conflict, a subsequent redetermination typically occurs, and in many cases a formal appeal and hearing. (Although the data do not indicate whether the conflict was resolved by an administrative redetermination or through a formal appeal, we refer to all these cases as "appeals" for simplicity.) In roughly 80 percent of the cases where the claimant's and employer's reasons for separation disagree, the worker reports "lack of work," and the employer reports either "discharge" or "voluntary quit," a difference implying the worker gave a reason that would result in eligibility, whereas the employer gave a reason that would lead to denial. (See Appendix Table A1 for the complete matrix). We know the outcome of the appeal because the claims records reflect the final benefits paid to a claimant, net of any repayments required following an appeal that went against the claimant.[18]

Additional details about the data are in Appendix A.

1.4 Estimating UI take-up

Our goal is to estimate the UI take-up rate, defined as the percentage of UI-eligible job losers who claim (and receive) benefits. We observe the numerator of this rate—the number of claimants who receive benefits—in the claims records. The denominator—the number of job losers who could have claimed and received UI, whether or not they claimed—is more problematic. We observe each worker's work history (work hours and earnings) in the quarterly wage records, so we can accurately determine whether a claimant would be monetarily eligible. But we observe the conditions of a job separation only for workers who claim UI, so we need to make some assumptions to infer whether a separation that did not result in a UI claim was due to lack of work and no fault of the worker, and we need to be aware of the weaknesses of the resulting estimates. Our approach builds on Anderson and Meyer (1994) and Anderson and Meyer (1997), as well as work by Bjelland et al. (2011), Hyatt et al. (2014), and Sorkin (2018).

The first approach to eliminating workers whose conditions of separation would make them ineligible is to drop separators who transitioned quickly to a new job and those who appear to have dropped out the labor force. Specifically, to eliminate job-to-job transitions, we drop any separator who moved to different employer in either the same or the following quarter, and whose work hours decreased by at most 15 percent in the quarter of transition or between the two quarters in which the transition took place. (The hours drop is calculated relative to the quarter before the transition. Over a quarter, a 15 percent hours drop corresponds to a roughly two-week reduction in work, and it is unlikely that a worker would claim UI.) To eliminate

multiple establishments some of which are located outside Washington, the employer covers only the firms' establishments located in Washington.

[18]The claims records also include basic demographic information, but the wage records do not. As a result, we observe the characteristics only of workers who claimed UI at some time during the years for which data are available, which limits our ability to perform subgroup analyses.

labor force dropouts, we drop separations that were followed by five or more quarters with zero work hours. (We use five or more quarters so we do not count seasonal hours reductions as labor force withdrawals.)

These screens are imperfect in two ways. First, they do not eliminate workers who were discharged for misconduct, and second, they do not eliminate all workers who separated voluntarily. We have no information that allows us to detect these conditions with certainty. As a result, the denominator of our UI take-up estimates is likely too large, and the take-up estimates should be considered lower bounds.

As a check on this first approach, we examine UI take-up for a subsample of separators who lost their job in a mass layoff. In particular, we restrict the sample of potential UI claimants to monetary-eligible workers who separated following a contraction of at least 50 percent in their employer's total work hours relative to the previous year. For these job losers, it less likely that separation resulted for reasons other than lack of work, so we can be more confident that, after dropping workers who transitioned quickly to a new job and labor force dropouts, we have a sample of workers who were fully eligible for UI. We use this feature of the data extensively in the model below.

We note two additional features of the analysis sample. First, we include all UI recipients who were on temporary layoff in both the numerator and denominator of the take-up calculation. Because these workers returned to their previous employer, our definition of separation does not include them, but the fact that they collected UI implies that they did separate and so we count them as both separating and as claiming UI. Second, we include only separations that were preceded by at least five quarters of employment with a single unique employer. Because Washington charges benefits to employers in proportion to base period earnings, and because the separating employer may not be a base period employer, there are a few cases where multiple employers are connected to a given separation. This restriction ensures that the separating employer is also the employer who would be charged for benefits if the worker claimed and received UI benefits.

2 A model of the role of firms in UI take-up and targeting

Having described the institutional environment and the data, we now describe the conceptual framework that organizes our thinking about the role of firms in UI take-up and targeting. In section 6, we return to this model and use it to provide a quantitative interpretation of our findings.

2.1 Overview

This model draws on some of the structure of Auray and Fuller (2020). The basic ingredients are as follows. UI is financed partially by an experience-rated tax, where firms pay a fee if workers collect UI. Workers can either be eligible or ineligible for UI. There is heterogeneity in the cost of applying for UI so that only some workers claim. Firms can appeal, and there is heterogeneity in the cost of the firm challenging. The firm observes whether a worker is eligible for UI, and applies a separate decision rule on whether to appeal eligible and ineligible applicants. Conditional on an appeal, workers collect UI with some probability, and this probability depends on their true eligibility type. In addition, firms can receive negative shocks and decide to lay off workers, where this layoff decision depends on the UI system.

The model thus gives us a simple and coherent framework to talk about the main forces at play in experience rating and the labor market: experience rating affects layoff rates, take-up and targeting. The main ingredient it misses is that experience rating does not affect the level of employment.

2.2 Environment and timing

A firm j enters the period with employment given by $E_{j,-1}$. The firm draws a productivity level from a distribution $\mathcal{G}(z)$. The production function is $F(E_j, z_j) = z_j E_j^{\alpha}$. The output sells for a unit price.

The wage is set exogenously, and is given by w. Hence, the firm's first best employment level solves $\alpha z_j E_j^{\alpha-1} = w$, or $\left(\frac{\alpha z_j}{w}\right)^{\frac{1}{1-\alpha}} = E_j^*$. In the absence of experience rating, this defines a hiring and layoff function such that if $E_j^* > E_{j,-1}$ the firm hires and if $E_j^* < E_{j,-1}$ the firm lays off.

All workers are monetarily eligible—they have adequate work histories. However, among the monetarily eligible workers, some are ineligible due to non-monetary separation issues (for example, because they were discharged for misconduct). We assume that share δ of workers exogenously separate each period, and share $\Pr(e = 1) = \sigma$ of them are eligible. We denote eligibility status by $e \in \{0, 1\}$, where $e = 1$ denotes eligible. If a firm wants to lay off additional workers in order to contract further, then it will lay workers off who are all eligible for UI. We need to have eligible and ineligible workers for the appeals process to make sense. In order to have ineligible workers separate, we need to have exogenous separations since the UI system typically views separations that arise from shocks to firms as eligible for UI.

A worker faces a fixed cost of applying for UI. This cost is heterogeneous. This heterogeneity could reflect unmodelled dependence on income, or else differences in information or hassle costs. Denote this cost by χ, and we assume it follows a different CDF depending on the worker's eligibility status: $\mathcal{P}_e$.

After a worker applies, a firm decides whether or not to appeal. A firm chooses an appeals rate. It is costly to have a higher appeals probability for a given worker. This cost is given by: $c(p_{e,j}) = \eta_j p_e^{\zeta}$, with $\zeta > 1$. That is, the firm picks a separate appeal probability for eligible and ineligible workers. The key firm heterogeneity comes through η_j, which captures firm-specific differences in the costs of appealing. This could reflect some cost to the firm of having economies of scale in challenging, or it could reflect the broader reputation cost of not treating workers well. (Below we show empirically that firm-level claims rates are positively related to worker wages, which suggests that the logic of some amenities being normal goods and thus ending up positively correlated with wages discussed in Lang and Majumdar (2004) and Sorkin (2018, Section 6) applies here).

Conditional on an appeal, the probability that someone whose true eligibility is e collects is given by r_e. We would therefore expect that $r_1 > r_0$; that is, eligible workers should be more likely to collect following an appeal than ineligible workers.

The UI system is financed from two sources: a lump sum tax on all workers, and an experience rated fee, τ. In this essentially static model, experience rating means that if a worker collects UI, then the firm pays a fee of τ. The lump-sum tax is so that we can finance the UI system. For expositional clarity, we do not include the lump sum tax in equations.

A worker who works earns a wage w. A worker who does not collect UI receives income d (perhaps from savings), and a worker who collects UI receives an income b. We assume $w > b > d$.

To summarize the model, the timing is as follows:

1. Firm enters period with employment;
2. Firm realizes productivity shock;
3. Exogenous separations realized;
4. Firm decides to lay worker off;
5. Worker decides to file;
6. Firm decides effort level on appeal, while aware whether a worker is eligible;
7. Outcome is realized: whether or not workers collect, and then firms produce and pay taxes (and workers get paid, and pay taxes).

An equilibrium of the model consists of firms and workers making optimal decisions. The worker optimal decision consists of cutoff rules of when to apply, which are firm and eligibility specific, $\{\chi^*_{e,j}\}$. The firm decisions consist of the appeal probabilities $\{p^*_{e,j}\}$ and an optimal layoff rule.

2.3 Equilibrium and properties of equilibrium

We summarize the optimal decision rules in the model in a number of formal results (proofs are in Appendix B).

Result 1. *Firm j's optimal appeal probability for a worker of type e is given by:*

$$\left(\frac{(1-r_e)\tau}{\eta_j\zeta}\right)^{\frac{1}{\zeta-1}} = p^*_{e,j}. \tag{2}$$

Recall that $\zeta > 1$. The equation above says that the appeal probability is increasing in experience rating (τ). It is decreasing in the accuracy of the UI appeals system (r_e.). It is also decreasing in the firm specific cost of appealing (η).

Result 2. *A worker of type e has a cutoff type at employer j given by:*

$$(1-(1-r_e)p^*_{e,j})(u(b)-u(d)) = \chi^*_{e,j}, \tag{3}$$

where a worker with $\chi < \chi^*_{e,j}$ applies and a worker with $\chi > \chi^*_{e,j}$ does not apply.

The cutoff cost is increasing in the difference in the level of utility when the collecting UI and when not collecting UI. The cutoff cost is decreasing in the appeal probability. And it is increasing in the probability of collecting conditional on appealing. We define the application rate among the eligible workers as $A_{e,j} \equiv \mathcal{P}_e(\chi^*_{e,j})$.

Result 3. *If z_j is such that* $\left(\frac{\alpha z_j}{w}\right)^{\frac{1}{1-\alpha}} > (1-\delta)E_{j,t-1}$ *then the firm hires and* $E^*_{j,t} = \left(\frac{\alpha z_j}{w}\right)^{\frac{1}{1-\alpha}}$*. then the firm hires and* $E^*_{j,t} = \left(\frac{\alpha z_j}{w}\right)^{\frac{1}{1-\alpha}}$.

If z_j is such that $\left(\frac{\alpha z_j}{w - A_{1,j}\tau[1-p^*_{1,j}(1-r_1)]}\right)^{\frac{1}{1-\alpha}} > (1-\delta)E_{j,t-1} > \left(\frac{\alpha z_j}{w}\right)^{\frac{1}{1-\alpha}}$ *then the firm neither hires nor fires and* $E^*_{j,t} = (1-\delta)E_{j,t-1}$.

If z_j is such that $(1-\delta)E_{j,t-1} > \left(\frac{\alpha z_j}{w - A_{1,j}\tau[1-p^*_{1,j}(1-r_1)]}\right)^{\frac{1}{1-\alpha}} > \left(\frac{\alpha z_j}{w}\right)^{\frac{1}{1-\alpha}}$ *then the firm lays workers off and* $E^*_{j,t} = \left(\frac{\alpha z_j}{w - A_{1,j}\tau[1-p^*_{1,j}(1-r_1)]}\right)^{\frac{1}{1-\alpha}}$.

This Result illustrates the employment "smoothing" benefits of experience rating. Experience rating acts as a layoff tax. As such, it induces a wedge between the cost of hiring and firing a worker (the $A_{1,j}\tau[1 - p^*_{1,j}(1-r_1)]$ term) and so induces a region of inaction. Similarly, because of this wedge, when a firm is laying off workers, it lays off fewer workers.

This model emphasizes that the endogeneity of the claiming and appeals decision mutes the effect of experience rating on smoothing employment because it decreases the odds that an eligible worker will apply for and ultimately collect UI.[19]

Define the layoff rate $l(z_t, \eta_j) \equiv \text{abs}\left(\max\{\delta + 1 - \frac{E(z_t,\eta_j)}{E_{j,-i}}, 0\}\right)$.

Result 4. *The benefit ratio at the firm is:*

$$br_j = b\frac{\frac{l(z_t,\eta_j)+\delta\sigma}{l(z_t,\eta_j)+\delta}A_{1,j}[p^*_{1,j}r_1 + (1-p^*_{1,j}] + \frac{\delta(1-\sigma)}{l(z_t,\eta_j)+\delta}A_{0,j}[p^*_{0,j}r_0 + (1-p^*_{0,j}]}{w}.$$

The benefit ratio is increasing in the layoff rate, and decreasing in the appeals probabilities.

Result 5. *Suppose that $1 > r_1 > r_0$. An increase in experience rating (raising τ):*

- *Increases the appeal probabilities ($\frac{\partial p^*_{e,j}}{\partial \tau} > 0$);*
- *Decreases application rates ($\frac{\partial A^*_{e,j}}{\partial \tau} < 0$);*
- *The effect on the firing cost is ambiguous ($\frac{\partial A_{1,j}\tau[1-p^*_{1,j}(1-r_1)]}{\partial \tau}$ cannot be signed).*

The first two parts of the Result show that conditional on the pool of separators, experience rating improves targeting: with experience rating, fewer ineligible workers apply for UI. But, at the same time, fewer eligible workers apply for UI. Thus, depending on how the social planner weights errors of inclusion and exclusion, it is not obvious whether increasing or decreasing experience rating is desirable.

The last statement in the Result shows that the employment smoothing benefits of experience rating can be undone by its effects on take-up. An increase in experience rating has the direct effect of increasing the

[19]Interestingly, MaCurdy, Pearce, and Kihlthau (2004, pg. 10) emphasize that the incomplete UI take-up decreases the desirability of work-sharing arrangements in the United States: "Because only a fraction of employees who are laid off will collect UI benefits, firms can expect total claims to be lower if they choose to lay off workers instead of selecting work sharing."

layoff tax which smoothes employment. At the same time, increasing the layoff tax results in an increase in the appeals rate and decrease in the claims rate. This in turn, decreases the effective layoff tax because laid-off workers are less likely to claim UI and also less likely to receive it if they do.

2.4 Discussion

Given experience rating and firm heterogeneity in the perceived cost of appeals, we expect important heterogeneity in appeals and claims rates across firms. Moreover, we would expect these to be negatively correlated. The model also shows that experience rating affects the targeting of UI. In the absence of experience rating all workers—both eligible and ineligible—would apply.[20] Experience rating ensures that UI is better targeted because it dissuades ineligible workers from applying. That said, the model emphasizes a key downside of experience rating: it deters some eligible workers from applying.[21] The model also emphasizes that the endogeneity of take-up to the extent of experience rating undoes some—or possibly all—of the employment smoothing benefits of experience rating. Finally, the model also shows that there are two sources of variation in the benefit ratio facing firms: the layoff rate (which in the model is a direct function of the productivity shock) and the take-up rate (which in the model is a direct function of the appeals rate).

3 The role of firms and firm heterogeneity in UI take-up

In this section we first show the that over the nine-year period we examine, the average UI take-up rate was about 45 percent. We then show that the incomplete take-up plays a quantitatively important role in determining the firms UI tax rate. We then turn to showing some correlates of incomplete take-up. We show that there is substantial industry variation and we show that there is a steep gradient in the relationships between the pre-separation hourly wage rate of claimants and several UI outcomes—take-up and appeals. Finally, we show that these relationships become markedly weaker after we account for firm heterogeneity.

3.1 UI take-up

The first two columns of Table 1 show summary statistics for all worker-quarter observations in the analysis sample just described (column 1) and for worker-quarter observations that would result in a monetarily-eligible UI claim if the worker separated in that quarter (column 2). (The samples in columns 1 and 2 do not condition on separation.) Conditioning on monetary eligibility reduces the sample size from 80.8 million to 58.5 million worker-quarters. Comparison of columns 1 and 2 shows that workers who would be monetarily eligible for UI if they separated earn more on average, are employed at larger firms, and have accumulated more tenure at their firms

Columns 3 and 4 of Table 1 show estimates of UI take-up. Of the 58.5 million worker-quarters in which a worker would have been monetarily eligible if she separated (column 2), about 3.2 million separations

[20] Doornik, Schoenherr, and Skrastins (2020) document evidence of gaming in a non-experience rated unemployment insurance system.

[21] Kleven and Kopczuk (2011) refer to eligible workers who do not apply as Type Ia errors, eligible workers who apply and are rejected as Type Ib errors, and workers who are ineligible but apply and receive benefits as Type II errors.

occurred (column 3), and about 29 percent of these separation resulted in a UI claim. Dropping separations that led quickly to a new job or to exit from the labor force greatly shrinks the sample to just over 1 million separations, and increases the estimated take-up rate to 45 percent. These take-up rates are slightly higher than those found by Anderson and Meyer (1997, Table 3) using similar samples. This makes sense because, although Anderson and Meyer were examining an earlier time period (1979–1983) when take-up rates were generally higher, the six states they examined all tend to have lower UI recipiency rates than Washington. Comparison of columns 3 and 4 suggests that workers who separate and do not make immediate transitions or exit the labor force are negatively selected compared with all separators: their earnings are lower on average and their work hours somewhat higher.

Table 1 also shows other characteristics of monetarily-eligible separations. For about four percent of the UI claims, the worker and employer gave different reasons for separation, leading to a redetermination or appeal, so what we are calling appeals are relatively rare. In more than 60 percent of these cases, the appeal was decided in favor of the claimant and resulted in benefits being paid. So from the employer's standpoint, most appeals are "unsuccessful" in that the employer's reason for separation was rejected in favor of the claimant's.

3.2 Firm heterogeneity and the benefit ratio

We have just showed that take-up is incomplete. Is this incompleteness quantitatively important? In this section, we show that from the firm's perspective the variation in take-up across firms is quantitatively important. To do so, we examine the determination of the benefit ratio (i.e., the ratio of UI charges to taxable wages), which determines the firm tax rate. In the model, the benefit ratio depends on two features of the firm: first, its layoff rate, and second, its take-up rate. Here, we show that variation in the take-up rate is as important in determining the firm's benefit ratio (and hence tax rate) as the separation rate, where the latter has been typically viewed as the firm's control variable when researchers have analyzed UI financing reforms.

We expand equation (1) as follows:

$$
\begin{aligned}
\text{Benefit ratio} &= \frac{\text{Benefits charged}}{\text{Number of employees}} \Big/ \frac{\text{Taxable wages}}{\text{Number of employees}} \\
&= \underbrace{\frac{\text{Number of separators}}{\text{Number of employees}}}_{\text{separation rate}} \times \underbrace{\Pr(\text{claiming}|\text{separating})}_{\text{claims rate}} \\
&\quad \underbrace{\times \underbrace{\Pr(\text{receiving}|\text{claiming})}_{\text{beneficiary rate}} \times \underbrace{\frac{\text{Mean benefit paid}}{\frac{\text{Taxable wages}}{\text{Number of employees}}}}_{\text{replacement rate}}}_{\text{realized replacement rate}} .
\end{aligned} \tag{4}
$$

That is, we write the benefit ratio as the product of the separations rate, the claims rate and the realized replacement rate. In practice, we first compute averages of number of separators, claims rate, beneficiary rate, and mean benefits paid in the last four years. Then we divide the terms by the average number of a firm's employees in the last four years. We do this for firm's benefit ratio in 2009.

Upon seeing equation (4), a typical inclination would be to take logs and report a linear variance decomposition. In this context, however, this step is unappealing because the benefit ratio in levels (not logs) is the object of interest. Instead, we pursue the following "nonlinear" decomposition. We compute "simulated" benefit ratios by in turn replacing each of the separation rate, the claims rate, and the realized replacement rate by their sample averages (as well as combinations of each of these three terms) and then recomputing the variance of the benefit ratio. We then compute the variance of the observed benefit ratio as well as these "simulated" benefit ratios. By dividing the variances, we get an estimate of the contribution of each term to the overall variance. To take one example and more formally, call the "claims-rate constant" benefit ratio $\text{BR}(\bar{claims})$ and the true benefit ratio BR. Then $1 - \frac{\text{var}(\text{BR}(\bar{claims}))}{\text{var}(BR)}$ represents the share of the variance explained by the claims rate; that is, if the claims rate is the only source of variation then we would find a one in this calculation. This calculation quantifies what share of the variance of the benefit ratio each component explains. Because it is nonlinear, it is order-dependent and so we report all possible orders.

Figure 1 shows this calculation for all three terms individually, as well as the three possible combinations of two terms. In terms of interpreting magnitudes, note that because this decomposition is nonlinear, the components do not sum to one. A few findings stand out. First, the claims rate explains slightly more of the variance in the benefit ratio than the separation rate (86% vs. 84%). Second, when combined with the realized replacement rate, the claims rate explains more of the variance than the separation rate.

Thus, the key finding is that the claims rate is at least as important as the separation rate in explaining the variation in the benefit ratio across firms. This stands in contrast to the theoretical and normative literature on experience rating, which typically assumes that the only control variable of the firm is the separation rate (Brechling (1981), Topel (1983), Topel (1984), and Ratner (2013)).[22] This finding emphasizes that take-up—and variation in take-up across firms—is a quantitatively important margin.

3.3 Heterogeneity in UI take-up by wage and industry

We now turn to showing correlates of heterogeneity of take-up.

Table 2 shows how UI take-up rates, appeals rates, and the outcome of appeals vary by industrial sector. Service industries—retail trade, health care and accommodation and food services—tend to have lower claims rates and higher appeals rates than unionized sectors such as construction, manufacturing, mining, public administration, and wholesale trade. Also, employers' appeals tend to fare better in service industries, where the claims rate is low.

How are UI take-up, appeals, and unsuccessful appeals related to the pre-separation wage rates of workers? Figure 2 shows these relationships nonparametrically. Panel (a) shows a binned scatterplot of the take-up rate (from the sample in column 4 of Table 1) against the average hourly wage rate that a worker earned in the base period. The relationship has an inverted-U shape. At \$10 an hour, the claims rate is only 30 percent, but rises steeply to over 50 percent at about \$20 an hour; so workers earning the the lowest wage rates are least likely to claim. At wage rates greater than \$20 an hour, the claims rate gradually falls.

[22] Auray, Fuller, and Lkhagvasuren (2019) and Auray and Fuller (2020) are notable exceptions to this tendency.

Panel (g) suggests a natural explanation for why claims rates fall at wage rates greater than \$20 an hour. The panel plots the average weekly benefit amount as a function of the base-period hourly wage rate. The weekly benefit amount increases with the base period wage rate up to about \$20 an hour, and is constant thereafter. This reflects the way the weekly benefit amount is calculated in Washington—3.85 percent of average earnings in the two high-quarters of the base period, up to a specified maximum (\$604 in 2013, the last year we examine). It follows that, as the wage rises above \$20 an hour, the UI replacement rate falls, and the incentive to claim also falls.

Panel (c) of Figure 2 shows a possible explanation for why claims increase between 10 an hour and 20 an hour: as the base-period wage rate rises, the appeals rate falls from over 5 percent to under 3 percent. That is, lower-wage claimants are more likely to have their claims appealed, creating a possible deterrent to claiming for low-earners. In addition to facing a higher probability of appeal, lower-wage workers face a higher probability that the appeal will be decided in favor of the employer: As panel (e) shows, on average, the appeals of higher-wage claimants are less likely to be successful (i.e., to be decided in favor of the employer). This finding can be interpreted in at least two ways. First, a lower-wage worker may be more likely to have a claim that is associated with a separation issue like voluntary quitting or discharge for misconduct. Second, a lower-wage worker may be less likely to have the legal means or institutional understanding to present her case effectively.

3.4 Initial evidence on firm heterogeneity

Figure 2 also shows some simple evidence suggesting the importance of firm-level differences in generating incomplete take-up. Panels (b), (d), (f), and (h) of Figure 2 repeat the binned scatterplots of take-up, appeals, unsuccessful appeals, and the weekly benefit amount against hourly wages, except that we residualize each vertical-axis variable for firm fixed effects. What is striking is how much the slopes of all four relationships flatten after netting out firm fixed effects. Specifically, controlling for firm fixed effects wipes out about half the dispersion in claiming and appeals that can be attributed to wage rates. Moreover, controlling for firm fixed effects almost completely eliminates the relationship between unsuccessful appeals and wage rates. This evidence suggests a large role for firm heterogeneity in explaining UI take-up, although it could also reflect worker sorting across employers rather than a causal effect of firms. In the next section we turn to addressing the role of worker sorting.

4 Estimating firm heterogeneity in UI take-up

The figures in previous section show that UI take-up might be related to firm characteristics. In this section, we discuss our approach to examining if the heterogeneity in UI take-up rates across firms can be causally linked with worker's UI take-up. First, we begin with a "switcher" analysis, where we relate how changes in firm-level UI claim rates affect the change in the likelihood that a worker claims UI. We show that there is clear evidence of an important role for firms in explaining worker take-up. Second, we estimate a Abowd, Kramarz, and Margolis (1999) (AKM) two-way fixed effect model of UI take-up and present a variance decomposition of UI take-up into worker effects, firm effects, and sorting of workers to firms.

4.1 Empirical model and estimation

Consider the following model of an eligible worker i's decision to claim UI after separating from firm j:

$$c_{ij} = a_i + \psi_j + \epsilon_{ij}, \tag{5}$$

where c_{ij} equals one if the worker claims UI following a separation and zero if the worker does not claim. This decision depends on a worker fixed effect a_i and firm effects ψ_j. In the context of the model presented in the previous section, we might think of the a_i as reflecting the worker's time-invariant take-up costs, and the ψ_j as reflecting the firm's cost of challenging. More broadly, these worker take-up costs could reflect differences in knowledge or resources that would lead to differences in claims rate. Similarly, the ψ_j could also capture differences in information provision or deterrent effects towards claiming.

Our goal is to relate worker claiming behavior to the leave-one-out claims rate at the firm. First, define the leave-one-out ($-i$) claims rate at firm j as:

$$\bar{c}_{j,-i} = \bar{a}_{j,-i} + \psi_j + \frac{1}{N_j - 1}\sum_{k \neq i} \epsilon_{kt}, \tag{6}$$

where the variables with bars over them are the natural sample averages. In this analysis, we leave out a worker-quarter and compute firm-year leave-out averages. Then, for workers who separate twice and who are eligible to claim UI twice, we can compute within-worker difference for each of the variables above. A switcher analysis then amounts to estimating the following regression:

$$\Delta c_{ij} = \delta \Delta \bar{c}_{j,-i} + \Delta \epsilon_{ij}, \tag{7}$$

where the Δ denotes differences over worker i's outcome at firm j and j'.

Because of relatively small samples, we use shrunken leave-one-out estimates of firm-year claims rates. Appendix C describes what we do.

When we use the shrunken estimates to compute $\Delta \bar{c}_{j,-i}$, we can express the OLS estimate of δ in equation (7) as (a formally similar result is in Chetty, Friedman, and Rockoff (2014, Appendix B)).

Result 6.

$$\mathit{plim}\ \hat{\delta} = \frac{\mathit{var}(\psi_j - \psi_{j'}) + \mathit{cov}(\psi_j - \psi_{j'}, \bar{a}_{j,-i} - \bar{a}_{j',-i})}{\mathit{var}(\psi_j - \psi_{j'}) + \mathit{var}(\bar{a}_{j,-i} - \bar{a}_{j',-i}) + 2\mathit{cov}(\psi_j - \psi_{j'}, \bar{a}_{j,-i} - \bar{a}_{j',-i})}. \tag{8}$$

If there is no worker-firm sorting with respect to UI take-up so that the covariance terms are zero, then $\hat{\delta}$ reflects the share of variance in Δc_{ij} that is explained by a change in the firm effects (ψ).[23] If the sorting is positive—which is typically the presumption in the literature (and we confirm this presumption below)—then this coefficient represents a lower-bound on the role of firms.

The switcher analysis assumes that workers are not moving on the basis of the error term, $\Delta \epsilon_{ij}$. Of

[23]Note, however, that $var(\psi_j - \psi_{j'}) \neq var(\psi_j)$ unless worker mobility is literally random, which is a much stronger assumption than is needed for a causal interpretation of the variance decomposition.

course, the error term is unobserved. Nonetheless, there are both theoretical reasons to suspect that this concern is less important in our setting, as well as empirical implications that we can test.

Economic theory suggests that, in our context, this concern should be less likely to be an issue. The reason is that our preferred analysis sample (in Table 1, column (4)) is restricted to workers who make a transition from employment to unemployment. This restriction means that the worker could not reasonably expect to be recalled and so a selection on a worker-firm match is unlikely. A related reason to be less concerned about selection on the error term is that the firm-level UI claims rate might be a less salient firm characteristic than other features of the firm when a worker is deciding on a job.

The first test of whether moves are selected on the error term is described in Finkelstein, Gentzkow, and Williams (2016). In our context, this test implies that if workers are moving on the basis of unobservable firm characteristics, then it seems plausible that they would also be moving in ways that would generate systematic patterns of selection on observables. We can therefore look at patterns of changes in firm observables around the move. In practice, if workers move on the basis of the error term in UI take-up, then we would expect them to also be moving towards firms with higher UI claims rates. A simple way to check that selection on the error term in UI take-up is small is to use the sample of switchers and to plot the distribution of changes in firm-level UI claims rates (say, in a histogram) to see whether the distribution is symmetric around the zero-change. As we describe below, this distribution of firm-level claim rates is symmetric around zero-change.

Our second test is described by Card, Heining, and Kline (2013): Moving on the basis of the error term will tend to generate asymmetry in the changes of worker level outcomes.[24] That is, workers who move to firms with lower UI claims rates would appear less "sensitive" to the firm-level claiming environment because they would have selected the lower UI claims rate firm on the belief that they would have a high draw of the error term (a high claims rate) at that firm. Thus, by considering whether the slope in Equation (7) changes around 0 offers an additional test of the validity of the switchers research design.

4.2 Results of the switcher analysis

Figure 3a plots the switcher analysis in the claims rates. We construct the figure as follows. First, we compute the shrunken estimate. That is, we use equation (A22) but define $N_{j,-i}$ and $C_{j,-i}$ to be the number of separators and number of claimers exclusive of worker i. We then shrink the firm-year leave-one-out claims rate as described in Appendix C. Next, we restrict the analysis to the sample of separators who are twice-eligible and whose two spells of eligibility did not occur within the same calendar year.[25] We then take the within-worker, across-firm difference. This results in 71,037 movers, see column (1) of Table 3.The average UI take-up rate for this switcher sample is 0.474.

The histogram in the backdrop of Figure 3a shows that the distribution of moves is approximately symmetric around the change in firm-level UI claims rates. That is, these twice-eligible separators do not appear to systematically move towards firms with higher UI claims rates. This suggests that selection on the error

[24] Bonhomme, Lamadon, and Manresa (2019, pg. 707) emphasize limitations of this test.

[25] To be eligible twice in the same year conditions on the outcome of the first employment spell—i.e., a worker cannot have been unemployed for too long—and so we omit it from the analysis.

term is hence is unlikely and so we pass the first test for the validity of the switchers research design.[26]

The binned scatterplot in Figure 3a has several notable features. First, the plotted relationship is remarkably linear. This lends support to the linear specification in Equation (7). Second, it appears that the slope of the line does not change at 0. To test this formally, column (2) of Table 3 reports the regression coefficient where we allow the coefficient to change at 0. We find an economically small and statistically insignificant change. This finding supports the symmetry of claims rate changes around zero, and thus we pass the second test for the validity of the switchers research design.

Another notable feature of Figure 3a is the steep slope. We estimate a slope of 0.82 (see column (1) of Table 3 regression coefficient). This slope indicates that the majority of the across-firm variance in UI take-up is attributable to the causal effects of firms on worker-level claim behavior rather than simply worker composition, a result we confirm more formally below.

The bottom line of this section is that, among workers who separate twice, there is substantial dispersion across firms in UI take-up rates.[27] Moreover, the vast majority of this dispersion represents a causal effect of firms on worker take-up, rather than sorting of worker to firms.[28]

4.3 Formal variance decomposition

The switcher analysis suggests that UI take-up is approximately additively separable in worker and firm effects. In this section, we turn to estimating the variance components of the variation in UI take-up and assessing the importance of firms and workers in effecting UI take-up. To do this, we estimate the two-way fixed effect model given by equation (5), however, we also include controls for the year-quarter in which the separation occurred. The variance components are corrected for limited worker mobility by using the Kline, Saggio, and Sølvsten (2020) (KSS) estimator.

Panel A of Table 4 shows the results. Because the KSS estimator is only defined for the leave-one-out connected set, this somewhat reduces the sample size.[29] For example, the number of movers in the leave-one-out set equals about 62,000 compared to 71,000 movers in the switcher analysis (for example, column (1) in Table 3). The mean UI take-up rate in this sample equals 50%.

There are five notable features of Panel A of Table 4. First, the variance of the firm effects, 0.022, is large. This variance corresponds to a standard deviation of about 0.15 and given that the average take-up rate equals 50% in this sample, the 16th to 84th percentile range corresponds to a 35% UI take-up rate to a 65% UI take-up rate.[30] Another way of seeing that the standard deviation of firm effect is large is to note that it equals about one-third of the average claims rate our preferred sample (in Table 1, column (4)). Second, this firm component is large in relative terms: while it explains only about 10% of the overall variance, it is

[26] One feature of the histogram worth noting is the spike at 0. What this spike reflects is that we are plotting the shrunken firm-level UI take-up rates and so for many small firms we shrink to the sample mean; hence, switchers between small firms get a change of 0.

[27] This dispersion is also persistent: we find a correlation in the claims rate from year to year of about 0.93.

[28] Table A3 shows that the δ-estimates estimated for each earnings decile are generally not statistically different from each other.

[29] We leave out a worker-quarter which in our context this is equivalent to leaving out the worker-firm match as the separators in our sample only separate from a particular firm once.

[30] This calculation holds either if we use the normal approximation or if we solve for the parameters of the beta distribution that give a mean of 0.50 and variance of 0.022.

almost half the size of the variance of the worker effects. Thus, firm heterogeneity plays a larger role relative to worker effects in explaining UI take-up than it does in explaining, for example, earnings and wages.[31] Third, the plug-in variance estimator is severely biased relative to the KSS estimator: as expected due to limited mobility bias, the plug-in variances of worker and firm effects overstate their importance. Fourth, after using the KSS correction, we find a weak positive correlation between the worker and firm effects in claiming. Fifth, the KSS-corrected variance of firm effects is about 49% (= 0.022/0.045) of the variance of $\hat{c}_j^{EB}$ from Equation (A22).[32]

One simple way of parameterizing the variance of the firm effects is to consider the following thought experiment: suppose that we replaced firms with below median firm effects in claiming with firms with the median of the firm effects, by how much would this change increase take-up? To do so, we simulate a beta distribution that matches the sample mean and the variance of firm effects found in the Table. We find that in this thought experiment UI take-up would increase by about six percentage points, or over ten percent.

In summary, the firm variance component in UI take-up is large.

4.4 Income gradient in UI take-up

Given that the previous section showed a substantial role for firm effects in UI take-up, and the evidence in Figure 2 shows a substantial income gradient in UI take-up, it is natural to ask to extent do firm effects account for the income incidence of UI claims. The top panel of Figure 4 plots the firm effects by base-period wage rates. The Figure is remarkably similar in shape to the **individual-level** claims rates in Figure 2. This implies that firm effects explain much of the relationship between individual-level UI take-up and income, but how much?

Table 5 quantifies this extent. In column (1), we regress the dummy for whether the separating worker claimed UI on the same set of deciles. In column (2), we regress the estimated AKM firm effect (from equation (5)) on a vector of dummy variables for each worker's base-period hourly earnings decile.[33] The estimates in column (1) approximate the relationship in Figure 2, and the estimates in column (2) approximate the relationship in the top panel of Figure 4.

We find that firm effects explain over half of the income gradient in take-up. Relative to the omitted category (the first decile of earnings), a worker observed in the fifth decile, experiences an average increase in the probability of claiming of about 20 percentage points. Turning to column (1), we see that a worker in the fifth decile experiences a 12 percentage point increase in the estimated AKM firm effect in claiming. Hence, at the median, firm effects "explain" about 60% (= 12/20) of the income gradient in claiming. The share accounted for by firm effects is at least 55% at other earnings deciles.

[31] For example, Kline, Saggio, and Sølvsten (2020, Table 2) the variance of the firm effect in wages is $\frac{.0240}{0.1119} = 0.21$ the size of the variance worker fixed effects. Similarly, Sorkin (2018, Table 1) finds the variance of the firm effects in earnings is $\frac{0.14}{0.51} = 0.27$ size of the variance of the worker effects. Finally, using Washington State data Lachowska, Mas, and Woodbury (2020, Appendix Table B2) finds the variance of firm effects relative to person effects to be $\frac{0.123}{0.309} = 0.40$ for log earnings and $\frac{0.053}{0.247} = 0.214$ for log hourly earnings.

[32] We report the parameters of this beta distribution in Appendix Table A2.

[33] Letting $\mathcal{I}_{di}$ be an indicator for whether individual i is in income decile d, we run the following two regression: $c_{ij} = \sum_{d=1}^{10} \gamma_d \mathcal{I}_{id} + \epsilon_{ij}$ and $\hat{\psi}_{i(j)} = \sum_{d=1}^{10} \gamma_d \mathcal{I}_{id} + \epsilon_{ij}$, where $\hat{\psi}_{i(j)}$ is the estimated AKM firm effect in claiming. The deciles are defined using information all workers in Table 1, column (1).

4.5 UI take-up and other demographic splits

We only have demographic information for the subsample of workers who have previously collected UI. This restriction means that the sample on which we can perform this analysis is potentially selected. Nevertheless, we carry out an analysis similar to what we did in Table 5 for income deciles, only we consider a variety of other splits: male/female, white/non-white, and levels of education.

Panel A of Table 7 shows the results. Given the stark income gradients, it is perhaps surprising that the main message of Table 7 is that we find few patterns as dramatic for other variables.[34] Men and more educated workers are more likely to claim UI, and these groups are also at firms with higher firm effects in claiming. But the magnitudes are small relative to what we find for income.

4.6 Information: whether or not previously claimed

One potential channel for UI low take-up is a lack of information. We can proxy for whether a worker has the information about how to claim UI by using the fact they that previously successfully claimed UI (this exercise is similar in spirit to the analysis in Aizer and Currie (2004)). For these workers, we have evidence that they know about UI and can—perhaps with help—successfully apply for UI. We therefore split the sample into subsamples of the workers we studied in the switcher analysis: those who claimed after separating the first time, and those who did not claim. We estimate the **level** version of the switcher regression (equation (7)), which is the following regression

$$c_{ij} = \delta \bar{c}_{j,-i} + \epsilon_{ij}. \tag{9}$$

If information is the only channel, we would expect to find the δ-coefficient to be 0: once workers know how to file, the firm is irrelevant. More broadly, if the only difference between those who previously claimed and those who did not previously claim was information, then the difference in δ-coefficients between the two samples would reflect the causal effect of information. Naturally, we do not have such a well-controlled comparison and so one potential driver of any difference across subgroups could be differences in worker composition. Plausibly, differences in worker composition will tend to overstate the role of information.

Column (3) of Table 3 reports the results where we interact the shrunken leave-out firm claims rate with an indicator for previous claiming.[35] The mean claims rate among those who previously claimed is 0.66 versus 0.43 among those who did not previously claim. Consistent with the idea that those who previously claimed are less dependent on their environment for information, the firm-level claims rate is less predictive of claims rates for those who previously claimed than for those who did not. This basic result is quite robust to alternative specifications and controls. In particular, we repeat the benchmark analysis controlling for firm fixed effects (where the variation is then the within-firm comparison of a worker who previously claimed and a worker who did not) earnings decile dummies (which we showed in the previous section to be a strong individual-level predictor of take-up). The inclusion of these additional controls appears to have little effect

[34] Appendix Table A4 shows that even in this subsample of previously claimed the income deciles look similar to the overall sample.

[35] Appendix Figure A2 shows the binned scatterplots highlighting the linearity in each sample split.

on the point estimates.[36]

In summary, those who previously claimed UI are more likely to claim UI. But previous claimers are also less sensitive to the firm environment in their claiming behavior. This evidence is consistent with the presence of an information channel explaining some of the switcher effect. That said, the information channel (the interaction term, -0.28) explains a perhaps surprisingly *small* share of the predictive power of the firm claims rate for worker claiming behavior (34% = $0.28/0.82$,where 0.82 is the δ-estimate from equation (7)). Put differently, one striking finding in this section is how much the firm environment matters even among those who previously claimed.

Accounting for information in the variance decomposition An information channel implies that worker fixed effects are not fixed. If the worker successfully collects UI, then they are more likely to apply in the future independent of their firm. To assess the extent to which this matters for the variance of firm effects estimated in model (5), we consider an augmented model where a worker i's effect changes from a_i to $a_i + b$ after they have successfully claimed in the past. Specifically, we estimate a version of equation (5) where we include an indicator that equals one if the separator had previously claimed. We find that in this specification, the KSS-corrected standard deviation of the firm effects equal is to 0.12 rather than 0.15 as in our main estimates. We conclude that the information channel does not appear quantitatively meaningful relative to the importance of firms in determining take-up.

5 Estimating firm heterogeneity in UI appeals

In the previous section, we argued that there is substantial dispersion in firm effects in claiming UI. Our model suggests that one source of this dispersion would be firm-level dispersion in appeal rates. In this section, we first document firm effects in appeals. We then show that the firm-level appeals rates have similar explanatory power for the income gradient in appeals as it does in claims. Finally, we show that the firm effects in claims and appeals are negatively related, consistent with deterrence effects.

5.1 Switcher analysis

We structure our analysis of the firm appeals in parallel to the way we structured the main analysis of claims rates. Specifically, we restrict the sample to workers who separated twice and claimed UI twice. Hence, their claim could have potentially been appealed twice. Figure 3b plots the switcher analysis in the appeals rates: it shows the relationship between the claim-level probability of appeal and the firm-level appeals rate: $\Delta appeal_{ij} = \delta \Delta \overline{appeal}_{j,-i} + \Delta u_{ij}$. The firm appeals rate is a shrunken leave-one-out firm-year average.

The binned scatterplot in Figure 3b reveals many similarities with the analogous switcher analysis in UI claims shown in Figure 3a. First, the histogram in the background shows that the change in the probability of appeals is approximately balanced around the 0-change change in firm-level appeals rates. Therefore, also

[36]In Appendix Table A5 we report an additional way of assessing the role of information: we consider the decay of information. We further split the sample of those who previously claimed by how long it has been since they claimed. We then run the level regression allowing the effects of firm environment to vary by time since claimed. We find that the magnitude of the firm coefficient grows as time between separations rises, consistent with information depreciation.

in the context of appeals we pass the first test for the validity of the switchers research design. Second, it is apparent that the slope of the line does not change at 0. This finding supports the symmetry of appeals rate changes around zero, and thus in the context of appeals we pass this second test for the validity of the movers research design.[37] Third, the conditional expectation function is again surprisingly linear. Remarkably, we estimate a slope of 1.075 (see column (6) of Table 3 for a tabular version of this result), and we cannot reject a coefficient of 1. Similarly, we cannot reject the hypothesis that the slope to the left and right of zero is the same. A slope coefficient close to one means that the change in firm-level appeals rates is an unbiased forecast of the worker-level outcomes.

5.2 Formal variance decomposition

Having established the approximate validity of the additively separable decomposition, we now estimate the variance components. Again, we estimate an AKM-style model where we decompose the variation in appeals into worker and firm components. Panel B of Table 4 shows the resulting variance components. There are a few notable features of the Table. First, the variance of the firm effects, 0.001, is large relative to the mean of 0.036 as it implies a standard deviation of about 0.029. Second, the firm component is even bigger relative to the worker component than in claiming: here the firm-worker effect ratio is 0.73 whereas in claiming it is 0.44. Thus, firm heterogeneity plays an even larger role in appeals than worker differences. Third, the plug-in estimator of variance components is severely biased relative to the KSS estimator. Fourth, we find a weak positive correlation between the worker and firm effects in claiming.

We conclude that the firm variance component in appeals is large.

5.3 Income gradient in appeals

Table 5 shows that firm effects explain even more of the income gradient in appeals than in claims. We find that, relative to the omitted category (the first decile of earnings), a worker observed in the fifth decile, experiences an average decrease in the probability of an appeal of about 0.8 percentage points. Turning to column (4), we see that a worker in the fifth decile experiences a 0.6 percentage point decrease in the firm effect in appeals. Hence, at the median, firm effects "explain" about three-quarters of the income gradient.[38]

5.4 Appeals and other demographic splits

Panel B of Table 7 shows other demographic splits besides income. The only cut where we find meaningful economic magnitudes is that white workers are less likely to have their claims appealed, and we find that they are also at firms with lower appeals rates. For the other two demographic splits (gender and education), we find that the point estimates on the individual-level outcomes and the firm effects are of the opposite sign.

[37] In column (6) of Table 3, we report the regression coefficient where we allow the coefficient to change at 0. We find a statistical zero (though an admittedly sizeable magnitude).

[38] Given that there is an increase in challenging at second decile relative to the first, some readers might prefer to compare the fifth decile to the second. In this case, the firm effects change by 1.2 percentage points and the individual appeal change by 1.5 percentage points. According to this calculation, the firm effects "explain" 80% of the income gradient.

5.5 Relationship between the firm appeals and the firm take-up rates

The model has the strong implication that, at the firm level, take-up rates and appeal rates should be perfectly negatively correlated. We now assess this relationship empirically. Figure 5 plots the shrunken firm-average claim rates, $\hat{c}_j^{EB}$, against the analogous firm-average appeals rates and shows a negative correlation.

To directly quantify the relationship between the firm effects in take-up and appeals, we estimate the regression of the firm effects in the take-up rates on the firm effects in appeals. The probability limit of the coefficient on the slope of this relationship is given by: $\frac{cov(\text{firm f.e., appeals,firm f.e. take-up})}{var(\text{firm f.e. appeals})}$. However, we know from the variance decompositions that the plug-in variance computed over the firm effects estimated with error, $var(\text{firm f.e. appeals})$, is biased up because of limited mobility bias. Hence, rather than using the plug-in variance estimate, we use the KSS estimate.[39] We then convert the KSS-corrected slope coefficient to an elasticity ϵ computed at the sample means of UI take-up and appeals rate in the leave-one-out sample.[40]

$$\frac{\partial \text{firm f.e. take-up}}{\partial \text{firm f.e. appeals}} \frac{\text{appeals}}{\text{take-up}} = \epsilon \tag{10}$$

We find that the elasticity is about -0.16. This estimate is quantitatively similar to the range of elasticities for claims to separation issue denials (which is conceptually close to an appeal) found in the natural experiment studied by Anderson and Meyer (2000). Across specifications and comparison groups, they find elasticities that range from -0.128 to -0.279.[41] Hence, our estimate of ϵ is in the range of the available causal estimates. We return to this elasticity in Section 6.5, where we use it to conduct counterfactuals and to quantify how much of the variation in the firm effect for take-up are accounted for by firm effects for appeals.

6 Quantifying the model

We now use our results to quantify the framework from Section 2. Specifically, we are interested in understanding how experience rating affects the mix of eligible-to-ineligible claimants (targeting), how experience rating affects take-up overall, and how experience rating affects the effective layoff tax.[42]

6.1 Assumptions and additional moments

To answer these questions, we need to know the application, appeals, and successful appeals rates by eligibility status, as well as an estimate of the elasticity of the claims rate with respect to experience rating.

[39] In practice, we estimate the regression of estimated firm effects in the claims rates on the estimated firm effects in appeals. Then we multiply the resulting coefficient by the ratio of KSS-corrected variance of firm effects in appeals to the plug-in estimate. See Table 4 for the various inputs into this calculation.

[40] Mean of UI take-up in the leave-one-out sample equals 0.50 and mean of appeals in the leave-one-out sample equals 0.03609.

[41] See Appendix E for details on this calculation.

[42] There is a conceptually distinct set of questions about how take-up affects optimal UI calculations in the spirit of Baily (1978)-Chetty (2006).This question is conceptually distinct because it involves a change in benefits while changing the tax rate—implicitly, this literature assumes that UI is 100% experience rated. The paper in the literature that comes closest to studying this point is Kroft (2008). In the context of his baseline model, note that the firm's endogenous appeal decision acts just to reduce the take-up elasticity.

To do so, we make the following assumptions in addition to the structure of the model we already stated in Section 2:

Assumption 1. *1. The excess separators when a firm contracts are all non-monetarily eligible for UI.*

2. The ratio of claims rates by eligible and ineligible separators is the same across firms ($\frac{A_{1j}}{A_{0j}} = \frac{A_1}{A_0} \forall j$) and the share of eligible separators at "zero" growth firms is the same across firms ($\sigma_j = \sigma$).

3. The extent of experience rating does not vary with the firm growth rate.

The first assumption was implicit in the model (and follows the logic of the UI system), and allows us to use the change in the claims rates as the firm contracts to learn about the behavior of eligible workers. The second assumption allows us to use the distribution of firm-level claims rates to back out the distribution of application costs in the eligible and ineligible population. Implicitly, this assumption defines $\mathcal{P}_e$. The third assumption allows us to use the variation in firm growth rates to identify model parameters. Below we provide evidence that this assumption is approximately satisfied over the range of growth rates we use in our empirical analysis.

We begin by defining the "representative firm" interpretation of the model, which defines our parameters of interest. For these purposes, define $A_e \equiv \sum_j \omega_j A_{e,j}$ and $p_e^* \equiv \sum_j \omega_j p_{e,j}^*$ as the firm-averaged variables. Similarly, we can add g subscripts to denote the firm-averaged values at different growth rates. This representative firm version of the model is what we will use to assess the targeting properties of UI (we do not have sufficient data to estimate these targeting parameters at the firm level). In particular, this representation transforms the economic model into a simple statistical model where we are interested in learning about six parameters: $\{A_0, A_1, p_0, p_1, r_0, r_1\}$, where implicitly we are interested in targeting at "zero growth" firms.

The key additional moments we use is how separations, claims rates, appeals rate and receipt rates vary as a function of firm growth. The reason that these moments are informative is the first assumption: this assumption tells us that as firms contract we change the mix of eligible and ineligible applicants because **all** the marginal applicants are eligible.

We compute how separation rates, claims rates, appeals, and receipt rates vary with firm growth rates using the following regression (as in Davis, Faberman, and Haltiwanger (2012, Figure 6) or Flaaen, Shapiro, and Sorkin (2019, Figure 1)):

$$y_{jt} = \psi_j + \sum_{g'=-10}^{+10} \mathbf{1}(g = g')\eta_g + \epsilon_{jt}, \tag{11}$$

where g is a firm growth rate, ψ_j is a firm fixed effect, and y_{jt} is an outcome variable. Including firm fixed effects allows us to isolate the (variance-weighted) average role of firm growth rates in changing outcomes. We are interested in the η-coefficients for the various outcome variables.

Figure 6 plots the estimates of η_g for separations, claims, appeals rates, as well as the probability of a firm being on the "flat" part of the experience rating schedule, against firm-growth rate bins. We construct each panel as follows. The firm growth rate is defined in terms of the change in the total hours at the firm. This measure has the benefit of allowing us to include part-time workers. For each panel we report both the results with and without firm fixed effects (i.e., we drop the ψ_j in equation (11). For the version with firm fixed effects, we normalize so that we match the sample means in the zero growth bin.

Panel (a) shows the probability of being on the "flat" part of the experience rating schedule the following year as a function of the firm growth rate. A firm on the "sloped" part of the experience rating schedule (see Appendix Figure A3) faces constant experience rating: additional workers claiming UI raise its tax rate. In contrast, firms on the "flat" part of the schedule face weaker marginal incentives: an additional claim does not affect the firm's tax rate. By looking at whether firms are on the flat part the following year, we approximate whether the firm faces constant marginal incentives.

The Figure shows that without firm fixed effects the probability of being on the flat part the following year is strongly related to firm growth. Once we add firm fixed effects, however, we find a much flatter relationship in firm growth. We view the flat part of this Figure as telling us the range of growth rates over which we can interpret the results in light of our model where firms face constant experience rating incentives.

Panel (b) shows the estimates of η_g for separation rates. The increase in the separation rate when the firm is contracting by 50% might seem small; e.g., it is dramatically lower than the rates reported in Davis, Faberman, and Haltiwanger (2012, Figure 6) where at a 50% contraction, the separation rate is closer to 50%, than the 10% in Panel (a). The reason is that the Figure reports the separations of a more stable subset of the workforce: workers who are monetarily eligible and who only have one base-period employer (and who do not make an employer-to-employer transition when separating). The increase in the separation rate is similar to in Flaaen, Shapiro, and Sorkin (2019, Figure 1) who look at separations among workers with at least a year of tenure.

Panel (c) shows that claims rates increase as the firm contracts. This increase is consistent with the logic of the model (and of robustness checks in Anderson and Meyer (1997)) that as the firm contracts the marginal separators are more likely to be eligible for UI. What is striking about this figure, however, is that the claims rate never exceeds 60%, even during a massive contraction of the firm.

Panel (d) shows that as the firm contracts the appeal rate eventually declines. Notably, there is a fairly wide window around 0 where the appeal rate is flat. By the time we get to contraction rates above 20%, the appeal rate starts to decline and by a 50% contraction the appeal rate is half what it is around 0.

Panel (e) shows that the receipt rate—conditional on appeal—rises as firms contracts and then falls. It should be said that by the time we get out to a 30% contraction or more that the data are very sparse for measuring the receipt rate conditional on appeal because appeals occur relatively rarely (see Table reftable:sumstats).

We need one additional moment beyond the moments we have introduced in order to learn about parameters related to the ineligible. We use a moment from the U.S. Department of Labor's Benefit Accuracy Measurement (BAM) program, under which each state investigates random samples of weekly benefit payments to determine whether claimants were paid the proper benefit amount U.S. Department of Labor and Administration (2020). For each investigation, the BAM record indicates what the payment should have been. For the 2005–2013 BAM samples, 11.8 percent of payments in the full US sample, and 12.7 percent of payments in the full WA sample, should have been zero.[43] In the context of the model, we interpret this number as the share of workers who receive UI at firms that are neither growing nor shrinking.

6.2 Sketch of identification

These moments and the assumptions that we stated provide sufficient information to identify the fundamental parameters of the model: $\{A_{0j}, A_{1j}, p_{0j}, p_{1j}, r_0, r_1, \sigma, \mathcal{P}_1, \mathcal{P}_0\}$. We now provide some discussion of the intuition of what we features of the data estimate various parameters. Appendix D provides the constructive proof of identification, which is also how we actually estimate the parameters.

For eligible workers, identifying UI take-up rate, the appeals rate, and the rate of receipt conditional on appeal (A_1,p_1, and r_1) is straight-forward. If we assume that, when a firm contracts any additional workers who separate are all eligible for UI, we can simply pick a firm contraction rate (say, equal to 25 percent) and compute the take-up rate and the appeals rates as firm-averages at that contraction rate. Figure 6 shows these averages in a graphical form. For example, at a firm contraction rate equal to 25 percent, the UI take-up rate of eligible workers equals about 0.541; see Table A6 for the exact values. Hence, the firm contraction rate is essentially an instrument for identifying the share of eligible claimants and their UI outcomes.

To compute the same three rates for the ineligible claimants, as well as the share of ineligible workers, we use the additional statistic from the BAM program of the share of claims that were deemed to have come from ineligible applicants. Intuitively, the overall claims rate depends on the claims rate of the ineligible and share of ineligibles. Knowledge of the share of claims that come from the ineligible allows us to separate these two explanations. The share of ineligibles (at 0-growth rate) also allows us to compute the mean appeal probabilities and receipt rates conditional on appeal among the ineligibles.

The estimates of $\{r_1, r_0, p_1, p_0\}$ are sufficient to identify ζ, which governs the elasticity of appeals with respect to experience rating $(1/1-\zeta)$. Why are those four averages sufficient? As noted in Appendix D.3, someone who is eligible for UI is much more experience-rated than someone who is ineligible for UI. This increased experience rating is because, conditional on a firm appealing an eligible worker's claim, an eligible worker's likelihood of benefit receipt rate is higher than that of an ineligible worker, $r_1 > r_0$. Hence, comparing the appeals rates of the eligibles with the appeals rates of ineligibles tells us how varying experience rating from r_0 to r_1 affects appeals.

Finally, we are interested in two distributions: the distribution of the cost of challenging (the η_j) and the distribution of the cost of applying, the $\mathcal{P}_e$. The distribution of the cost of challenging is closely related to the distribution of appeals probabilities. Hence, we generate a beta distribution that has the mean equal to the mean appeals rates (which is equal to 0.03609, see Table 4 and a variance equal to the KSS-corrected variance of the firm effects in appeals (which is equal to 0.00086; see Table 4. This procedure gives us the distribution of firm-level appeals rates, and we can use this to estimate firm-specific challenge rates by eligibility type (and, if wanted, the η_j). (See Appendix D.4 for details). To learn how firm-specific challenge rates translate into claims rates, we need to know the distribution of the costs of applying. To do so, we use the estimated elasticity, $\hat{\epsilon} = -0.16$ (from Section 5.5) and assume that it holds at all levels of claims. The

[43] We thank Ross Miller of the Employment and Training Administration, U.S. Department of Labor, for providing the data and documentation of the BAM data, and for helpful advice.

strong assumptions that the cross-sectional elasticity is causal and that the elasticity of claims to appeals is constant allows us to compute a distribution of claims rates based on the distribution of appeals.[44] Imposing this constant elasticity thus implicitly defines $\mathcal{P}_e$.[45]

6.3 Parameter estimates

Table 8 reports parameter estimates from the model.[46] We find a claims rate among eligible workers of about 60%, while among ineligible workers we find a claims rate of about 20%. Thus, among eligible workers we find claims rates that are closer to those documented in survey-based methods.[47] We find appeal rates for ineligible applicants almost an order of magnitude higher than those among eligible applicants. Conditional on appeal, we find somewhat large gaps in the probability of receiving UI (80% vs. 50%). Finally, we find that at firms that are not growing or shrinking, just over half of the "exogenous" separators are non-monetarily eligible.

The dotted lines in panels (c) through (e) of Figure 6 summarize the model fit, where we feed in the separation rate from panel (b) and use model parameters to simulate the claims rate, the appeal rate, and the receipt rate. For each rate, we select the values observed at the firm growth rate equal to -0.25 and, therefore at that point, the model prediction and the observed value align perfectly.[48] At other values of the firm growth rate, the fit is not mechanical and also not perfect. Nonetheless, the model does a fairly reasonable job at fitting "untargeted" moments. One aspect of the data that the model struggles with is that the appeal rate in the data is "too flat" at very negative growth rates.

To summarize these results differently, in Panel B of Table 8 we report our estimates of the errors in the UI system, following the typology introduced in Kleven and Kopczuk (2011). Kleven and Kopczuk (2011) distinguish between three types of errors (rather than the more usual two): Type IA errors are false negatives that stem from eligible workers not applying. We find that about 25% of workers fall in this category. Type IB errors are false negatives that stem from eligible workers who apply but do not collect (because they are challenged). This category is quite small: only 0.2% of workers fall in this category. Finally, Type II errors are false positives that arise from ineligible workers who apply and ultimately receive UI. We find that about 5% of workers fall into this category. Thus, about 70% of workers correctly receive or do not receive UI, and the dominant source of error in the UI system arises from eligible workers who do not apply.[49]

We estimate the elasticity of appeals with respect to experience rating to be high, over 2. The reason is that the differences in the probability of receiving benefits conditional on an appeal at different points of the firm growth rate are "small" compared to the differences in being challenged across the eligibility types.

[44] The constant elasticity implies that decreasing experience rating actually *increases* the variance of firm effects in claiming.

[45] To ensure that the level of the claims match what it is in the data, we solve a simple numerical problem—essentially, we pick the minimum point of the distribution such that the mean matches. Appendix D.5 provides more details on this procedure.

[46] See Appendix Table A7 for a summary of the moments we use.

[47] E.g., Auray, Fuller, and Lkhagvasuren (2019) and Auray and Fuller (2020) update Blank and Card (1991) with more recent data and find a take-up rates above 70% (e.g., Auray, Fuller, and Lkhagvasuren (2019, Figure 1)).

[48] We use the values associated with the solid lines—these are preferred estimates of rates, net of firm fixed effects.

[49] A small literature studies targeting in other programs: Reeder (1985) studies housing assistance, Benitez-Silva, Buchinsky, and Rust (2004) study Supplemental Security Income and disability insurance, Low and Pistaferri (2015) and Deshpande and Li (2019) study disability insurance, and Finkelstein and Notowidigdo (2019) study food stamps, and Lieber and Lockwood (2019) study Medicaid home health care.

Intuitively, in Figure 6, as we move to the left—which the model interprets as changing the composition of from ineligible to eligible separators—the "receipt" rate changes by a small amount compared to the change in the appeals rate. This results in a large elasticity of appeals with respect to experience rating because the appeals rate changes by a lot while the apparent experience rating changes very little.

6.4 Results: counterfactual

We now consider how a change in experience rating would affect take-up and targeting. We consider a 10% decrease in experience rating. (See Appendix D.7 for details on what we do.)

Panel C of Table 8 shows the results. Following a 10% decrease in experience rating, the appeals rate falls by about 20% ($\approx -0.1 \times 2$). Similarly, 10% decrease in experience rating increases the application rate for both eligible and ineligible workers by about 4% ($\approx -0.1 \times -0.16 \times 2.3$). This result highlights the basic trade-off presented by experience rating: On the one hand, experience rating discourages ineligible workers from applying; on the other hand, experience rating discourages eligible workers from applying.[50]

Panel D of Table 8 that decreasing experience rating decreases targeting errors. Essentially, because the largest source of targeting error is eligible workers not applying, it is not surprising that a policy that encourages applications reduces targeting errors. Specifically, we find that the Type IA errors (eligible and do not apply) decrease by almost 1.5 percentage points, which is offset by an increase of Type II (ineligible collect) of about 0.3 percentage points. Overall, we find that the total targeting errors decrease by just over one percentage point. Thus, if the objective is to reduce targeting errors (i.e., we weight errors of inclusion and exclusion equally), then this policy change is desirable.

Panel C of Table 8 also shows the elasticity of the layoff "tax" with respect to experience rating. Intuitively, when we decrease experience rating by 10% we would expect the layoff tax to decrease by 10% as well. However, that reasoning does not account for an offsetting behavioral response: when experience rating goes down, workers are more likely to claim and less likely to be challenged if they claim and so the layoff tax decreases by a smaller amount. In fact, following a 10% decrease in experience rating, the layoff tax only decreases by 6.3%. Therefore, about one-third of the employment "smoothing" benefits of experience rating is undone by behavioral responses. Although this number relies on strong assumptions, it suggests that workers' and firms' endogenous responses may dampen the employment smoothing benefits of experience rating.

More generally, how big would a change in experience rating have to be to achieve the same gains as the simple thought experiment of replacing the below-median firm effects in take-up firms with those at the median? Given that the model is constant elasticity and the percent increase in take-up in that thought experiment was about 12%, we would need a decrease in experience rating of about 30%. Note that this number is sensitive to the elasticity of claims with respect to challenges. Nevertheless, this exercise gives us some sense of the extent of firm heterogeneity in claims, and policy tools that would increase take-up.

[50] To see this, compare Panel A to Panel C of Table 8. Reducing experience rating increases the application rate among eligible workers from 59.54 to 61.92 percent, and increases the application rates among ineligible workers from 13.80 to 14.35 percent.

6.5 How much of the dispersion in firm effects in UI take-up are plausibly related to appeals?

We now use the model to compute the share of the variance of firm effects in take-up that are plausibly related to appeals. Because firm appeals are affected by experience rating, this share will roughly tell us to what extent the firm heterogeneity in UI take-up is explained by experience rating (given our model).

To do this, we take the model-implied variance of firm-level claims rates, as described in section 6.2. We find that the variance of simulated firm effects in take-up equals 0.0019. This variance corresponds to less than 10 percent of the estimated KSS-variance of firm effects (= $0.0019/0.022$) in Table 4. This means that the variance in firm effects in appeals accounts for a relatively small share of variance of firm effects in claiming.

How sensitive is this result to the choice of the elasticity of claims to appeals? Figure 7 plots the share of of variance of firm effects in claiming accounted for by the variance in firm effects in appeals at different values of the elasticity. The slope is steep; for example, if we take the maximum point estimate of claims with respect to claim denials from Anderson and Meyer (2000), (-0.279), we find that the variance in firm effects in appeals explains about 30% of the variance of firm effects in take-up. In order for the variance in firm effects in appeals to explain all of the variance of firm effects in claiming, we would need an elasticity of -0.48, which is within the confidence intervals of the Anderson and Meyer (2000) estimates. Thus, while the point estimate suggests that this channel explains a fairly small share of the variance, the plausible range of parameter values suggests that it could explain the vast majority of the variance in firm-level claims rates.

7 Sources of firm heterogeneity in UI take-up

In the model, firms differ in their cost of appealing claims (η_j). But where does this heterogeneity come from? In models with perfectly competitive labor markets, we would expect that firms with lower firm effects in claims rates would pay a compensating differential. Alternatively, in models of imperfect competition where some amenities are normal goods, we would expect positive correlations between firm-level wages and claims rates (see, e.g., Lang and Majumdar (2004) and Sorkin (2018, Section 6)).

To assess the correlation of firm heterogeneity in UI take-up with respect to wages, consider the following regression:

$$\Delta \log wage_{ij} = a + b\Delta \bar{c}_{j,-i} + r_{ij}, \tag{12}$$

where $\Delta \log wage$ is the worker-level change in log wage and $\bar{c}_{j,-i}$ is the firm UI take-up rate computed as a leave-one-out firm-by-year average where we shrink in the same way as we have elsewhere in the paper.[51]

Panel A of Figure 8 shows that, on average, when workers move to higher claim-rate firms, they also receive wage increases. This Figure shows a strong upward slope of $\hat{b} = 0.092$; that is, a change in the UI claims rate of 30% is associated with a wage increase of about 0.03 log points (for point estimates, see Table

[51]To compute the firm- UI take-up rate, we use all separations (voluntary and involuntary). Specifically, we use column (3) separators in Table 1, rather than the restricted set in column (4)).

9). On its face, this evidence is inconsistent with a compensating differential for the firm-level UI take-up rate, though it could be that firms compensate by offering non-pay amenities.

To evaluate the plausibility of this hypothesis, we estimate the following model:

$$\Delta \bar{s}_{j,-i} = a + b\Delta \bar{c}_{j,-i} + e_{ij}, \tag{13}$$

where $\bar{c}_{j,-i}$ is defined as above and $\bar{s}_{j,-i}$ is the is the *firm*-level separation rate, computed as a leave-one-out firm-by-year average (adjusted for measurement error by fitting a two-parameter beta distribution by maximum likelihood). The separation rate can be thought of as a simple "revealed preference" measure of the desirability of a firm that captures both pay and non-pay amenities. In order for $\bar{s}$ to reflect desirability of a firm, we allow it to include voluntary separations. Accordingly, we compute the separation rate using column (3) separators in Table 1 in the numerator and use firm size as the denominator.

Estimates from equation (13) show a negative relationship between the firm-level take-up rate and the separation rate; see Panel B of Figure 8 and Table 9. This finding suggests that—from the worker's perspective—firms with the higher take-up rates are on the whole more desirable firms.

Together, these results are inconsistent with typical predictions from models of perfect competition. Instead, the evidence is more consistent with a model where in equilibrium some firms choose to offer higher utility to workers than other firms. This higher utility is offered through paying higher wages and offering amenities such as the ability to claim UI upon separation.[52] This interpretation is broadly consistent with the positive association between social benefit take-up rates and measures of firm-level pay and separation rates in Bana et al. (2018).

8 Summary and conclusion

Consistent with earlier work on UI take-up, we estimate that fewer than half of UI-eligible job losers claimed UI benefits in Washington during 2005–2013. We find a striking income gradient in this incomplete take-up. Workers with low pre-separation wage rates have the lowest UI take-up rates: for example, a median-wage job loser is 20 percentage points (or 44 percent) more likely to claim UI than a job loser with a wage rate in the bottom decile.

We use our linked employer-employee data to show the important role of the employer in explaining take-up. We find substantial dispersion in firm effects in UI claims as well as appeals. Moreover, more than half of the relationship between UI take-up and the wage rate is accounted for by firm effects in UI take-up.

We also find a striking negative correlation between the firm effects in claims and appeals. This combination is consistent with deterrence effects, whereby workers are discouraged from applying for UI. Our conceptual framework and empirical estimates emphasize that experience rating plays an important role in generating this cross-firm heterogeneity and in affecting the level of take-up.

Taken together, our results emphasize the central role of firm factors in explaining UI take-up. We also show that from the perspective of the firm, take-up plays an important role in determining its tax rate, which

[52] An important caveat to this interpretation is that it does not say that workers do not value UI—if we varied UI claims rates holding all else equal, then we would expect to find more evidence for compensating differentials.

emphasizes the basic message of the paper that take-up is an important margin to consider when studying UI financing. Thus, one promising direction for future research is to study the optimal financing of UI when we recognize that financing UI through experience rating affects its take-up and targeting properties.

References

Abowd, John M. and Orley C. Ashenfelter. 1981. "Anticipated Unemployment, Temporary Layoffs, and Compensating Wage Differentials." In *Studies in Labor Markets*, NBER Chapters. National Bureau of Economic Research, 141–170.

Abowd, John M., Francis Kramarz, and David N. Margolis. 1999. "High wage workers and high wage firms." *Econometrica* 67 (2):251–333.

Aizer, Anna and Janet Currie. 2004. "Networks or neighborhoods? Correlations in the use of publicly funded maternity care in California." *Journal of Public Economics* 88 (12):2573–2585.

Anderson, David. 1994. "Compensating Wage Differentials and the Optimal Provision of Unemployment Insurance." *Southern Economic Journal* 60 (3):644–656.

Anderson, Patricia M. and Bruce D. Meyer. 1994. "The Extent and Consequences of Job Turnover." *Brookings Papers on Economic Activity. Microeconomics* 1994:177–248.

———. 1997. "Unemployment Insurance Takeup Rates and the After-Tax Value of Benefits." *Quarterly Journal of Economics* 112 (3):913–937.

———. 2000. "The effects of the unemployment insurance payroll tax on wages, employment, claims and denials." *Journal of Public Economics* 78 (1-2):81–106.

Auray, Stéphane and David L Fuller. 2020. "Eligibility, experience rating, and unemployment insurance take-up." *Quantitative Economics* 11 (3):1059–1107.

Auray, Stephane, David L. Fuller, and Damba Lkhagvasuren. 2019. "Unemployment insurance take-up rates in an equilibrium search model." *European Economic Review* 112:1–31.

Baicker, Katherine, Claudia Goldin, and Lawrence F. Katz. 1998. "A Distinctive System: Origins and Impact of US Unemployment Compensation." In *The Defining Moment: The Great Depression and the American Economy in the Twentieth Century*, edited by Michael Bordo, Claudia Goldin, and Eugene N. White. University of Chicago Press.

Baily, Martin Neil. 1978. "Some aspects of optimal unemployment insurance." *Journal of Public Economics* 10 (3):379–402.

Bana, Sarah, Kelly Bedard, Maya Rossin-Slater, and Jenna Stearns. 2018. "Unequal use of social insurance benefits: The role of employers." Tech. rep., National Bureau of Economic Research.

Benitez-Silva, Hugo, Moshe Buchinsky, and John Rust. 2004. "How large are the classification errors in the social security disability award process?" Tech. rep., National Bureau of Economic Research.

Bjelland, Melissa, Bruce Fallick, John Haltiwanger, and Erika McEntarfer. 2011. "Employer-to-employer flows in the united states: estimates using linked employer-employee data." *Journal of Business & Economic Statistics* 29 (4):493–505.

Blank, Rebecca M. and David E. Card. 1991. "Recent trends in insured and uninsured unemployment: is there an explanation?" *The Quarterly Journal of Economics* 106 (4):1157–1189.

Blaustein, Saul J. 1993. *Unemployment Insurance in the United States: The First Half Century.* Kalamazoo, MI: W.E. Upjohn Institute for Employment Research.

Bonhomme, Stéphane, Thibaut Lamadon, and Elena Manresa. 2019. "A distributional framework for matched employer employee data." *Econometrica* 87 (3):699–739.

Brechling, Frank. 1981. *Studies in Labor Markets*, chap. Layoffs and Unemployment Insurance. University of Chicago Press, 187–208.

Card, David, Jörg Heining, and Patrick Kline. 2013. "Workplace heterogeneity and the rise of West German wage inequality." *The Quarterly journal of economics* 128 (3):967–1015.

Card, David and Phillip B Levine. 1994. "Unemployment insurance taxes and the cyclical and seasonal properties of unemployment." *Journal of public Economics* 53 (1):1–29.

Chetty, Raj. 2006. "A general formula for the optimal level of social insurance." *Journal of Public Economics* 90 (10-11):1879–1901.

Chetty, Raj, John N. Friedman, and Jonah E. Rockoff. 2014. "Measuring the Impacts of Teachers I: Evaluating Bias in Teacher Value-Added Estimates." *American Economic Review* 104 (9):2593–2632.

Currie, Janet. 2006. *Poverty, the Distribution of Income, and Public Policy*, chap. The Take-up of Social Benefits. New York: Russell Sage, 80–148.

Davis, Steven J., R. Jason Faberman, and John Haltiwanger. 2012. "Labor Market Flows in the Cross Section and Over Time." *Journal of Monetary Economics* 59 (2012):1–18.

Deshpande, Manasi and Yue Li. 2019. "Who is screened out? application costs and the targeting of disability programs." *American Economic Journal: Economic Policy* 11 (4):213–48.

Doornik, Bernardus Ferdinandus Nazar Van, David Schoenherr, and Janis Skrastins. 2020. "Strategic Formal Layoffs: Unemployment Insurance and Informal Labor Markets." *Available at SSRN 3168769* .

Ebenstein, Avraham and Kevin Stange. 2010. "Does inconvenience explain low take-up? Evidence from Unemployment Insurance." *Journal of Policy Analysis and Management* 29 (1):111–136.

Finkelstein, Amy, Matthew Gentzkow, and Heidi Williams. 2016. "Sources of geographic variation in health care: Evidence from patient migration." *The Quarterly Journal of Economics* 131 (4):1681–1726.

Finkelstein, Amy and Matthew J. Notowidigdo. 2019. "Take-Up and Targeting: Experimental Evidence from SNAP." *Quarterly Journal of Economics* 134 (3):1505–1556.

Flaaen, Aaron, Matthew D. Shapiro, and Isaac Sorkin. 2019. "Reconsidering the consequences of worker displacements: Firm versus worker perspective." *American Economic Journal: Macroeconomics* 11 (2):193–227.

Ganong, Peter and Pascal Noel. 2019. "Consumer spending during unemployment: Positive and normative implications." *American economic review* 109 (7):2383–2424.

Gerard, François and Joana Naritomi. 2021. "Job displacement insurance and (the lack of) consumption-smoothing." *American Economic Review* 111 (3):899–942.

Gould-Werth, Alix. 2016. "Workplace experiences and unemployment insurance claims: How personal relationships and the structure of work shape access to public benefits." *Social Service Review* 90 (2):305–352.

Guo, Audrey and Andrew C Johnston. 2020. "The Finance of Unemployment Compensation and its Consequence for the Labor Market." *Available at SSRN* .

Hyatt, Henry R, Erika McEntarfer, Kevin L McKinney, Stephen Tibbets, and Doug Walton. 2014. "Job-to-job (J2J) flows: New labor market statistics from linked employer-employee data." *US Census Bureau Center for Economic Studies Paper No. CES-WP-14-34* .

Johnston, Andrew C. 2021. "Unemployment Insurance Taxes and Labor Demand: Quasi-experimental Evidence from Administrative Data." *American Economic Journal: Economic Policy* 13 (1):266–293.

Kleven, Henrik Jacobsen and Wojciech Kopczuk. 2011. "Transfer program complexity and the take-up of social benefits." *American Economic Journal: Economic Policy* 3 (1):54–90.

Kline, Patrick, Raffaele Saggio, and Mikkel Sølvsten. 2020. "Leave-out estimation of variance components." *Econometrica* 88 (5):1859–1898.

Kroft, Kory. 2008. "Takeup, social multipliers and optimal social insurance." *Journal of Public Economics* 92 (3-4):722–737.

Lachowska, Marta, Alexandre Mas, Raffaele Saggio, and Stephen A Woodbury. 2021. "Do Workers Bargain over Wages? A Test Using Dual Jobholders." Working Paper 28409, National Bureau of Economic Research. URL `http://www.nber.org/papers/w28409`.

Lachowska, Marta, Alexandre Mas, and Stephen A Woodbury. 2020. "Sources of displaced workers' long-term earnings losses." *American Economic Review* 110 (10):3231–66.

Lachowska, Marta, Merve Meral, and Stephen A. Woodbury. 2016. "Effects of the Unemployment Insurance Work Test on Long-term Employment Outcomes." *Labour Economics* 41:246–265. URL `https://ideas.repec.org/a/eee/labeco/v41y2016icp246-265.html`.

Lachowska, Marta, Wayne Vroman, and Stephen A. Woodbury. 2020. "Experience Rating and the Dynamics of Financing Unemployment Insurance." *National Tax Journal* 73 (3):673–698.

Lang, Kevin and Sumon Majumdar. 2004. “The Pricing of Job Characteristics When Markets Do Not Clear: Theory and Policy Implications.” *International Economic Review* 45 (4):1111–1128.

Lieber, Ethan MJ and Lee M Lockwood. 2019. “Targeting with in-kind transfers: Evidence from Medicaid home care.” *American Economic Review* 109 (4):1461–85.

Low, Hamish and Luigi Pistaferri. 2015. “Disability insurance and the dynamics of the incentive insurance trade-off.” *American Economic Review* 105 (10):2986–3029.

MaCurdy, Thomas, James Pearce, and Richard Kihlthau. 2004. “An alternative to layoffs: work sharing unemployment insurance.” *California Policy Review* .

Miller, Michael and Robert Pavosevich. 2019. “Alternative Methods of Experience Rating Unemployment Insurance Employer Taxes.” *Public Budegting and Finance* Winter:28–47.

Ratner, David. 2013. “Unemployment Insurance Experience Rating and Labor Market Dynamics.” FEDS Working Paper 2013-86. Unpublished manuscript.

Reeder, William J. 1985. “The benefits and costs of the Section 8 existing housing program.” *Journal of public Economics* 26 (3):349–377.

Sorkin, Isaac. 2018. “Ranking firms using revealed preference.” *Quarterly Journal of Economics* 133 (3):1331–1393.

Toohey, Desmond. 2017. “The effectiveness of work-search requirements over the business cycle: evidence for rationing.” Working paper. Unpublished manuscript.

Topel, Robert. 1983. “On Layoffs and Unemployment Insurance.” *American Economic Review* 73 (4):541–59.

———. 1984. “Experience Rating of Unemployment Insurance and the Incidence of Unemployment.” *Journal of Law and Economics* 27 (1):61–90.

U.S. Advisory Council on Unemployment Compensation. 1996. *Defining Federal and State Roles in Unemployment Insurance: A Report to the President and Congress*. Washington, D.C.: Advisory Council on Unemployment Compensation.

U.S. Department of Labor, Employment and Training Administration. 2020. “‘Benefit Accuracy Measurement Methodology and Program Description.” URL `https://oui.doleta.gov/unemploy/bam/2007/bam-facts.pdf`. [Last accessed July 15, 2021].

Vroman, Wayne. 2009. “Unemployment insurance recipients and nonrecipients in the CPS.” *Monthly Labor Rev.* 132:44–53.

Vroman, Wayne and Stephen A. Woodbury. 2014. “Financing Unemployment Insurance.” *National Tax Journal,* 67 (1):253–268.

Table 1: Summary statistics and UI take-up, worker-quarter and separation samples

	(1)	(2)	(3)	(4)
	Worker-quarter observations		Monetarily eligible separations	
	All	Monetarily eligible	All	Restricted
Claimed UI	0.020	0.023	0.288	0.453
	(0.141)	(0.150)	(0.453)	(0.498)
Claim appealed (conditional on claiming)	0.035	0.033	0.041	0.041
	(0.184)	(0.178)	(0.197)	(0.198)
Benefits received (conditional on appeal)	0.567	0.622	0.618	0.626
	(0.496)	(0.485)	(0.486)	(0.484)
Base-period earnings (in 2005 $)	39291	51073	42470	38752
	(78026)	(50332)	(46024)	(39911)
Base-period work hours	1477	1885	1810	1837
	(793)	(457)	(516)	(545)
Base-period quarters	3.44	3.90	3.82	3.83
	(1.01)	(0.37)	(0.50)	(0.50)
Number of base-period employers	1.00	1.00	1.00	1.00
	(0.00)	(0.00)	(0.00)	(0.00)
Mean size of base-period employer	27	32	92	157
	(328)	(361)	(686)	(978)
Median size of base-period employer	5	6	18	28
Number of worker-quarter observations	80,787,086	58,486,190	3,193,088	1,010,961

Notes: 1. The sample starts with 80,787,086 worker-quarter observations in Washington from 2005:1 to 2013:4 in which the worker had a single unique employer in the five preceding quarters (column 1). In 58,486,190 of these quarters, the worker had at least 560 work hours in either the previous four quarters, or the first four of the previous five quarters, and hence would have been "monetarily" eligible for UI if s/he had separated in that quarter (column 2).

2. Column 3 shows summary statistics for the 3,193,088 separations that occurred out of the 58.5 million worker-quarters in column 2. Of these 3.2 million separations, 1,010,961 met the following restrictions (column 4): (i) the worker transitioned to another employer in either the same or the following quarter that was accompanied by decreased work hours of at most 15% in the quarter of transition or between the two quarters when the transition took place; (ii) the separating employer was the same as the base period employer; and (iii) the separation was not followed by five or more quarters with zero reported work hours (so it was not a clear labor force withdrawal).

3. Base period is the standard base period (i.e., the first four of the last five completed quarters).

Table 2: UI take-up rates and appeals rates by NAICS sector

Sector	UI take-up rate	Appeals rate	Unsuccessful appeals rate
Agriculture	0.316	0.036	0.553
Mining	0.655	0.021	0.750
Utilities	0.421	0.031	0.636
Construction	0.573	0.033	0.598
Manufacturing	0.537	0.042	0.632
Wholesale trade	0.502	0.046	0.672
Retail trade	0.411	0.048	0.569
Transport/warehousing	0.436	0.045	0.629
Information	0.471	0.025	0.728
Finance and insurance	0.471	0.031	0.742
Real estate	0.495	0.045	0.684
Professional/sci./tech/ services	0.452	0.035	0.761
Management of..	0.372	0.028	0.672
Admin. support/waste management	0.468	0.049	0.616
Education	0.194	0.043	0.677
Health care	0.402	0.051	0.643
Arts/enter./rec.	0.480	0.039	0.570
Accommodation and food services	0.354	0.055	0.498
Other services	0.434	0.061	0.621
Public admin.	0.638	0.014	0.683
All	0.453	0.041	0.626
Number of observations	1,010,961	457,696	18,769

Notes: This Table reports take-up rates, appeals rate and unsuccessful appeals rates by sector. The sample in the take-up rate column is Table 1, column (4). The subsequent two columns condition on the previous column. The bottom row reports the weighted average of the rate in the sample.

Table 3: Switcher analysis of UI take-up and appeals

Outcome variable	(1) ΔPr(UI)	(2) ΔPr(UI)	(3) Pr(UI)	(4) Pr(UI)	(5) Pr(UI)	(6) Pr(UI)	(7) ΔPr(Appeal)	(8) ΔPr(Appeal)
Predictors								
ΔFirm UI	0.816***	0.837***						
	(0.022)	(0.048)						
Pr(ΔFirm UI > 0) × ΔFirm UI		-0.038						
		(0.063)						
Firm UI			1.055***	1.039***	0.570***	0.560***		
			(0.013)	(0.013)	(0.035)	(0.036)		
Claimed UI after first separation			0.309***	0.309***	0.269***	0.263***		
			(0.013)	(0.013)	(0.019)	(0.018)		
Firm UI × Claimed UI after first separation			-0.283***	-0.290***	-0.230***	-0.226***		
			(0.024)	(0.024)	(0.034)	(0.033)		
ΔFirm appeals rate							1.075***	0.904***
							(0.116)	(0.256)
Pr(ΔFirm appeals rate > 0) × ΔFirm appeals rate								0.277
								(0.354)
Firm effects	No	No	No	No	Yes	Yes	No	No
Decile effects	No	No	No	Yes	No	Yes	No	No
Constant	0.036***	0.039***	-0.111***	0.195***	0.102***	0.282***	0.003	0.001
	(0.004)	(0.004)	(0.014)	(0.017)	(0.023)	(0.013)	(0.002)	(0.003)
Mean UI	0.474	0.474	0.538	0.538	0.538	0.538		
Mean UI if claimed first time			0.659	0.659	0.659	0.659		
Mean UI if did not claime first time			0.429	0.429	0.429	0.429		
Mean appeals rate							0.0334	0.0334
Worker-quarters	71,037	71,037	71,037	71,037	71,037	71,037	20,767	20,767
Subsample	Workers who separated twice	Workers who separated twice	Workers who separated twice	Workers who separated twice	Workers who separated twice	Workers who separated twice	Workers who claimed UI twice	Workers who claimed UI twice
Adj. R-squared	0.0871	0.0871	0.156	0.161	0.180	0.184	0.00397	0.00396

Notes : The analysis sample consists of separations as defined in Table 1, column 4, and further restricted to workers who separated twice. Average firm UI rates and appeal rates are computed as a leave-one-out firm-by-year averages, adjusted for measurement error by fitting a two-parameter beta distribution by maximum likelihood. For the analysis of appeals, the sample is further restricted to workers who claimed UI twice. Deciles are indicators for deciles of base-period hourly earnings computed using workers in Table 1, column 1. Standard errors, clustered at the employer level, are in parentheses (*** p < 0.01; ** p < 0.05; * p < 0.1).

Table 4: Variance decomposition of UI claims and appeals rates

	Panel A. UI Claims	
Variance	0.250	
	Plug-in	Leave-one-out (KSS)
Firm	0.079	0.022
Worker	0.169	0.049
Covariance (firm, worker)	-0.038	0.001
Corr.	-0.326	0.022
N (firms)	16,737	
N (worker-quarters)	160,708	
N (movers)	62,117	
	Panel B. UI Appeals	
Variance	0.034789	
	Plug-in	Leave-one-out (KSS)
Firm	0.0195	0.0008599
Worker	0.029	0.0011692
Covariance (firm, worker)	-0.0120	0.0004
Corr.	-0.507	0.0446
N (firms)	6,160	
N (worker-quarters)	39,623	
N (movers)	16,641	

Notes: Leave-one-out leaves out a worker-quarter, which in this setting equals leaving out a worker-firm match. Mean UI claims in panel A equals = 0.50. Mean in UI appeals in Panel B equals = 0.03609. The KSS-corrected covariance between firm effects in UI claims and firm effects in UI appeals equals -0.0018.

Table 5: UI take-up and appeals by earnings decile: worker-level probabilities and firm effects

Outcome variable	(1) Pr(UI)	(2) AKM firm effect for UI	(3) Pr(appeal)	(4) AKM firm effect for appeal
Deciles of base-period hourly earnings				
Decile 2	0.067***	0.037*	0.007**	0.006
	(0.010)	(0.022)	(0.003)	(0.006)
Decile 3	0.126***	0.073***	0.002	0.004
	(0.011)	(0.024)	(0.003)	(0.007)
Decile 4	0.178***	0.110***	-0.004	-0.003
	(0.013)	(0.027)	(0.003)	(0.007)
Decile 5	0.197***	0.117***	-0.008***	-0.006
	(0.012)	(0.026)	(0.003)	(0.007)
Decile 6	0.198***	0.120***	-0.009***	-0.006
	(0.011)	(0.025)	(0.003)	(0.007)
Decile 7	0.186***	0.121***	-0.016***	-0.007
	(0.012)	(0.025)	(0.003)	(0.008)
Decile 8	0.165***	0.133***	-0.020***	-0.012
	(0.013)	(0.025)	(0.003)	(0.008)
Decile 9	0.108***	0.126***	-0.021***	-0.014*
	(0.014)	(0.025)	(0.003)	(0.008)
Decile 10	0.014	0.131***	-0.020***	-0.016*
	(0.014)	(0.025)	(0.003)	(0.009)
Constant	0.316***	0.354***	0.049***	0.046***
	(0.011)	(0.025)	(0.003)	(0.007)
Worker-quarters	733,482	1,010,961	548,775	457,696
Adj. R-squared	0.0191	0.0165	0.00223	0.00193

Notes: The analysis sample consists of separations as defined in Table 1, column 4. The outcome variable in column (1) equals one if the separation resulted in a UI claim and zero otherwise. The outcome variable in column (2) is the firm fixed effect for UI estimated using the Abowd, Kramarz, and Margolis (AKM, 1999) approach. The outcome variable in column (3) equals one if the UI claim resulted in an appeal and zero otherwise. The outcome variable in column (4) is the firm fixed effect for appeals estimated using the AKM approach. Deciles are the indicators for deciles of base-period hourly earnings computed using workers in Table 1, column 1. Standard errors, clustered at the employer level, are in parentheses (*** p < 0.01; ** p < 0.05; * p < 0.1).

Table 6: UI take-up and appeals by demographic characteristics: sample of previously claimed

Panel A: claims

	Male	White	Any college or more
I: Outcome variable is whether a separation resulted in a UI claim			
Predictor	0.022***	-0.004	0.023***
	(0.006)	(0.006)	(0.006)
II: Outcome variable is the AKM firm effect for UI			
Predictor	0.042***	0.005	0.021***
	(0.005)	(0.004)	(0.004)

Panel B: appeals

	Male	White	Any college or more
I: Outcome variable is whether a UI claim resulted in an appeal			
Predictor	0.002	-0.011***	-0.004
	(0.003)	(0.003)	(0.003)
II: Outcome variable is the AKM firm effect for appeals			
Predictor	-0.004	-0.007**	0.001
	(0.003)	(0.003)	(0.003)

Notes : The analysis sample consists of separations as defined in Table 1, column 4, for separators who claimed once before. The outcome variable in the top panel equals one if the separation resulted in a UI claim and zero otherwise. The outcome variable in the bottom panel is the firm fixed effect for UI estimated using the Abowd, Kramarz, and Margolis (AKM, 1999) approach. Standard errors, clustered at the employer level, are in parentheses (*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$).

Table 7: UI take-up and appeals by demographic characteristics: sample of previously claimed

	Male	White	Any college or more
Panel A: claims			
I: Outcome variable is whether a separation resulted in a UI claim			
Predictor	0.022***	-0.004	0.023***
	(0.006)	(0.006)	(0.006)
II: Outcome variable is the AKM firm effect for UI			
Predictor	0.042***	0.005	0.021***
	(0.005)	(0.004)	(0.004)
Panel B: appeals			
I: Outcome variable is whether a UI claim resulted in an appeal			
Predictor	0.002	-0.011***	-0.004
	(0.003)	(0.003)	(0.003)
II: Outcome variable is the AKM firm effect for appeals			
Predictor	-0.004	-0.007**	0.001
	(0.003)	(0.003)	(0.003)

Notes: The analysis sample consists of separations as defined in Table 1, column 4, for separators who claimed once before. The outcome variable in the top panel equals one if the separation resulted in a UI claim and zero otherwise. The outcome variable in the bottom panel is the firm fixed effect for UI estimated using the Abowd, Kramarz, and Margolis (AKM, 1999) approach. Standard errors, clustered at the employer level, are in parentheses (*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$).

Table 8: Model results

Panel A. Parameters			
	Eligible	Ineligible	
Application rate (A_e)	0.5954	0.1348	
Challenge rate (| application) (p_e)	0.0237	0.2355	
Receive rate (| challenge) (r_e)	0.8095	0.4889	
Eligible share (σ)	0.6051		
Elasticity of challenging w.r.t. exp. rating ($\frac{1}{\zeta-1}$)	2.3248		
Elasticity of elig. receive given apply w.r.t. exp. rating	-0.0106		
Var. of firm f.e. in applying	0.002		
Panel B. Targeting errors			
Type IA (Eligible, do not apply)	0.2448		
Type IB (Eligible, apply, do not collect)	0.0016		
Type II (Ineligible collect)	0.0468		
Total	0.2933		
Panel C. Counterfactual: reduce exp. rating by 10%			
	Eligible	Ineligible	% Change
Application rate (A_e)	0.6191	0.1401	3.9728
Challenge rate (| application) (p_e)	0.0186	0.1840	-21.8703
% Change in layoff tax	-6.33		
Panel D. Counterfactual: reduce exp. rating by 10%, targeting errors			
		P.p. change	
Type IA (Eligible, do not apply)	0.2305	-0.0143	
Type IB (Eligible, apply, do not collect)	0.0013	-0.0003	
Type II (Ineligible collect)	0.0501	0.0033	
Total	0.2819	-0.0113	

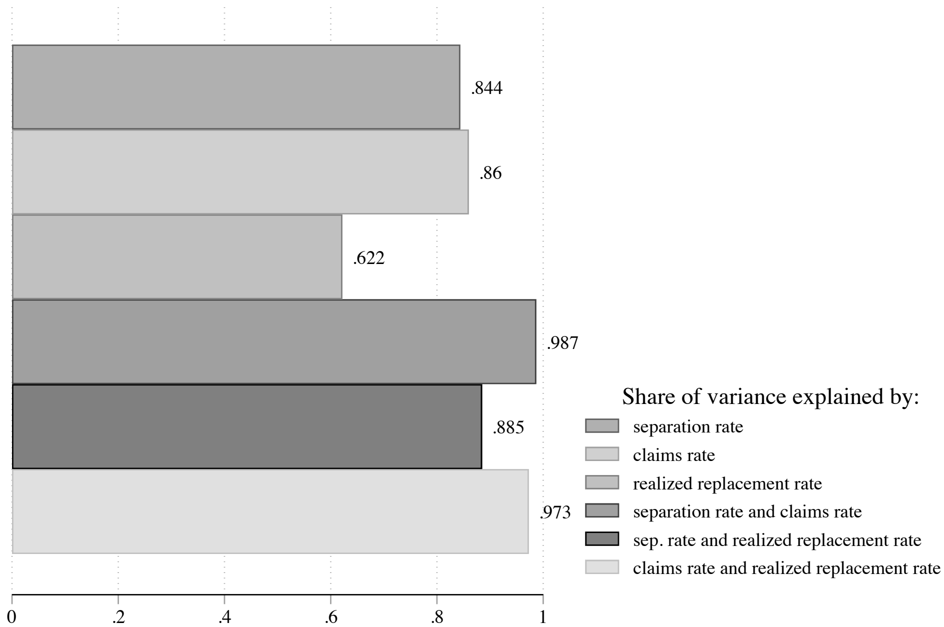
Notes: This Table reports a variety of statistics related to the model.

Table 9: Switcher analysis: firm-level UI take-up and firm characteristics

Outcome variable	(1) Δlog wage	(2) ΔFirm separation rate	(3) Δlog wage
Predictors			
ΔFirm UI	0.092***	-0.155***	
	(0.017)	(0.060)	
ΔFirm separation rate			0.046***
			(0.007)
Constant	0.130***	-0.027***	0.134***
	(0.003)	(0.008)	(0.003)
Worker-quarters	401,251	401,251	401,251
Subsample	Workers who separated twice	Workers who separated twice	Workers who separated twice
Adj. R-squared	0.00300	0.00656	0.00275

Notes : The analysis sample consists of separations as defined in Table 1, column (3), and further restricted to workers who separated twice. Firm UI rate and firm separation rate are computed as a leave-one-out firm-by-year averages, adjusted for measurement error by fitting a two-parameter beta distribution by maximum likelihood. log wages are measured at the worker-level. Standard errors, clustered at the employer level, are in parentheses (*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$).

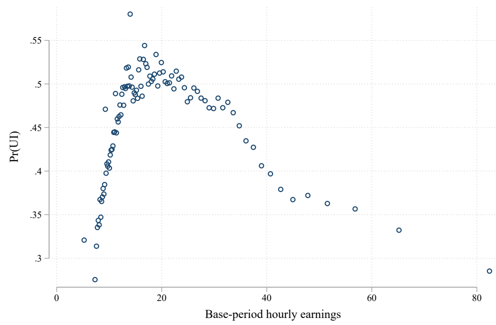
Figure 1: Decomposition of the benefit ratio



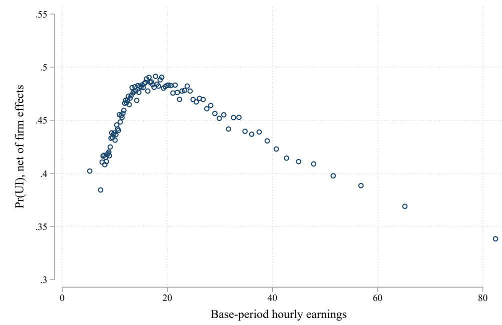
Notes: A firm's benefit ratio is computed as the product of the four-year averages of the separation rates, claims rates, and realized replacement rates (as described in Section 3.2) for year 2009 (hence, values are based on four prior years' values 2005–2008). Each rates' share of variance is computed by replacing the firm's observed rate by the sample average. Therefore, each number in the bar chart shows the share of the variance in the benefit ratio that would be reduced if the rate corresponding to a given bar was made equal across all firms.

Figure 2: UI outcomes versus base-period hourly earnings

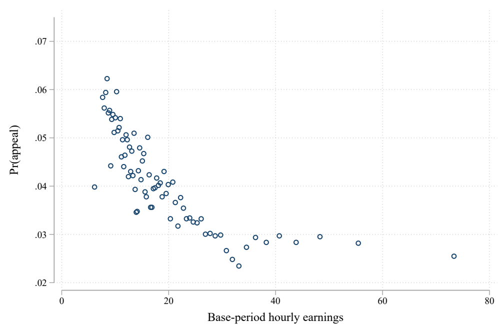
(a) UI take-up



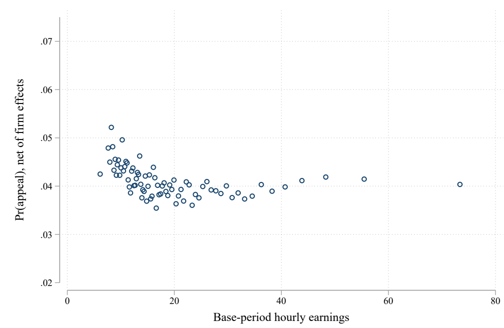
(b) UI take-up: residualized



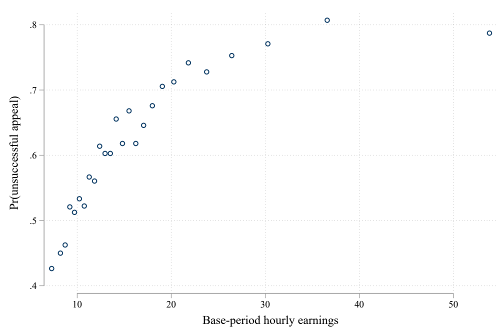
(c) Appeals



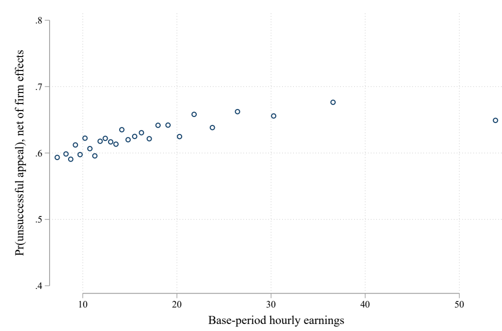
(d) Appeals: residualized



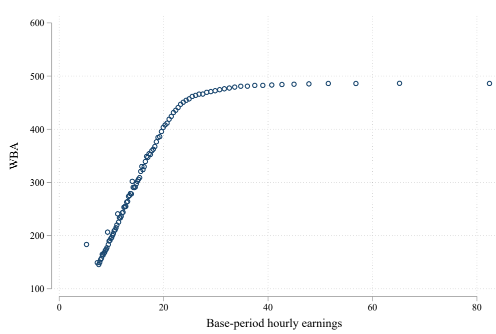
(e) Unsuccessful Appeals



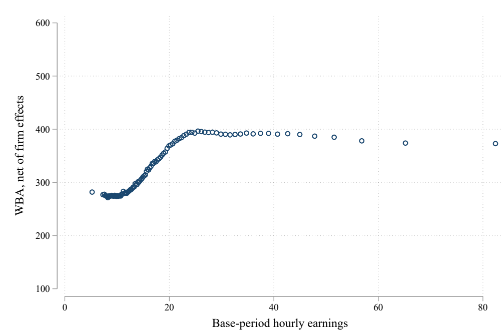
(f) Unsuccessful Appeals: residualized



(g) Weekly Benefit Amount



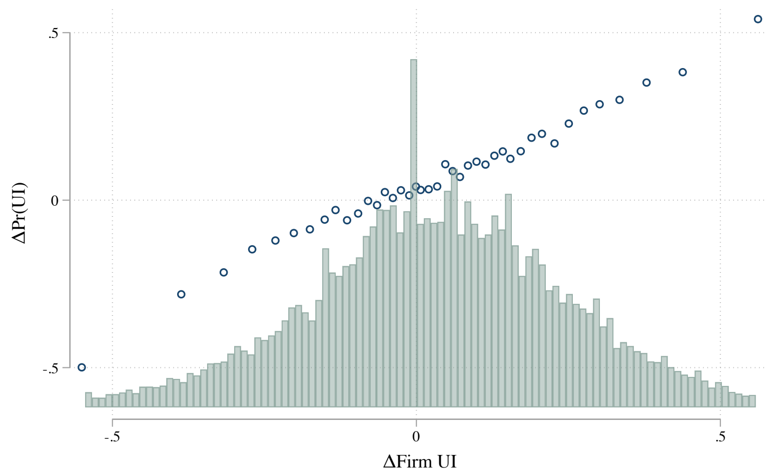
(h) Weekly Benefit Amount: residualized



Notes: The panels of this Figure shows scatter plots of UI take-up rate, appeals rate, and the weekly benefit amount as a function of base-period hourly earnings (earnings divided by hours) for the sample of monetarily-eligible separators, as defined in Table 1, column (4). The subfigures in the left column show simple scatter plots; the subfigures in the right column net out employer fixed effects from the y-axis variable.

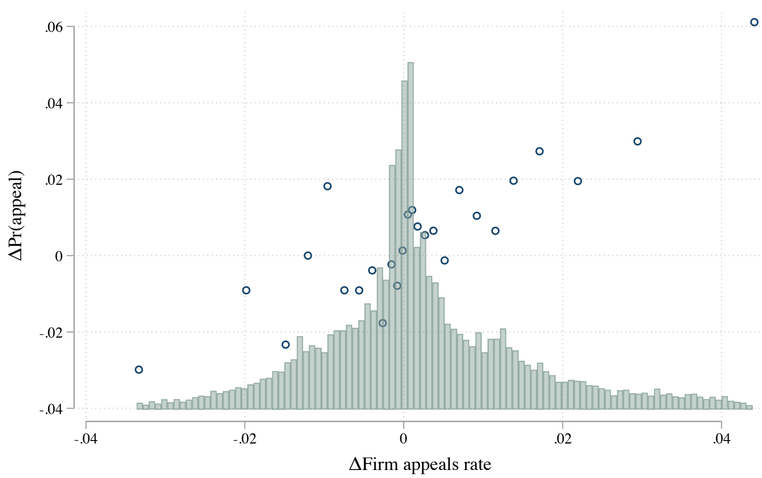
Figure 3: Switcher analyses of UI take-up and appeals

(a) UI take-up



ΔPr(UI) = .036 + .816ΔFirm UI, N = 71,037

(b) UI Appeals

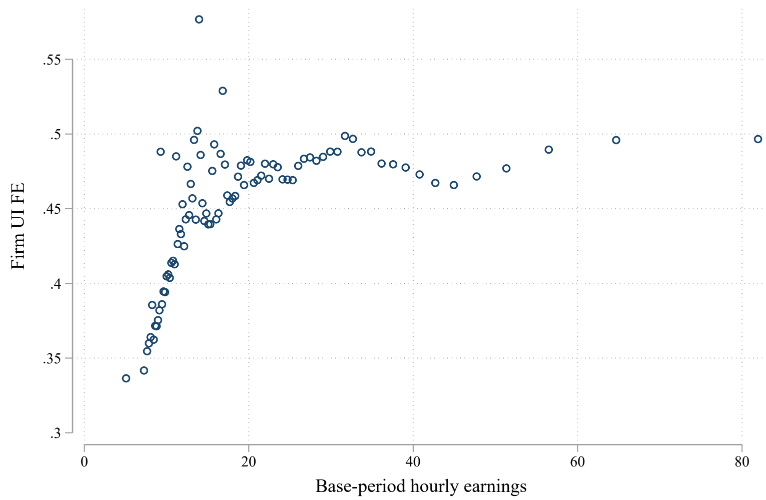


ΔPr(appeal) = .003 + 1.075ΔFirm appeals rate, N = 20,767

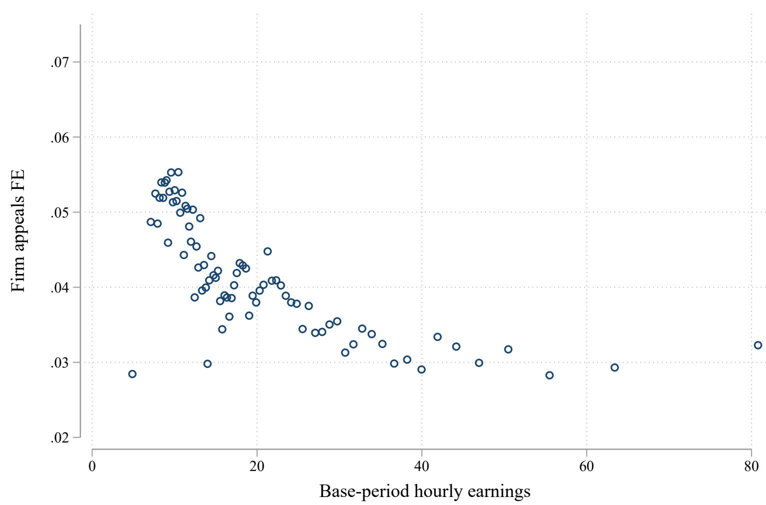
Notes: This Figure shows a switcher analysis in UI take-up (a) and appeals (b). In Panel (a), the sample consists of the separators in Table 1, column (4) who separate twice, but not within the same year. In Panel (b), these two-time separators also needed to have claimed UI both times. The top figure shows the change in the probability that a worker claims UI against the change in the firm-level UI take-up rate, where the firm-level UI take-up rate is the leave-one out average at the firm-year which we then shrink using the procedure described in Section C. The bottom figure shows the change in the probability of the worker having their UI claim appealed for workers who separate twice and claim twice against the change in the firm-level UI appeals rate, where the (leave-one-out) firm-level UI appeals rate is corrected using the procedure described in Section C. In the background are histograms of the distribution of the change in the firm-level UI take-up and appeals rate. The number of points in the scatterplots are based on the cubed root of the sample size.

Figure 4: Firm effects in UI take-up and appeals vs. worker-level earnings

(a) Firm effects in UI take-up and worker-level earnings



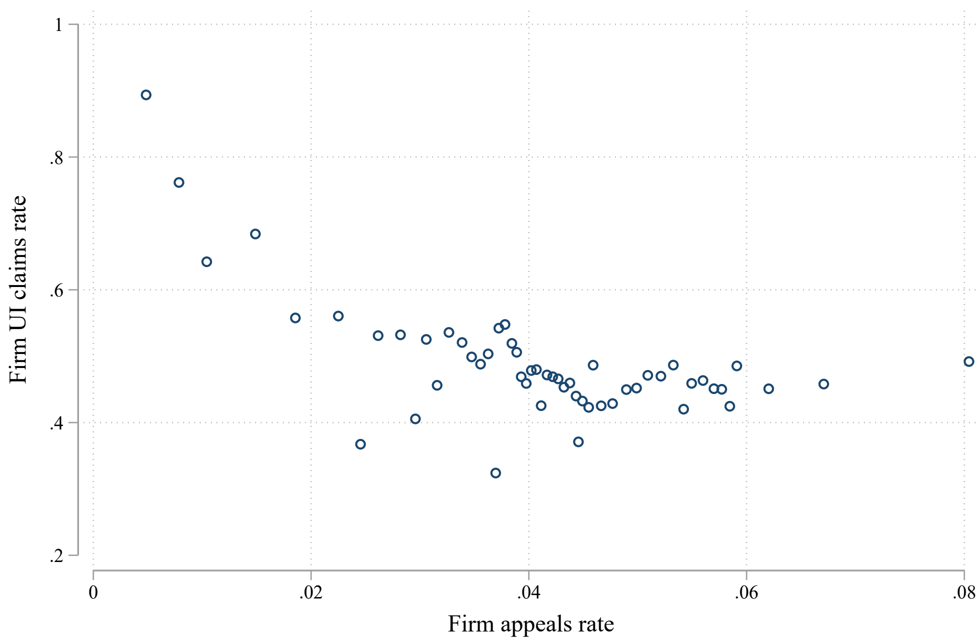
(b) Firm effects in appeals and worker-level earnings



Notes: The top panel of the Figure shows a scatterplot of estimated firm effects in UI take-up rate against the worker-level base-period hourly earnings income. The sample is all separators in Table 1, column (4). The bottom panel shows a scatterplot of estimated firm fixed effects for UI appeals rate against the worker-level base-period hourly earnings income. The firm fixed effects in UI take-up (appeals) are estimated using equation (5) and have been demeaned and rescaled by the average value of UI take-up (appeals). The number of points in the scatterplots are based on the cubed root of the sample size.

Figure 5: Firm-level appeals rates against firm-level take-up rates

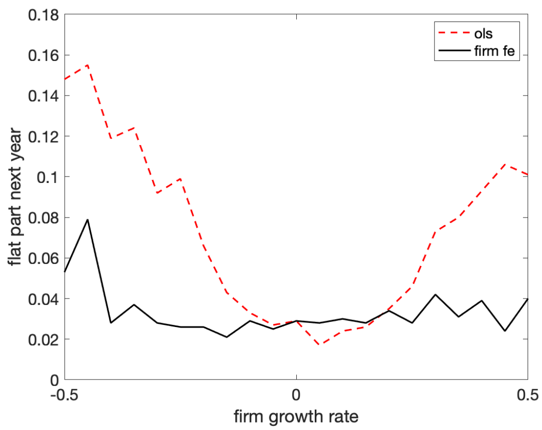
(a) UI take-up and appeals



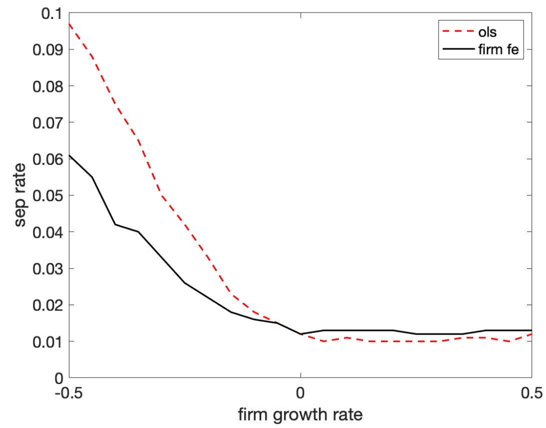
Notes: This Figure plots the firm-level take-up rate agains the firm-level appeals rate.The firm-level UI take-up rate and appeals rate are the leave-one out averages at the firm-year, which we then shrink using the procedure described in Section C. We weight by the number of separating workers associated with each firm (as defined in Table 1, column (4)). The number of points in the scatterplot is based on the cubed root of the sample size.

Figure 6: How UI outcomes vary with firm growth rates

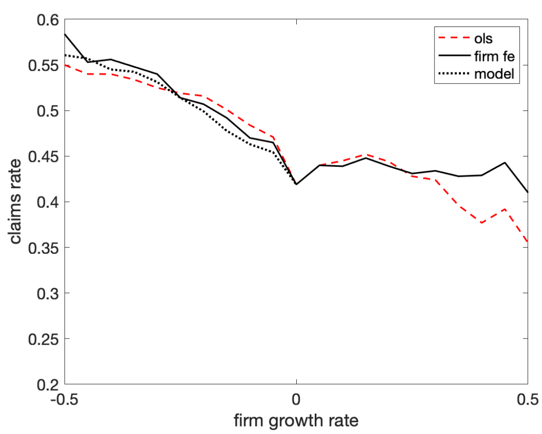
(a) Probability of being on the "flat" part of the experience rating schedule next year



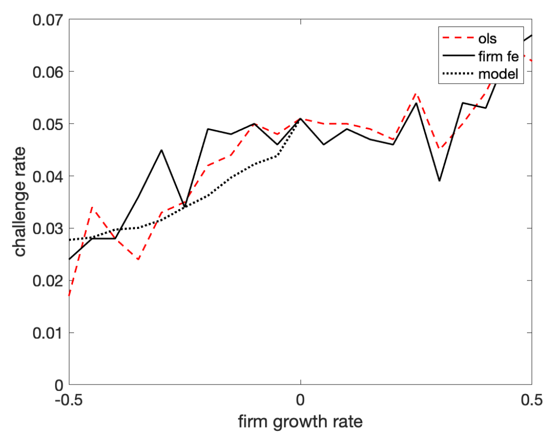
(b) Separation rate



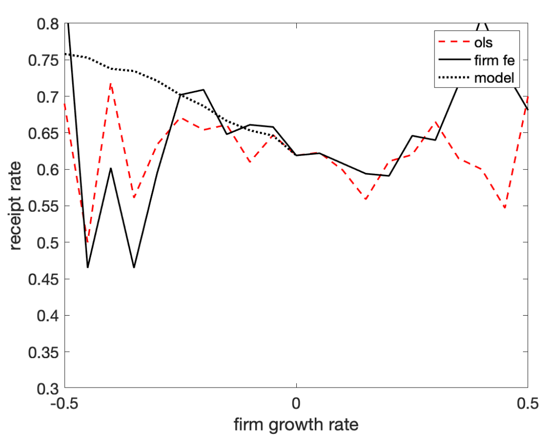
(c) UI take-up rate



(d) Appeals rate

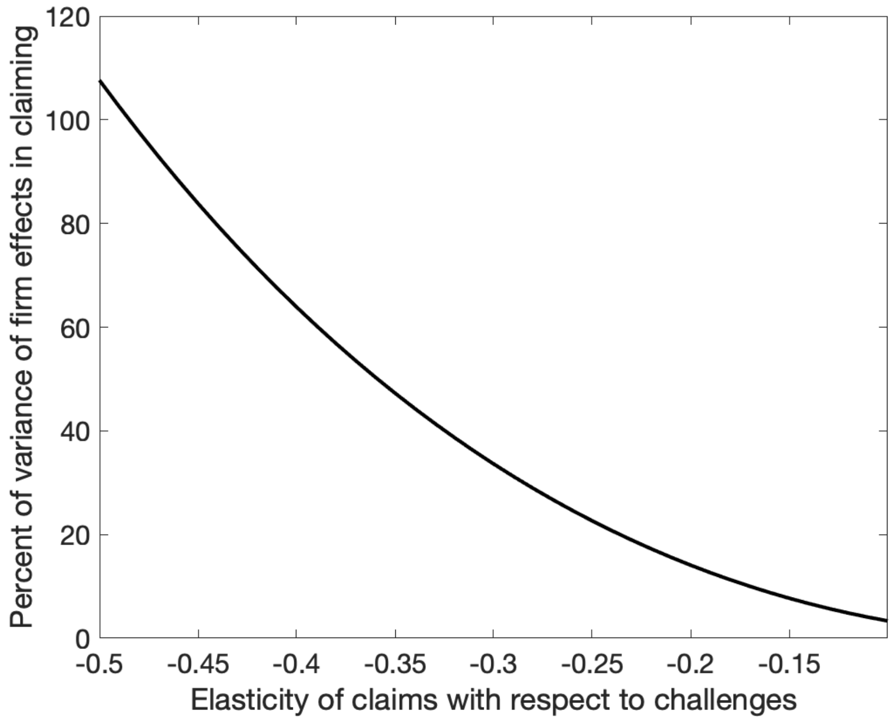


(e) Receipt rate (conditional on appeal)



Notes: The analysis sample consists of separations as defined in Table 1, column (4). The firm growth rate is defined as the difference in annual total hours at the firm and grouped using 40 5 percentage-point bins. The outcome variable "flat part next year" is an indicator that equals one if the firm's benefit ratio is on the flat part of the experience-rating schedule the following year. Other outcome variables are defined in the first three rows of Table 1. Each panel of the figure plots the coefficients resulting from a regression of the variable listed on the vertical axis against the growth-rate bin dummies. The dashed lines show coefficients from a simple OLS regression. The solid lines show coefficients from a regression controlling for firm effects. The dotted lines show numerical results from the theoretical framework. See Table A6 for the regression coefficients.

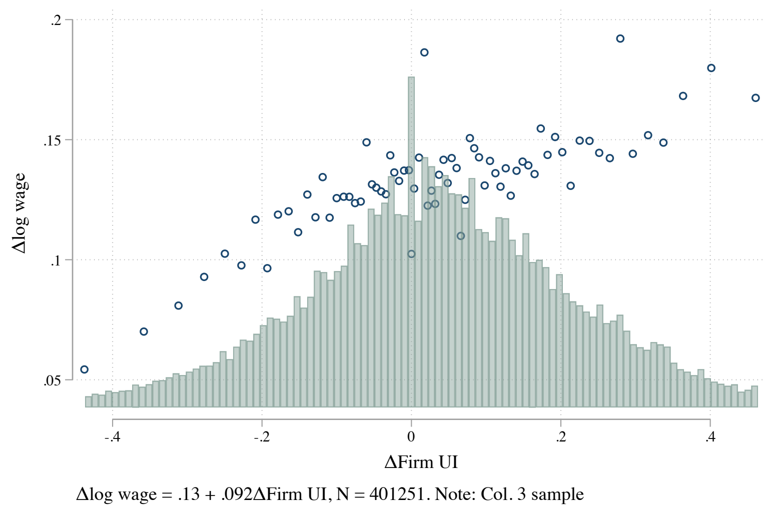
Figure 7: Relationship between elasticity of UI take-up with respect to appeals and the share of variance of firm effects in UI take-up explained by the model



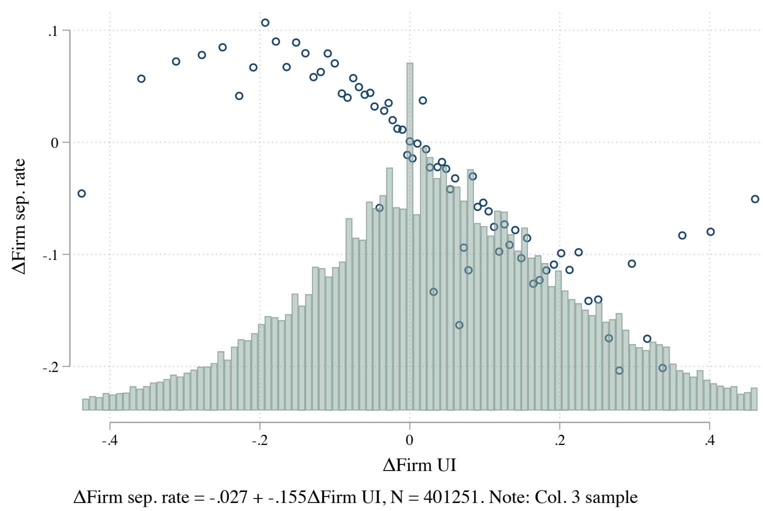
Notes: The figure shows the share of variance in firm effects in UI take-up explained by firm effects in appeals as a function of ϵ, the elasticity of firm effects in UI take-up with respect to firm effects in appeals.

Figure 8: Firm-level UI take-up rates are positively correlated with other desirable firm characteristics

(a) Individual wage changes against change in firm-level UI take-up rate



(b) Change in firm-level separation rate against change in firm-level UI take-up rate



Notes: The sample consists of all separators in Table 1, column (3), who separated twice. The number of points in the scatterplots are based on the cubed root of the sample size.

A Data and variable description

The data consist of Washington State administrative wage records and unemployment insurance (UI) claims records. In this appendix, we describe the variables and procedures for constructing the dataset used in the analysis.

A.1 Further description of the wage and claims records

The data used in this paper are based on the quarterly administrative wage and UI records maintained by the Employment Security Department (ESD) of Washington State to administer the state's UI system.[53]

The wage records provide quarterly information on earnings and work hours of all workers employed by UI-covered employers in the state between 2001:1–2014:4.[54] UI-covered employers in Washington are required to report each worker's quarterly earnings and work hours, which allows us to construct an hourly wage rate in each quarter for most workers in Washington's formal labor market. Each worker's quarterly record also includes an employer identifier and the employer's four-digit North American Industry Classification System (NAICS) code, making it possible to conduct the analysis at either the employer or industry level.

Claims are only available for individuals who claim UI benefits.[55] These records are available at a weekly frequency and include information on the when a claim was filed (the effective date of claim, EDC) and the subsequent amount and weeks of UI benefits paid. The data also include information whether the claim was appealed, by whom the appeal was made (the claimant or the employer), and what the stated reason for the appeal was.

A.2 Linking wage and claim records

To construct the analysis sample, we need to link the information from the UI claims records to the wage records for a given individual at a given point in time. To do this, we need to link the quarter of the EDC with the separation quarter. However, note that for a UI claim to be associated with a separation, such claim need not be filed in the same quarter as the separation quarter. An individual may file for UI up to a year after a separation. Furthermore, it is also possible that a UI claim gets filed in anticipation of a layoff. Accordingly, in order to allow for "early" and "late" UI claims, we devise a rule where, for a separation occurring in quarter t, we allow any UI claim occurring in quarter $t-1$, t, or $t+1$ to be associated with separation in quarter t. About 2/3 of the claims were done in the quarter of separation.

As described above, the data allow us devise a way to link a claim with a separation. However, the data do not allow us to link a claim with a separating employer in a situation where a worker had multiple

[53]This section draws on the data description in Lachowska et al. (2021).

[54]Workers who drop out of the labor force, become self-employed, work in the underground economy, or move out of state will not appear in the records. This is because self-employed workers are not covered by UI, underground earnings are not reported, and out-of-state earnings will be picked up in the earnings records of another state.

[55]We observe demographic characteristics (for example, sex, race, or education) for a subset of claimants. This is because state employment security agencies typically record workers' characteristics once they receive employment services. For worker who claim and receive benefits but do not receive employment services (because they quickly find a new employer), we do not observe these characteristics.

employers in the base period. Hence, we do not observe which of these employers is the base period employer charged for laying off a worker and thus might have the incentive to appeal the claim. To overcome this limitation, we restrict the analysis to workers who had one employer in the base period (according to the standard base-period definition and the alternative base-period definition). Doing so allows us to identify the separating employer as the base-period employer.

Table A1: Worker and employer reasons for separations

Panel A: All claims

Applicant reason	Employer reason										
Description	Discharge	Gross misconduct	Labor dispute	Lack of work	Reduced hours	Leave of absence	Partially employed	Still employed	Unknown	Voluntary quit	Total
Discharge	1,545	< 30	< 30	1,712	< 30	< 30	< 30	< 30	< 30	1,337	4,678
Gross misconduct	< 30	< 30	< 30	< 30	< 30	< 30	< 30	< 30	< 30	< 30	< 30
Labor dispute	74	< 30	< 30	252	< 30	< 30	< 30	< 30	< 30	87	426
Lack of work	62,511	< 30	< 30	3,880	142	2,124	140	219	< 30	69,993	139,000
Reduced hours	519	< 30	< 30	10,332	150	66	87	686	< 30	2,142	13,982
Leave of absence	169	< 30	< 30	438	< 30	61	< 30	< 30	< 30	467	1,144
Partially employed	179	< 30	< 30	586	51	54	60	32	< 30	601	1,563
Still employed	< 30	< 30	< 30	70	< 30	< 30	< 30	< 30	< 30	< 30	153
Voluntary quit	1,050	< 30	< 30	1,419	49	77	< 30	30	< 30	2,059	4,700
Total	66,069	< 30	135	18,696	504	2,419	307	1,002	< 30	76,744	165,799

Notes: All claims with reasons for separation recorded. Counts less than 30 are not reported.

Panel B: Compensated claims

Applicant reason	Employer reason										
Description	Discharge	Gross misconduct	Labor dispute	Lack of work	Reduced hours	Leave of absence	Partially employed	Still employed	Unknown	Voluntary quit	Total
Discharge	973	< 30	< 30	1,369	< 30	< 30	< 30	< 30	< 30	648	3,045
Gross misconduct	< 30	< 30	< 30	< 30	< 30	< 30	< 30	< 30	< 30	< 30	< 30
Labor dispute	< 30	< 30	< 30	142	< 30	< 30	< 30	< 30	< 30	31	207
Lack of work	36,739	< 30	41	3,350	116	1,151	112	131	< 30	33,408	75,000
Reduced hours	394	< 30	< 30	7,322	122	52	69	449	< 30	1,531	9,939
Leave of absence	86	< 30	< 30	354	< 30	< 30	< 30	< 30	< 30	178	648
Partially employed	74	< 30	< 30	418	41	< 30	55	< 30	< 30	209	834
Still employed	< 30	< 30	< 30	40	< 30	< 30	< 30	< 30	< 30	< 30	83
Voluntary quit	518	< 30	< 30	1,025	39	42	< 30	< 30	< 30	1,086	2,740
Total	38,823	< 30	51	14,025	327	1,307	254	643	< 30	37,120	92,558

Notes: All claims that were compensated. Counts less than 30 are not reported.

Table A2: Distribution of shrunken and raw UI take-up rates, appeals rates, and unsuccessful appeals rate

Variable	Mean	Variance	Worker-quarters	Estimate of α	Estimate of β
Firm UI ∈ [0,1]	0.458	0.099	841,530		
Corrected firm UI ∈ [0,1]	0.460	0.045	841,530	2.572	3.257
Firm appeals rate ∈ [0,1]	0.039	0.014	732,133		
Corrected firm appeals rate ∈ [0,1]	0.042	0.000	732,133	3.489	72.186
Firm compensated appeals rate ∈ [0,1]	0.583	0.161	266,272		
Corrected firm compensated appeals rate ∈ [0,1]	0.620	0.004	266,272	7.464	4.373

Notes: The correction applies the posterior estimates based a two-parameter (α,β) beta distribution fitted by maximum likelihood.

Table A3: Switcher analysis of UI take-up by earnings deciles

	(1)	(2)
Outcome variable	ΔPr(UI)	Decile ($/hour)
Predictors		
ΔFirm UI	0.859***	8
	(0.049)	
ΔFirm UI×Decile 2	-0.016	9
	(0.066)	
ΔFirm UI×Decile 3	-0.023	11
	(0.053)	
ΔFirm UI×Decile 4	0.005	14
	(0.056)	
ΔFirm UI×Decile 5	-0.069	17
	(0.054)	
ΔFirm UI×Decile 6	-0.017	20
	(0.056)	
ΔFirm UI×Decile 7	-0.082	24
	(0.059)	
ΔFirm UI×Decile 8	-0.107*	30
	(0.059)	
ΔFirm UI×Decile 9	-0.147**	40
	(0.060)	
ΔFirm UI×Decile 10	-0.140**	73
	(0.065)	
Decile 2	-0.039***	
	(0.011)	
Decile 3	-0.051***	
	(0.010)	
Decile 4	-0.076***	
	(0.011)	
Decile 5	-0.091***	
	(0.011)	
Decile 6	-0.088***	
	(0.011)	
Decile 7	-0.086***	
	(0.011)	
Decile 8	-0.083***	
	(0.011)	
Decile 9	-0.081***	
	(0.012)	
Decile 10	-0.071***	
	(0.013)	
Constant	0.103***	
	(0.009)	
Mean claims rate	0.474	
Person-quarters	71,037	
Subsample	Workers who separated twice	
Adj. R-squared	0.089	

Notes : The analysis sample consists of separations as defined in Table 1, column (4) and further restricted to workers who seprated two times. Average firm UI claims rates are computed as a leave-one-out firm-by-year averages, adjusted for measurement error by fitting a two-parameter beta distribution by maximum likelihood. Decile is the indicator for the decile of base-period hourly earnings, based on Table 1, column (1). Standard errors, clustered at the employer level, are in parentheses (*** p < 0.01; ** p < 0.05; * p < 0.1).

Table A4: Claims and appeals by earnings deciles: sample of previously claimed

Outcome variable	(1) Pr(UI)	(2) AKM firm effect for UI	(3) Pr(appeal)	(4) AKM firm effect for appeal
Deciles of base-period hourly earnings				
Decile 2	0.091***	0.018	0.026*	0.016
	(0.028)	(0.036)	(0.013)	(0.013)
Decile 3	0.119***	0.068*	0.017	0.010
	(0.029)	(0.037)	(0.013)	(0.013)
Decile 4	0.163***	0.098***	0.007	0.007
	(0.028)	(0.037)	(0.013)	(0.013)
Decile 5	0.178***	0.112***	0.003	0.002
	(0.029)	(0.038)	(0.013)	(0.013)
Decile 6	0.190***	0.130***	0.003	0.000
	(0.029)	(0.038)	(0.013)	(0.013)
Decile 7	0.201***	0.157***	-0.012	-0.001
	(0.029)	(0.038)	(0.013)	(0.013)
Decile 8	0.219***	0.174***	-0.012	-0.011
	(0.029)	(0.037)	(0.013)	(0.013)
Decile 9	0.216***	0.198***	-0.017	-0.009
	(0.029)	(0.037)	(0.013)	(0.013)
Decile 10	0.137***	0.166***	-0.009	-0.003
	(0.030)	(0.038)	(0.013)	(0.014)
Constant	0.494***	-0.534***	0.037***	-0.026**
	(0.027)	(0.037)	(0.012)	(0.013)
Worker-quarters	33,706	30,879	20,767	17,348
Adj. R-squared	0.0105	0.0419	0.00374	0.00270

Notes: The analysis sample consists of separations as defined in Table 1, column 4, who had claimed once before. The outcome variable in column (1) equals one if the separation resulted in a UI claim and zero otherwise. The outcome variable in column (2) is the firm fixed effect for UI estimated using the Abowd, Kramarz, and Margolis (AKM, 1999) approach. The outcome variable in column (3) equals one if the UI claim resulted in an appeal and zero otherwise. The outcome variable in column (4) is the firm fixed effect for appeals estimated using the AKM approach. Deciles are the indicators for deciles of base-period hourly earnings computed using workers in Table 1, column 1. Standard errors, clustered at the employer level, are in parentheses (*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$).

Table A5: Sensitivity to UI take-up rate to firm-level UI rate depending on time between claims

	(1)
Outcome variable	Pr(UI)
Predictors	
Firm UI	0.576***
	(0.070)
Firm UI×Separation 2 years apart	0.198***
	(0.075)
Firm UI×Separation 3 years apart	0.249***
	(0.076)
Firm UI×Separation 4 years apart	0.149*
	(0.079)
Firm UI×Separation 5 years apart	0.171**
	20
Firm UI×Separation 6 years apart	0.309***
	(0.090)
Firm UI×Separation 7 years apart	0.240***
	(0.093)
Firm UI×Separation 8 years apart	0.221*
	(0.128)
Constant	0.272***
	(0.036)
Mean claims rate	0.659
Worker-quarters	33,706
Subsample	Workers who claimed once before
Adj. R-squared	0.077

Notes: The analysis sample consists of separations as defined in Table 1, column 4 and further restricted to workers who claimed once before. Average firm UI claims rates are computed as a leave-one-out firm-by-year averages, adjusted for measurement error by fitting a two-parameter beta distribution by maximum likelihood. Each "Separation X years apart" is a dummy denoting that the second separation occured X years after the first separation. Regression contols for years-since-separation effects. Standard errors, clustered at the employer level, are in parentheses (*** p < 0.01; ** p < 0.05; * p < 0.1).

Table A6: Firm-UI outcomes and firm growth rate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Outcome variable	Pr(flat part in t+1)		Separation rate		Pr(UI)		Pr(appeal)		Pr(Unsuccessful appeal)	
	OLS	Firm FE	OLS	Firm FE	OLS	Firm FE	OLS	Firm FE	OLS	Firm FE
5 p.p. firm-growth bins*										
-0.5	0.148	0.066	0.097	0.063	0.55	0.585	0.017	0.024	0.69	0.851
-0.45	0.155	0.092	0.088	0.057	0.54	0.554	0.034	0.028	0.5	0.453
-0.4	0.119	0.041	0.075	0.044	0.54	0.557	0.028	0.028	0.719	0.59
-0.35	0.124	0.05	0.065	0.042	0.534	0.549	0.024	0.036	0.561	0.453
-0.3	0.092	0.041	0.05	0.035	0.525	0.541	0.033	0.045	0.634	0.583
-0.25	0.099	0.039	0.042	0.028	0.519	0.515	0.035	0.034	0.671	0.69
-0.2	0.066	0.039	0.033	0.024	0.516	0.508	0.042	0.049	0.654	0.697
-0.15	0.043	0.034	0.023	0.02	0.501	0.493	0.044	0.048	0.661	0.636
-0.1	0.033	0.042	0.018	0.018	0.484	0.471	0.05	0.05	0.61	0.649
-0.05	0.027	0.038	0.015	0.017	0.471	0.466	0.048	0.046	0.647	0.646
0 (-4.99% to 0%)	0.029	0.042	0.012	0.014	0.419	0.42	0.051	0.051	0.619	0.607
Observations	63,788	63,788	116,513	116,513	116,513	116,513	73,978	73,978	6,722	6,722
R-squared	0.076	0.759	0.248	0.836	0.547	0.386	0.062	0.343	0.632	0.598

Notes: The analysis sample is a firm-by-quarter averaged dataset based on column (4) in Table 1. The outcome Pr(flat part in t+1) is defined as the probability that the firm is on the flat part of the experience-rating schedule next year. To compute separation rate, we use firm size in the denominator. Each outcome variable is regressed on 40 dummies indicating 5 percentage-point quarter-to-quarter changes in firm growth (defined as percentage change in total annual hours at the firm). For each outcome variable, the first column presents estimates obtained using OLS. The second column presents estimates (scaled by the sample average) obtained after controlling for firm fixed effects. The table only presents coefficients from -50% to 0% percent growth.

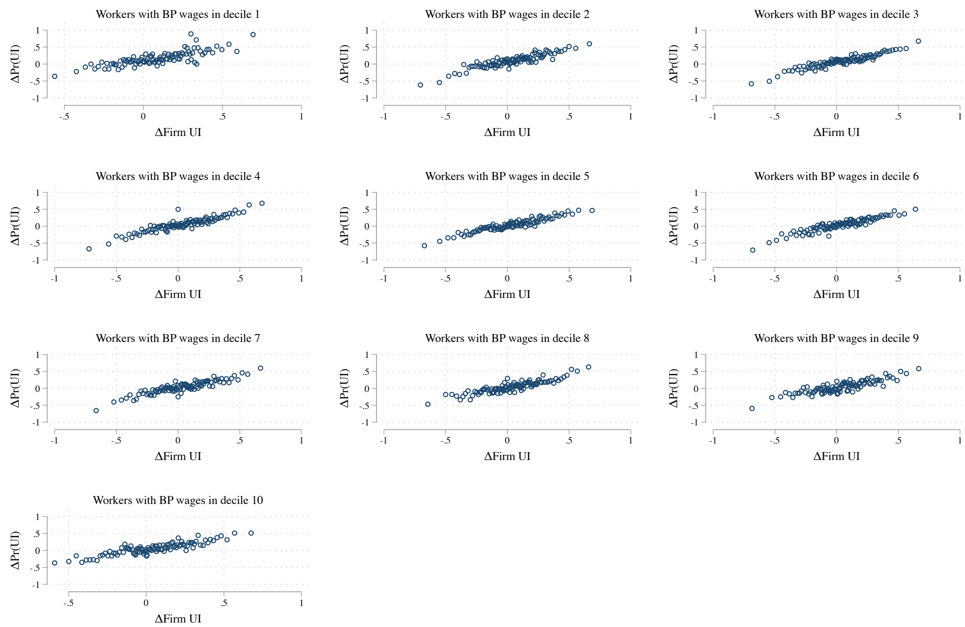
*Note that the 0-percent growth bin spans -4.99% to 0% -5-percent bin spans -9.99% to 5%, etc.

Table A7: Moments used to estimate the model

Moment	Value	Source
Sep_0	0.012	Figure 6
Sep_{-25}	0.026	Figure 6
$Claim_0$	0.419	Figure 6
$Claim_{-25}$	0.514	Figure 6
$Pr(appeal)_0$	0.051	Figure 6
$Pr(appeal)_{-25}$	0.034	Figure 6
$Pr(rec)_0$	0.619	Figure 6
$Pr(rec)_{-25}$	0.702	Figure 6
$Pr(Ineligible \mid claim)$	0.127	BAM

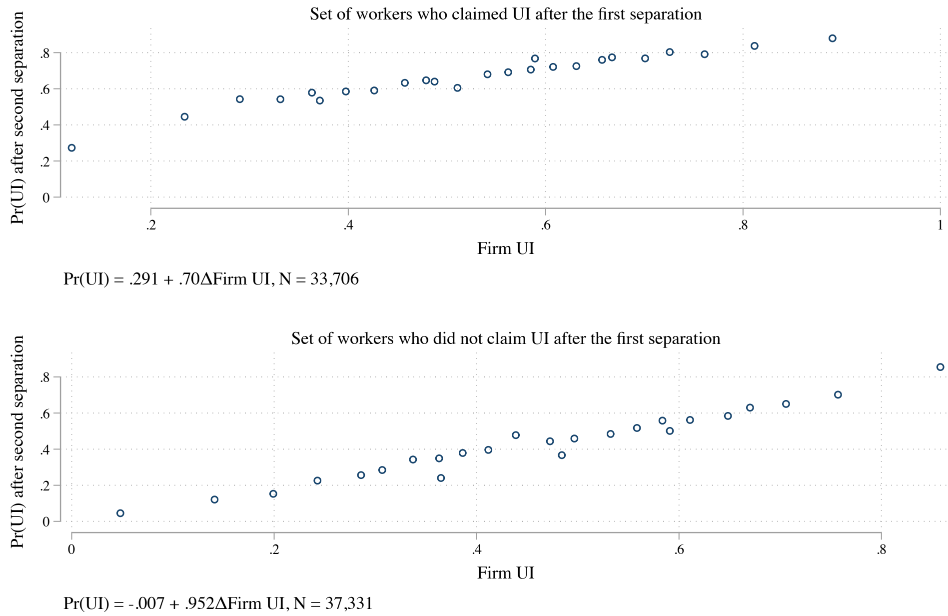
Notes: This Table presents values used to estimate the model. Because the constant in the fixed effect regressions are not identified, values in Table A6 are renormalized so that in the fixed effect regression the values match OLS at 0.

Figure A1: Probability of UI take-up, shown separately by deciles of base-period hourly earnings



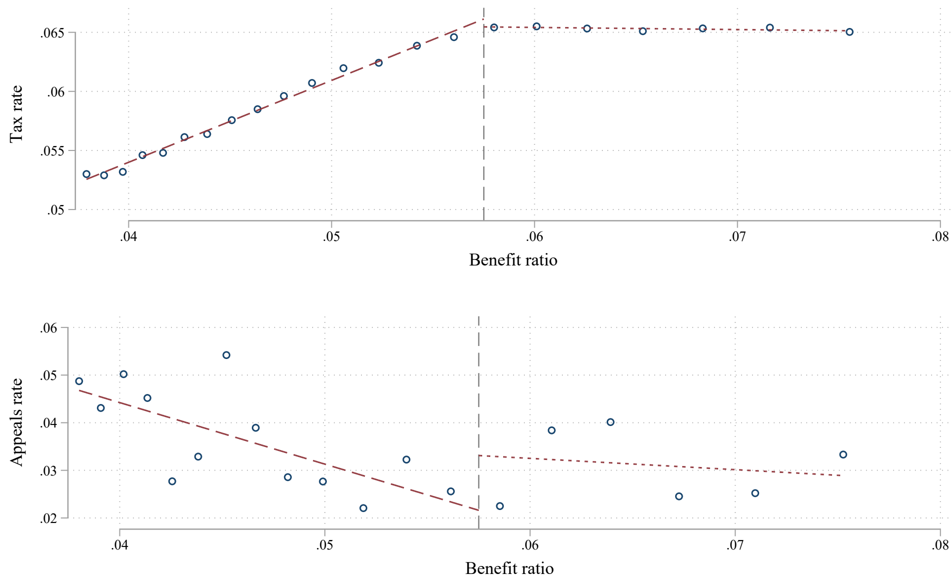
Notes: The analysis sample consists of separations as defined in Table 1, column (4), and further restricted to workers who separated two times. Deciles denote the decile of base-period hourly earnings, calculated using all workers. The mean UI take-up rate rate is calculated as a leave-one out average at the firm-year level and adjusted using the estimated beta distribution.

Figure A2: Claiming UI after the second separation by whether claimed on first separation



Notes: The analysis sample consists of separations as defined in Table 1, column (4), and further restricted to workers who separated two times. The figure shows scatter plots of the probability to claim UI after the second separation for persons who separated twice. The top figure shows this scatter plot for workers who separated two times and claimed UI after the first separation. The bottom figure shows this scatter plot for workers who separated two times but did not claim UI after the first separation. The mean UI claims rate is calculated as a leave-one out average at the firm-year level and adjusted using the estimated beta distribution.

Figure A3: Firm UI tax rate and firm appeals rate as a function of the benefit ratio



Note: Years 2005-2010

Notes: The analysis sample consists of monetarily-eligible separators as defined in Table 1, column (4). (The sample is restricted to years 2005–2010 out of convenience—kink is in the same place). The number of points in the scatterplots are based on the cubed root of the sample size.

B Omitted proofs

Result 1

Proof. For a worker with eligibility status e, the firm payoff function is:

$$-p_{e,j}r_e\tau - p_{e,j}(1-r_e)\times 0 - (1-p_{e,j})\tau - \eta_j p_{e,j}^{\zeta}. \tag{A1}$$

Taking the first order condition with respect to $p_{e,j}$ we get:

$$(1-r_e)\tau = \eta_j \zeta p_{e,j}^{\zeta-1} \tag{A2}$$

$$\frac{(1-r_e)\tau}{\eta_j\zeta} = p_{e,j}^{\zeta-1} \tag{A3}$$

$$\left(\frac{(1-r_e)\tau}{\eta_j\zeta}\right)^{\frac{1}{\zeta-1}} = p_{e,j}^{*}. \tag{A4}$$

The restriction that $\zeta > 1$ ensures that the second order condition holds. □

Result 2

Proof. A worker of eligibility type e who draws χ and separates from a firm of type j has the following payoff from applying:

$$p_{e,j}^{*}r_e u(b) + p_{e,j}^{*}(1-r_e)u(d) + (1-p_{e,j}^{*})u(b) - \chi. \tag{A5}$$

The first term captures the event that the worker claims, the firm appeals, and the worker ends up collecting. The second term captures the event of the firm appealing and the worker not collecting. The third term captures the firm not appealing. The final term records the cost to the worker of applying.

The payoff from not applying is $u(d)$. Therefore, the cutoff type for applying for eligibility type e at firm j is given by:

$$p_{e,j}^{*}r_e u(b) + p_{e,j}^{*}(1-r_e)u(d) + (1-p_{e,j}^{*})u(b) - \chi_{e,j}^{*} = u(d) \tag{A6}$$

$$(1-(1-r_e)p_{e,j}^{*})(u(b)-u(d)) = \chi_{e,j}^{*}. \tag{A7}$$

□

Result 3

Consider a firm's decision to layoff workers. Because δ share of workers separate in the absence of a firm level shock, if a firm enters the period with $E_{j,-1}$ workers, then it has only $(1-\delta)E_{j,-1}$ to decide whether or not to lay a worker off. The expected cost of laying off an eligible worker is:

$$A_{1,j}\tau[p_{1,j}^{*}r_1 + (1-p_{1,j}^{*})] = A_{1,j}\tau[1-(1-r_1)p_{1,j}^{*}]. \tag{A8}$$

This equation says: there is some probability $A_{1,j}$ that an eligible worker applies, the worker collects either if the firm challenges and the worker collects anyway, or if the firm does not challenge, and finally the firm pays τ if the worker applies and collects. Hence, the shadow cost of the marginal worker is not w, but is instead $w - A_{1,j}\tau[p^*_{1,j}r_1 + (1 - p^*_{1,j})]$ because by retaining the worker the firm does not pay the implicit firing cost.

Hence, there are three regions of optimal decisions.

If z_j is such that

$$\left(\frac{\alpha z_j}{w}\right)^{\frac{1}{1-\alpha}} > (1-\delta)E_{j,t-1}$$

then the firm hires and $E^*_{j,t} = \left(\frac{\alpha z_j}{w}\right)^{\frac{1}{1-\alpha}}$.

If z_j is such that

$$\left(\frac{\alpha z_j}{w - A_{1,j}\tau[p^*_{1,j}r_1 + (1-p^*_{1,j})]}\right)^{\frac{1}{1-\alpha}} > (1-\delta)E_{j,t-1} > \left(\frac{\alpha z_j}{w}\right)^{\frac{1}{1-\alpha}}$$

then the firm neither hires nor fires and $E^*_{j,t} = (1-\delta)E_{j,t-1}$.

If z_j is such that

$$(1-\delta)E_{j,t-1} > \left(\frac{\alpha z_j}{w - A_{1,j}\tau[p^*_{1,j}r_1 + (1-p^*_{1,j})]}\right)^{\frac{1}{1-\alpha}} > \left(\frac{\alpha z_j}{w}\right)^{\frac{1}{1-\alpha}}$$

then the firm lays workers off and $E^*_{j,t} = \left(\frac{\alpha z_j}{w - A_{1,j}\tau[p^*_{1,j}r_1 + (1-p^*_{1,j})]}\right)^{\frac{1}{1-\alpha}}$.

Define the layoff rate

$$l(z_t, \eta_j) = \max\{1 + \delta - \frac{E(z_t, \eta_j)}{E_{j,-i}}, 0\}.$$

This says that the firm only lays workers off if it wants to contract by more than δ percent.

Result 5

Part 1. For the first part:

$$p^*_{e,j} = \left(\frac{(1-r_e)\tau}{\eta_j \zeta}\right)^{\frac{1}{\zeta-1}} \tag{A9}$$

$$\frac{\partial p^*_{e,j}}{\partial \tau}\frac{\tau}{p^*_{e,j}} = \frac{1}{\zeta - 1} > 0. \tag{A10}$$

Part 2. For the second part:

$$\chi_{e,j}^{*} = (1-(1-r_e)p_{e,j}^{*})(u(b)-u(d)) \tag{A11}$$

$$\frac{\partial \chi_{e,j}^{*}}{\partial \tau} = -(1-r_e)(u(b)-u(d))\frac{\partial p_{e,j}^{*}}{\partial \tau} < 0, \tag{A12}$$

since $(1-r_e)(u(b)-u(d)) > 0$ and $\frac{\partial p_{e,j}^{*}}{\partial \tau} > 0$.

Since $A_{e,j} = \mathcal{P}_e(\chi_{e,j}^{*})$, decreasing the cutoff type that applies decreases the application rate.

Part 3. For the third part:

$$\frac{\partial A_{1,j}\tau[1-p_{1,j}^{*}(1-r_1)]}{\partial \tau} = \underbrace{A_{1,j}[1-p_{1,j}^{*}(1-r_1)]}_{>0} + \underbrace{\frac{A_{1,j}}{\partial \tau}\tau[1-p_{1,j}^{*}(1-r_1)]}_{<0} + \underbrace{A_{1,j}\tau[1-\frac{\partial p_{1,j}^{*}}{\partial \tau}(1-r_1)]}_{<0}. \tag{A13}$$

In elasticities:

$$\frac{\partial A_{1,j}\tau[1-p_{1,j}^{*}(1-r_1)]}{\partial \tau}\frac{\tau}{A_{1,j}\tau[1-p_{1,j}^{*}(1-r_1)]} = \underbrace{1}_{>0} + \underbrace{\frac{\partial A_{1,j}}{\partial \tau}\frac{\tau}{A_{1,j}}}_{<0} + \underbrace{\frac{\partial[1-p_{1,j}^{*}(1-r_1)]}{\partial \tau}\frac{\tau}{[1-p_{1,j}^{*}(1-r_1)]}}_{<0}. \tag{A14}$$

The first term is the direct effect, and the second and third terms are the indirect effects (the application rate, and the probability of receiving UI conditional on applying and being eligible). There is nothing in the theory that restricts the magnitudes of the indirect effects and thus the overall sign is ambiguous.

For some purposes, it is helpful to write out the third term:

$$\frac{\partial[1-p_{1,j}^{*}(1-r_1)]}{\partial \tau} = \frac{-1}{\zeta-1}(1-r_1)p_{1,j}^{*}\frac{1}{\tau} \tag{A15}$$

$$\frac{\partial[1-p_{1,j}^{*}(1-r_1)]}{\partial \tau}\frac{\tau}{[1-p_{1,j}^{*}(1-r_1)]} = \frac{-1}{\zeta-1}(1-r_1)p_{1,j}^{*}\frac{1}{\tau}\frac{\tau}{[1-p_{1,j}^{*}(1-r_1)]} \tag{A16}$$

$$= \frac{1}{\zeta-1}\frac{-(1-r_1)p_{1,j}^{*}}{[1-p_{1,j}^{*}(1-r_1)]}. \tag{A17}$$

Result 6

$$\text{plim } \hat{\beta} = \frac{cov(\Delta\bar{a}_{j-i}, \Delta a_{ij})}{var(\Delta\bar{a}_{j-i})} \tag{A18}$$

$$= \frac{cov(\psi_j - \psi_{j'}, \bar{\alpha}_{j,-i} - \bar{\alpha}_{j',-i} + \psi_j - \psi_{j'}}{var(\bar{\alpha}_{j,-i} - \bar{\alpha}_{j',-i} + \psi_j - \psi_{j'})} \tag{A19}$$

$$= \frac{var(\psi_j - \psi_{j'}) + cov(\psi_j - \psi_{j'}, \bar{\alpha}_{j,-i} - \bar{\alpha}_{j',-i})}{var(\psi_j - \psi_{j'}) + 2 \times cov(\psi_j - \psi_{j'}, \bar{\alpha}_{j,-i} - \bar{\alpha}_{j',-i}) + var(\bar{\alpha}_{j,-i} - \bar{\alpha}_{j',-i})}. \tag{A20}$$

C Shrinking firm-level rates

First, we define notation. Let there be N_j separators from firm j and C_j workers who claim UI. Then a natural estimate of the claims rate is $\hat{c}_j = \frac{C_j}{N_j}$. This estimate will be over-dispersed. We assume that the true claims rate follows a beta distribution: $c \sim \mathcal{B}(\alpha, \beta)$. Then, the probability of the observed data given c follows a binomial distribution (i.e, $Pr(C_j|c, N_j) = \binom{N_j}{C_j} c^{C_j}(1-c)^{N_j - C_j}$). Because we are ultimately interested in making statements about the labor market as perceived by workers, we weight observations by the number of separators, $\omega_j = \frac{N_j}{\sum_j N_j}$. Letting $\theta = \{\alpha, \beta\}$ denote our parameter vector, and $\mathcal{O}$ denote the matrix of data (the j^{th} row is (N_j, C_j)), we are interested in the following maximization problem:

$$\begin{aligned}\max_\theta \mathbb{P}\{\mathcal{O}|\theta\} &= \max_\theta \Pi_j \omega_j \mathbb{P}\{\mathcal{O}_j|\theta\} \\ &= \max_\theta \Pi_j \omega_j \bigg(\int_{c=0}^1 \mathbb{P}\{\mathcal{O}_j|c\} \times \mathbb{P}\{c|\theta\} dc \bigg), \end{aligned} \tag{A21}$$

where $\mathbb{P}\{c|\theta\}$ is the probability density function (PDF) of the beta distribution and $\mathbb{P}\{\mathcal{O}_j|c\}$ is the probability mass function (PMF) of the binomial distribution. Casting the problem in this way takes small samples into account: even if a firm has a true claims rate that is in the interior of the support, say, 0.2, there is some probability (given by the binomial probability mass function) that we instead observe a claims rate of 0 or 1. More generally, the binomial PMF captures the over-dispersion that we expect given that we do not observe infinite samples for each firm. We numerically maximize this expression.[56]

This maximization problem gives us estimates of the beta distribution parameters $\hat{\theta} = \{\hat{\alpha}, \hat{\beta}\}$. We then use these parameters to compute the posterior mean of the firm-level claims rate, which takes into account the sample size:

$$\hat{c}_j^{EB} = \frac{C_j + \hat{\alpha}}{N_j + \hat{\alpha} + \hat{\beta}}, \tag{A22}$$

where the super-script indicates empirical Bayes.

[56] We approximate the integral with 99 points, which in Monte Carlo experiments was sufficient for stability.

D Details on estimating the model

D.1 Firm-averaged parameters for eligible workers

At firm growth rate $g = 0$ the claim rate can be expressed as a simple weighted average of the claim rate of eligible workers (A_1) and of ineligible workers (A_0), weighted by $\sigma = \Pr(e = 1)$, the share of eligible workers. At $g < 0$, we assume that all separators are eligible and so the claim rate can be expressed as a weighted average of claims rates of the "excess" separators (all eligible) at point g and of the remaining share of ineligible separators. Specifically:

$$cl_0 = \sigma A_1 + (1-\sigma)A_0 \tag{A23}$$

$$cl_g = \frac{sep_g - sep_0}{sep_g} A_1 + \frac{sep_0}{sep_g} cl_0. \tag{A24}$$

This gives rise to one equation in one unknown. Hence:

$$A_1 = \frac{sep_g}{sep_g - sep_0}\left(cl_g - \frac{sep_0}{sep_g} cl_0\right). \tag{A25}$$

Similarly, for the probability of appeal at 0 and at g gives rise to one equation in one unknown:

$$pa_0 = p_0 \frac{(1-\sigma)A_0}{(1-\sigma)A_0 + \sigma A_1} + p_1 \frac{\sigma A_1}{(1-\sigma)A_0 + \sigma A_1} \tag{A26}$$

$$pa_0 = p_0 \frac{(1-\sigma)A_0}{cl_0} + p_1 \frac{\sigma A_1}{cl_0} \tag{A27}$$

$$pa_g = pa_0 \frac{sep_0 cl_0}{sep_g cl_g} + \frac{sep_g cl_g - sep_0 cl_0}{sep_g cl_g} p_1 \tag{A28}$$

$$p_1 = (pa_g - pa_0 \frac{sep_0 cl_0}{sep_g cl_g}) \frac{sep_g cl_g}{sep_g cl_g - sep_0 cl_0}. \tag{A29}$$

Finally, for the probability of receiving UI conditional on applying and being challenged:

$$rec_0 = \frac{p_0(1-\sigma)A_0}{p_0(1-\sigma)A_0 + p_1\sigma A_1} r_0 + r_1 \frac{p_1 \sigma A_1}{p_0(1-\sigma)A_0 + p_1 \sigma A_1} \tag{A30}$$

$$rec_g = \frac{sep_0 cl_0 pa_0}{sep_g cl_g pa_g} rec_0 + \frac{sep_g cl_g pa_g - sep_0 cl_0 pa_0}{sep_g cl_g pa_g} r_1 \tag{A31}$$

$$r_1 = \frac{sep_g cl_g pa_g}{sep_g cl_g pa_g - sep_0 cl_0 pa_0}(rec_g - \frac{sep_0 cl_0 pa_0}{sep_g cl_g pa_g} rec_0). \tag{A32}$$

D.2 Firm-averaged parameters for the ineligible

To compute the parameters related to the ineligible population, we use the additional moment from the BAM data that the share of ineligible workers among dollars paid out is 12.7%, which we assume refers to firms with zero growth rate, $g = 0$. We further assume that the dollars paid out to the eligible and ineligible are identical.

The mass of ineligible workers who collect is given by:

$$(1-\sigma)A_0p_0r_0 + (1-\sigma)A_0(1-p_0) = (1-\sigma)A_0(1-(p_0(1-r_0))). \tag{A33}$$

The first term says that a worker applies, is challenged and collects. The second terms sys that a worker applies and is not challenged (and so collects). Analogous expressions apply to the eligible. Hence, the share of ineligible workers among those who collect UI is given by:

$$inelig_0 = \frac{(1-\sigma)A_0(1-(p_0(1-r_0)))}{(1-\sigma)A_0(1-(p_0(1-r_0))) + \sigma A_1(1-p_1+p_1r_1)}. \tag{A34}$$

We now have four equations ((A23), (A26), (A30), and (A34)) in four unknowns (σ, A_0, p_0 and r_0).

We first rearrange (A23), (A26), and (A30):

$$A_0 = \frac{cl_0 - \sigma A_1}{1-\sigma} \tag{A35}$$

$$p_0 = \frac{pa_0 - p_1\frac{\sigma A_1}{(1-\sigma)A_0+\sigma A_1}}{\frac{(1-\sigma)A_0}{(1-\sigma)A_0+\sigma A_1}} = \frac{pa_0((1-\sigma)A_0+\sigma A_1) - p_1\sigma A_1}{(1-\sigma)A_0} \tag{A36}$$

$$r_0 = \frac{rec_0 - r_1\frac{p_1\sigma A_1}{p_0(1-\sigma)A_0+p_1\sigma A_1}}{\frac{p_0(1-\sigma)A_0}{p_0(1-\sigma)A_0+p_1\sigma A_1}} = \frac{rec_0(p_0(1-\sigma)A_0+p_1\sigma A_1) - r_1p_1\sigma A_1}{p_0(1-\sigma)A_0}. \tag{A37}$$

We combine equation (A36) and (A37) to write:

$$p_0(1-r_0) = \frac{pa_0((1-\sigma)A_0+\sigma A_1) - p_1\sigma A_1}{(1-\sigma)A_0}\left(1 - \frac{rec_0(p_0(1-\sigma)A_0+p_1\sigma A_1) - r_1p_1\sigma A_1}{p_0(1-\sigma)A_0}\right) \tag{A38}$$

$$= \frac{pa_0((1-\sigma)A_0+\sigma A_1) - p_1\sigma A_1}{(1-\sigma)A_0}\left(\frac{(1-rec_0)p_0(1-\sigma)A_0 - (rec_0-r_1)p_1\sigma A_1}{p_0(1-\sigma)A_0}\right) \tag{A39}$$

$$= \frac{pa_0((1-\sigma)A_0+\sigma A_1) - p_1\sigma A_1}{(1-\sigma)A_0}\left(\frac{(1-rec_0)(1-\sigma)A_0 - (rec_0-r_1)\frac{p_1(1-\sigma)A_0}{pa_0((1-\sigma)A_0+\sigma A_1)-p_1\sigma A_1}\sigma A_1}{(1-\sigma)A_0}\right) \tag{A40}$$

$$= \frac{pa_0((1-\sigma)A_0+\sigma A_1) - p_1\sigma A_1}{(1-\sigma)A_0}\left(\frac{(1-rec_0) - (rec_0-r_1)\frac{p_1}{pa_0((1-\sigma)A_0+\sigma A_1)-p_1\sigma A_1}\sigma A_1}{1}\right). \tag{A41}$$

Now we substitute in for (A35):

$$
\begin{aligned}
p_0(1-r_0) &= \frac{pa_0cl_0 - p_1\sigma A_1}{cl_0-\sigma A_1}\left(\frac{(1-rec_0)-(rec_0-r_1)\frac{p_1}{pa_0cl_0-p_1\sigma A_1}\sigma A_1}{1}\right) && \text{(A42)}\\
&= \frac{(1-rec_0)(pa_0cl_0-p_1\sigma A_1)-(rec_0-r_1)p_1\sigma A_1}{cl_0-\sigma A_1} && \text{(A43)}\\
&= \frac{(1-rec_0)pa_0cl_0-(1-r_1)p_1\sigma A_1}{cl_0-\sigma A_1} && \text{(A44)}\\
1-p_0(1-r_0) &= \frac{cl_0-\sigma A_1-(1-rec_0)pa_0cl_0+(1-r_1)p_1\sigma A_1}{cl_0-\sigma A_1}. && \text{(A45)}
\end{aligned}
$$

Now substitute (A35) and (A45) into equation (A34) to have:

$$
\begin{aligned}
inelig_0 &= \frac{cl_0-\sigma A_1-(1-rec_0)pa_0cl_0+(1-r_1)p_1\sigma A_1}{cl_0-\sigma A_1-(1-rec_0)pa_0cl_0+(1-r_1)p_1\sigma A_1+\sigma A_1(1-p_1+p_1r_1)} && \text{(A46)}\\
&= \frac{cl_0-\sigma A_1-(1-rec_0)pa_0cl_0+(1-r_1)p_1\sigma A_1}{cl_0-(1-rec_0)pa_0cl_0}. && \text{(A47)}
\end{aligned}
$$

Now we simplify to solve for σ in closed form:

$$
\begin{aligned}
inelig_0\,(cl_0-(1-rec_0)pa_0cl_0) &= cl_0-\sigma A_1-(1-rec_0)pa_0cl_0+(1-r_1)p_1\sigma A_1 && \text{(A48)}\\
\frac{(1-inelig_0)\,(cl_0-(1-rec_0)pa_0cl_0)}{A_1(1-(1-r_1)p_1)} &= \sigma. && \text{(A49)}
\end{aligned}
$$

Given σ, we solve for $\{A_0, p_0, r_0\}$ using equations (A35)-(A37).

D.3 Elasticity of appeals rate with respect to experience rating

If firm j has weight ω_j among applicants, then:

$$
\begin{aligned}
p_1^* &= \sum_j \omega_j \left(\frac{(1-r_1)\tau}{\eta_j\zeta}\right)^{\frac{1}{\zeta-1}}\\
&= \left(\frac{(1-r_1)\tau}{\zeta}\right)^{\frac{1}{\zeta-1}} \sum_j \omega_j \left(\frac{1}{\eta_j}\right)^{\frac{1}{\zeta-1}}. && \text{(A50)}
\end{aligned}
$$

And, analogously for p_0:

$$
p_0^* = \left(\frac{(1-r_0)\tau}{\zeta}\right)^{\frac{1}{\zeta-1}} \sum_j \omega_j \left(\frac{1}{\eta_j}\right)^{\frac{1}{\zeta-1}}. \qquad \text{(A51)}
$$

Note that $r_1 > r_0 \implies p_1 < p_0$. Someone eligible for UI ($e = 1$) is much more experience-rated than someone not UI-eligible.

Finally, dividing the two p^*s and rearranging in terms of estimates gives that,

$$\frac{\hat{p}_1}{\hat{p}_0} = \left(\frac{1-r_1}{1-r_0}\right)^{\frac{1}{\zeta-1}} \tag{A52}$$

$$\zeta = \frac{\ln {}^{1-r_1}/_{1-r_0}}{\ln {}^{p_1}/_{p_0}} + 1. \tag{A53}$$

Thus, given $\{\hat{p}_1, \hat{p}_0, \hat{r}_1, \hat{r}_0\}$ we can get an estimate of ζ.

D.4 Firm-level distributions of appeals rates

In Table 4, we show the estimated (worker-weighted) firm-level distributions of appeals rates. We map these into firm-level claims rates by assuming that the firm-level rates follow a beta distribution where the mean is the overall sample mean and the variance is given from our estimates.

We use the assumption that the share of eligible and ineligible workers is the same across firms. Hence, we can write:

$$\hat{p}_j = \frac{\sigma \hat{A}_1}{\sigma \hat{A}_1 + (1-\sigma)\hat{A}_0} p_{1,j} + \frac{(1-\sigma)\hat{A}_0}{\sigma \hat{A}_1 + (1-\sigma)\hat{A}_{0j}} p_{0,j} \tag{A54}$$

$$\hat{p}_j = \frac{\sigma \hat{A}_1}{\sigma \hat{A}_1 + (1-\sigma)\hat{A}_0} p_{0,j} \left(\frac{1-r_1}{1-r_0}\right)^{\frac{1}{\zeta-1}} + \frac{(1-\sigma)\hat{A}_0}{\sigma \hat{A}_1 + (1-\sigma)\hat{A}_0} p_{0,j} \tag{A55}$$

$$\hat{p}_{0,j} = \frac{\hat{p}_j}{\frac{\sigma \hat{A}_1}{\sigma \hat{A}_1 + (1-\sigma)\hat{A}_0} \left(\frac{1-r_1}{1-r_0}\right)^{\frac{1}{\zeta-1}} + \frac{(1-\sigma)\hat{A}_0}{\sigma \hat{A}_1 + (1-\sigma)\hat{A}_{0j}}} \tag{A56}$$

$$\hat{p}_{1,j} = \hat{p}_{0,j} \left(\frac{1-r_1}{1-r_0}\right)^{\frac{1}{\zeta-1}}, \tag{A57}$$

where the second equation uses the firm-level version of equation (A52). Combined, this step gives us estimates of $\{p_{1j}, p_{0j}\}$. Note that given these values, and $\{r_0, r_1, \zeta\}$ we can use equation (2) to back out η_j up to a scale factor that depends on the units of τ.

D.5 Simulated firm-level distribution of take-up rates

Here, we describe how we calculate the simulated distribution of firm effects of UI take-up.

First, we make the strong assumption that the cross-sectional elasticity between firm effects for take-up and firm effects appeals, $\hat{\epsilon} = -0.16$, estimated in Section 5.5 is causal.

Second, we generate a simulated distribution of firm appeals rates. We do this by generating a beta distribution with a support equal to $J = 20,000$ observations. We assign its mean to equal the mean of the appeals rate in the leave-one-out sample, and its variance to equal the KSS-variance in the leave-one-out sample. We then sort the simulated observations by their appeals rates, $\tilde{p}_j$, for $j = 1, ..., J$.

Third, we re-write the elasticity of firm-level take-up rates with respect to firm-level appeals rates, ϵ, as

$$\frac{\partial A}{\partial p}\frac{p}{A} = \epsilon, \tag{A58}$$

Where A denotes firm-level application rates (take-up) and p denotes firm-level appeals. We can approximate this elasticity as follows:

$$\frac{\frac{A_{j+1}-A_j}{A_j}}{\frac{p_{j+1}-p_j}{p_j}} \approx \epsilon \tag{A59}$$

Re-arranging the equation above in terms of A_{j+1} and denoting simulated moments by "$\sim$" we have:

$$\tilde{A}_{j+1} \approx \epsilon(\tilde{A}_j \frac{\tilde{p}_{j+1}-\tilde{p}_j}{\tilde{p}_j}) + \tilde{A}_j. \tag{A60}$$

Fourth, given some initial starting point for the take-up rate for firm 1, $\tilde{A}_{j=1}$ we search over a grid (width 0.00001) for an updated guess of $\tilde{A}_j$ such that the simulated mean application rate matches the mean take-up rate in the data.

Finally, we compute the variance over the vector of $\tilde{A}$s, which equals 0.0019, and relate it to the KSS-variance of firm effects for take-up, which equals 0.022 (se Table 4). The share of variance firm effects for take-up explained by firm appeals is thus about 10 percent (= $0.0019/0.022$).

We then use the assumption that the share of eligible and ineligible separators is the same across firms ($\frac{A_{1j}}{A_{0j}} = \frac{A_1}{A_0}$) to split the A_j:

$$\sigma A_{1j} + (1-\sigma)A_{0j} = A_j \tag{A61}$$

$$A_{1j} = \frac{A_j}{\sigma + (1-\sigma)\frac{A_0}{A_1}}. \tag{A62}$$

Finally,

$$A_{0j} = \frac{A_j - \sigma A_{1j}}{1-\sigma}. \tag{A63}$$

This gives $\{A_{1j}, A_{0j}\}$.

D.6 Model fit

We fit the model using two points of firm growth: firm growth around 0, and a negative growth rate, $g = -0.30$. To assess the fit of the model, we ask how the model fits the data at growth rates that we did not use. To do so, we take as given the separation rates by firm growth rate, and then compute the resulting model predictions for the UI take-up rate, challenge rate, and receipt rate.

$$cl_g = \frac{sep_g - sep_0}{sep_g} A_1 + \frac{sep_0}{sep_g}(\sigma A_1 + (1-\sigma)A_0). \tag{A64}$$

$$pa_g = pa_0 \frac{sep_0 cl_0}{sep_g cl_g} + \frac{sep_g cl_g - sep_0 cl_0}{sep_g cl_g} p_1. \tag{A65}$$

Finally, for the probability of receiving UI conditional on applying and being challenged:

$$rec_g = \frac{sep_0 cl_0 pa_0}{sep_g cl_g pa_g} rec_0 + \frac{sep_g cl_g pa_g - sep_0 cl_0 pa_0}{sep_g cl_g pa_g} r_1. \tag{A66}$$

D.7 Details on counterfactuals

For a 10% decrease in experience rating, we use our estimates of ζ to compute the firm-specific changes in challenge probabilities.

We can write:

$$p^*_{e,j} = \left(\frac{(1-r_e)\tau}{\eta_j \zeta}\right)^{\frac{1}{\zeta-1}} \tag{A67}$$

$$\frac{\eta_j}{\tau} = \frac{1-r_e}{p^{*\zeta-1}_{e,j}\zeta} \tag{A68}$$

Then we can replace $\frac{\tau}{\eta_j}$ with $0.9\frac{\tau}{\eta_j}$ to solve for the counterfactual $p^{*c}_{e,j}$. From there, we find the $\{j,k\}$ that minimizes the distance between p^c_j and p_k. Then we set $A^c_j = A_k$. And then iterate forward and backward using our knowledge of the p^c_j and the elasticities of claiming with respect to challenges to solve for the remaining A^c_j.

E Elasticities in Anderson and Meyer (2000)

Table 4 of reports the mean of monthly claims in Washington State from 1972-1984 of 0.0304. The quarterly separation issue denials/quarterly claims in the same period and state is 0.0521.

We use these levels to convert the estimates in Table 5 and Table 6 of implied elasticities of claims with respect to separation issue denials, which is the closest conceptually to a measure of claims with respect to challenges (Table 5 compares to all other states and DC; table 6 compares to Oregon and Idaho). Each of these tables has 3 columns corresponding to no controls, state times log US unemployment rate, and state times log state unemployment rate.

	(1)	(2)	(3)
Table 5 (50 states, DC)	-0.277	-0.279	-0.183
Table 6 (Oregon and Idaho)	-0.149	-0.237	-0.128
Controls	None	State $\times$ ln(US UR)	State $\times$ ln (state UR)