Worker Beliefs about Layoff Risk

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Abstract

Job loss is one of the most costly economic risks workers face, but a firm's layoff risk is difficult to observe. We document substantial, persistent variation in firm layoff rates, creating scope for workers to change their job loss risk through firm choice. We exploit linked survey, experimental, and administrative data from Austria to examine how unemployed workers perceive and respond to information about firm-level layoff risk. Workers believe that past layoffs are predictive of future risk and prefer jobs at firms with lower historical layoff rates, but have significant misperceptions about which firms are safer. Providing workers with information about firm layoff histories causes them to redirect their search toward historically safer employers. Using a search and matching model, we show that imperfect information distorts equilibrium outcomes: it reverses the compensating differential for layoff risk and raises the average layoff rate by allocating more workers to high-risk firms.

Keywords: job search, employment risk, beliefs, separation rates, field experiment
JEL codes: C93, D83, E24, J01, J64

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1 Introduction

Job loss is one of the most costly economic risks workers face—it generates large earnings losses, adverse health and family outcomes, and ranks as a top concern when workers evaluate jobs (Jacobson et al., 1993; Schmieder et al., 2023; Sullivan and von Wachter, 2009; Charles and Stephens, 2004; Schoefer, 2025). Employers vary strongly and persistently in their layoff rates. This heterogeneity has consequences for workers: workers who switch to firms with higher past layoff rates face a greater risk of future job loss. In theory, workers can mitigate their layoff risk by working at a safer firm, but in practice, layoff risk may be harder to observe than wages and amenities. Incomplete information about firm layoff risk could affect workers' labor market choices, distorting compensating differentials workers receive for risk, the sorting of workers into safe jobs, and firms' choices of layoffs.

This paper establishes that workers have imperfect information about firm-level layoff risks and assesses the individual and market-level consequences of those beliefs. First, we use Austrian administrative data to show that workers could reduce their employment risk through firm choice. Second, we survey unemployed workers to measure their knowledge of layoff rates and conduct an information provision experiment to test how new information affects their beliefs about personal risk and job search behavior. Third, we develop and estimate a search model to quantify the equilibrium effects of imperfect information on compensating differentials and aggregate separation rates.

To motivate our survey and experimental design, we examine the extent to which observable firm-level layoff rates can provide job seekers with useful predictive information about employment risk. If firm layoff rates vary unexpectedly from year to year, or if there is very little variation in the layoff rates among otherwise similar firms, a worker's choice of firm may have little impact on their exposure to job loss risk. Our results show that this is not the case: layoff rates vary significantly across firms, even among observably similar firms. These differences are persistent. Past layoffs are strongly predictive of future layoffs. Variation in layoff rates across similar firms tends to be driven by persistent differences in churn rather than by differences in growth rates, consistent with the Burgess et al. (2000) theory that differences in churn across firms reflect different choices of "personnel policy." Next, we ask whether these differences are driven by worker effects or firm effects. If differences across firms are driven by worker sorting (for example, less reliable workers working at different firms), then workers cannot change their exposure to layoff risk by moving firms. We find that these differences *cannot* be fully explained by worker selection: *moving* to historically "riskier" firms increases a worker's future risk of job loss.

Having shown that workers *could* reduce their job loss risk by working at safer firms, we then ask: do workers know which firms have lower layoff rates, and do they care? To answer these questions, we survey unemployed individuals in Lower Austria, the second most populous state in Austria (after Vienna), in partnership with the Public Employment Service of Lower Austria. Constructing an objective benchmark to evaluate worker beliefs presents two challenges: we cannot directly measure workers' future layoff risk, and we do not observe the set of firms workers may apply to. To address these challenges, we leverage the fact that past layoffs provide an observable measure of layoff risk. We ask workers about the layoff rate last year at the firm they used to work at before becoming unemployed. Asking about the firm they worked at allows us to link them to the correct firm in the administrative data and calculate the empirical benchmark. A worker's knowledge of layoffs at their most recent firm likely provides an upper bound on their knowledge of layoffs at prospective firms.

We find that workers have limited information about the firm they used to work at. Just 52% of respondents are correct about whether their firm's 2023 layoff rate was above or below median—no better than if they guessed randomly. Workers from firms with layoff rates in the top 10% believe their firms were near the median on average. These results suggest that workers know very little about differences in layoff rates across firms they are considering applying to.

Next, we show that these misperceptions matter for worker choices. Workers may not care about past layoff rates: they may not believe that past layoffs are predictive of future layoffs, or they may have private information about their ability or fit at different types of firms. To understand whether workers value accurate information about a firm's historical layoffs, we conduct a hypothetical choice experiment and an information provision experiment within the survey. In the hypothetical choice experiment, workers make repeated choices between two hypothetical jobs, which vary in their compensation and the share of workers the firm laid off in the previous year. The elicitation reveals workers' willingness to pay (WTP) for lower historical layoff risk. We estimate that the median participant is willing to sacrifice 2.2% of their compensation to work at a firm that laid off 1 percentage point fewer workers last year.

We then use an information provision experiment to understand worker beliefs about the relationship between past layoffs and future risk and to test how these beliefs affect job search behavior. The treatment provides information about historical layoffs at different types of firms. Since we cannot provide information about specific firms, we leverage the fact that highly observable firm characteristics (e.g. firm size) are correlated with layoff risk. Consistent with the firm-level evidence, we document substantial misperceptions about which firm characteristics are safer. After treatment, we elicit workers' beliefs about their own future layoff risk if they were to work at each firm type. Workers who learn a firm type had a 10 percentage point higher layoff rate believe they are 4.3 (std. err. 0.97) percentage points more likely to be laid off at that firm type, revealing they correctly view past rates as predictive of personal risk. Next, we ask whether this information causes workers to direct their search towards firms they learn are safer. We find that believing they are 10 percentage points more likely to be laid off at a type of firm causes workers to plan to submit 0.6 (std. err. 0.3) or 26% fewer applications to that type of firm.

The survey provides evidence that workers value information about which firms lay off more of their staff, yet they are generally misinformed. These misperceptions may also affect workers by distorting wages, equilibrium separation rates, and the allocation of workers across firms. Combining evidence from the administrative data and the survey, we use a model to quantify the equilibrium effects of correcting the beliefs of all workers. We write and estimate a search and matching model in which firms have heterogeneous layoff rates and unemployed workers make decisions based on the posted wage and incomplete information about the layoff rate. The model generates several key insights. First, it shows how incomplete information can generate a negative compensating differential, which we observe in the data. Second, we find that even substantial improvements in information precision (short of perfect information) only modestly restore compensating differentials. Third, the equilibrium effect of information on the average layoff rate is theoretically ambiguous: information causes some high layoff rate firms to grow by forcing them to pay relatively more, while causing some to exit. The effect of information on aggregate separation rates is thus a quantitative question: we find that providing information lowers the average separation rate, moving workers to lower layoff rate firms, and increasing employment overall.

Our work contributes to existing research on job loss, worker beliefs, and job characteristics. First, this paper contributes to the literature studying the causes of job loss. There is substantial research on how unexpected, time-varying, or industry-wide shocks can cause job loss (Autor et al., 2013; Chodorow-Reich, 2014; Bloom, 2009). These are often difficult to observe ex-ante or difficult for workers to respond to. They are also generally tied to firms contracting in size. By contrast, this paper contributes to a much smaller literature studying persistent, cross-sectional variation in layoff rates across similar firms (Burgess et al., 2000; Jarosch, 2023; Davis and Haltiwanger, 1992). We document substantial heterogeneity among observably similar firms, show evidence of persistent firm effects in layoff rates, and show that this persistence cannot be explained by worker selection. We also contribute to this literature by showing that workers are relatively uninformed about these differences across firms and showing how these beliefs shape the equilibrium distribution of layoff rates.

This paper is also closely related to the literature on worker beliefs about the labor market and the consequences of these beliefs. Previous work has shown how worker beliefs about their outside options (Jäger et al., 2024), aggregate employment risk (Roth and Wohlfart, 2020; Roth et al., 2022), managers' pay (Cullen and Perez-Truglia, 2022), coworkers' pay (Card et al., 2012), and alternative occupations (Belot et al., 2019) affect their labor market decisions. We consider a new characteristic of jobs, the layoff rate, establish that it has important consequences for employment risk, and show how beliefs about the distribution of firm-level layoff rates affect worker decisions. Importantly, workers *correctly* believe that higher past layoffs increase future job loss risk, but do not know which firms had lower past layoffs. Beliefs about layoffs matter because job loss risk is highly consequential for workers while hard to observe. We also contribute to this literature by building a general equilibrium model of imperfect information about layoff rates in the labor market and quantifying the equilibrium consequences of worker beliefs.

We contribute to the literature measuring worker valuations of job characteristics, as previously documented for scheduling flexibility (Mas and Pallais, 2017), working conditions (Maestas et al., 2023), stress and meaning (Kaplan and Schulhofer-Wohl, 2018), flexibility and job stability (Wiswall and Zafar, 2018), and other firm-specific factors (Caldwell et al., 2025). We show that workers value jobs with historically lower layoff rates and provide willingness to pay estimates that can be benchmarked against other job characteristics. We also contribute to this literature by exploring the relationship between the characteristics workers value and the extent to which they can observe them. We show that workers value lower employment risk and (correctly) believe past layoffs are predictive of future layoffs, but have poor information about which firms had lower past layoffs. This suggests that workers may value job characteristics in a way that may not be fully captured by real-world decisions in cases when workers have poor information.

The paper proceeds as follows. Section 2 provides institutional context. Section 3 shows evidence on the heterogeneity and persistence of firm effects in layoff rates. Section 4 describes the survey and experimental design. Section 5 presents survey results on misperceptions and the experimental results. Section 6 presents a search model with imperfect information. We estimate the model in Section 7. Section 8 concludes.

2 Setting and Institutional Context

Our study is conducted in partnership with Austria's Public Employment Service (PES; Arbeitsmarktservice, AMS), which assists in the dissemination of our survey to the full population of registered unemployed individuals in the state of Lower Austria.[1] The PES serves as a one-stop shop for the unemployed, administering unemployment benefits and

[1] We do not receive compensation from the PES and retain full rights to independently publish all findings.

implementing active labor market programs. The agency delivers a comprehensive portfolio of services including job search assistance, training, employment subsidies, and public job creation schemes. Eligibility for unemployment benefits requires prior contributions through insured employment and continued engagement with the PES, typically through scheduled meetings, documentation of search effort, and compliance with job and training referrals.

Lower Austria (Niederösterreich) is Austria's second most populous state, with a population of around 1.7 million. The state encircles the capital city of Vienna and combines urbanized commuter regions near Vienna, older industrial towns, and rural agricultural areas. Its employment structure closely mirrors the national composition, with 72.3 percent of workers employed in services (72.3 percent nationally), 23.6 percent in industry (24.8 percent nationally), and 4.0 percent in agriculture (2.8 percent nationally) (Statistics Austria, 2025). Approximately 20 percent of Lower Austria's population has a migration background and the labor force includes a sizable share of cross-border commuters from neighboring countries, who are equally eligible for unemployment benefits and PES support, provided they satisfy the required contribution period. At the time of the experiment, Lower Austria had an unemployment rate of 6 percent, compared to the national rate of 7.1 percent.

Under Austrian law, employer contributions to unemployment insurance are not experience-rated and therefore do not vary with a firm's layoff history. This contrasts with the United States but aligns with common practice across much of Europe. All employers pay a uniform percentage of each employee's wage. The unemployment insurance system provides earnings-related benefits to unemployed workers, with a baseline net replacement rate of 55 percent of the previous wage. After six to twelve months of an unemployment spell, this rate declines slightly to about 52 percent, after which benefits can be drawn indefinitely, conditional on active job-search requirements. Additional supplements are provided to individuals with dependent children, unemployed spouses, or very low benefit entitlements. Employment protection is modest by European standards: fixed-term contracts are permitted, and dismissals of permanent employees are allowed with formal justification and adherence to statutory notice periods. In practice, many separations occur through mutual agreements that allow the notice period to be shortened or waived.

Compared to other countries, Austria combines above EU-average employment (74.1% of working-age adults) with below EU-average unemployment (5.2% of the labor force), though many women work part-time while raising children (Kleven et al., 2024). This compares to a 71.9% employment rate and 4% unemployment rate in the US. The Austrian labor market is relatively dynamic by European standards, with annual transitions across jobs or into/out of employment slightly above the EU average (24% versus 22.5%), but still far below the US at 60% (Causa et al., 2021). Whereas hiring from non employment has declined across most

OECD countries over the past two decades, it has increased in Austria. These patterns reflect sectoral composition, the prevalence of seasonal work (concentrated in tourism, agriculture, and construction), and institutional features including medium-low employment protection, medium-high unemployment benefits, and highly developed active labor market policies, particularly training (Card et al., 2007; Lehner and Schwarz, 2024).

3 Firm effects in layoff rates: motivation from administrative data

Our survey design and interpretation are motivated by three key empirical patterns, which we establish in this section: first, that firms vary meaningfully in their layoff rates; second, that this variation persists over time, making past layoffs informative about future risk; and third, that this variation reflects systematic firm differences rather than purely idiosyncratic shocks or worker sorting.

3.1 Data

Our primary data source is the Austrian Labour Market Database (AMDB), a comprehensive linked employer-employee administrative dataset based on social insurance records that covers the universe of employment in Austria. It records daily employment and unemployment spells, wages, worker demographics (age, gender, nationality), and firm attributes (industry, region, firm size). Additionally, the PES provided information on individuals' previous jobs and the reason for unemployment where available.

Given that we do not directly observe whether a job separation is voluntary, we define a layoff as being a separation where the worker spends at least seven days in unemployment. This is a standard measure of involuntary separations, as it excludes quits for another job or quits out of the labor force. Our definition also includes the termination of fixed-term contracts. Though, in theory, workers know when the fixed-term contract will end when they begin the job, workers often (correctly) expect that the job may convert to a permanent job.[2] In other words, there is still substantial uncertainty about the odds of being employed at that firm one year later, even if the contract will have ended by then.[3] Importantly, we tell our survey participants that this is our definition of a layoff.

[2]This is also often an explicit policy aim. For example, firms in Austria are legally required to inform fixed-term employees of any permanent employment relationships that become available.

[3]It is also worth noting that employment on fixed contracts is below the EU average at about 8% of employment and is concentrated among workers age 15-29.

We also validate this measure with data on the reason for unemployment collected by the Public Employment Services. This information is incomplete, so we are not able to construct measures of the layoff rate using it. We can use it to validate our measure of layoffs. Of the job spells we classify as ending with transitions "from employment to at least 7 days of unemployment", only 2% are recorded as quits.[4] However, it is important to note that terminations of employment by mutual agreement are very common in Austria. Mutual agreement allows for the end of an employment relationship without a notice period, though it makes it difficult to identify the party responsible for initiating the termination. For this reason, we prefer our definition of separations into unemployment.

3.2 Distribution and persistence of firm-level layoff rates

Firms vary widely in their layoff rates. Figure 1 plots a histogram of annual firm layoff rates in 2023. If this heterogeneity reflects purely transitory shocks hitting different firms in different years, there is little workers can do to improve their layoff risk. To understand whether this heterogeneity is persistent, or reflects idiosyncratic shocks, Figure 2 presents a binscatter plot of current-year layoff rates against prior-year rates, controlling for year fixed effects. Next, we regress firm layoff rates this year on their layoff rates last year, with no fixed effects. We estimate

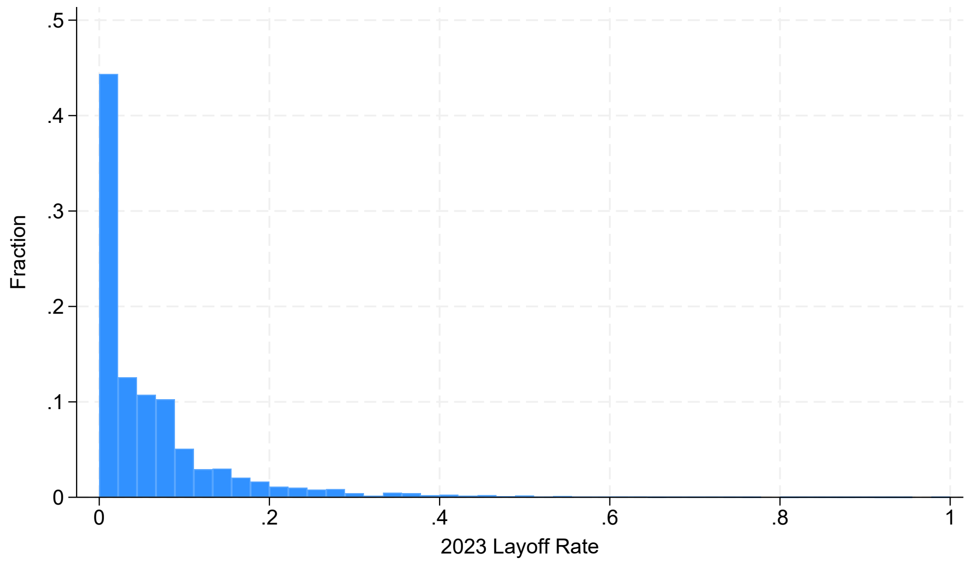
$$\delta_{it} = \beta\delta_{i,t-1} + \epsilon_{it} \tag{1}$$

where δ_{it} is the layoff rate for firm i at year t. Table 1 shows regression estimates of equation 1. Column 1 shows estimates for all firms with over 10 employees. A 1 percentage point higher layoff rate last year predicts a 0.64 ppt higher layoff rate this year. The R-squared of last year's layoff rate is 0.39. That is, last year's layoff rate is strongly predictive of this year's. This relationship is even stronger for larger firms, which employ a majority of the population. Column 2 shows the results for firms with more than 100 workers. The R-squared is 0.75. The high predictive power could also be explained by the fact that firms that grow in one year are likely to be growing in the next year. However, Column 3 shows that the firm's growth rate is not strongly predictive of its layoff rate.

To what extent is this pattern explained by observable characteristics of firms? If layoff rates are bundled with other firm characteristics (wages, industry), then workers may be unable to find a job at a lower layoff rate firm without switching to a job that is substantially different in other ways. Column 4 regresses layoff rates on firm size bin X wage X NACE 6 (6 digit industry codes) X year fixed effects and growth rates. These detailed observable

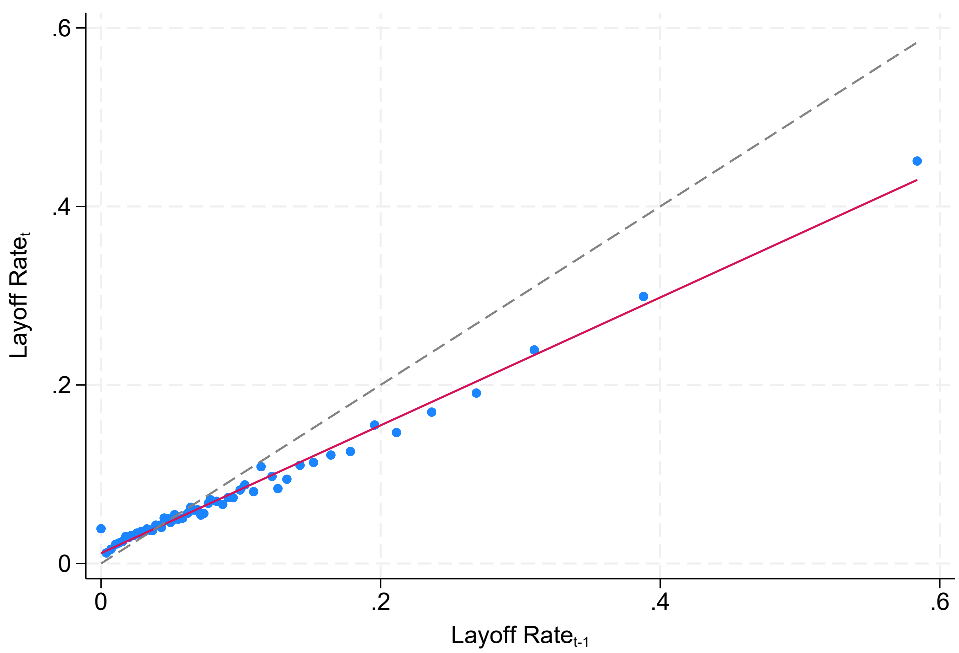
[4] By contrast, 19% of spells ending with an EE transition are recorded as quits. However, this is likely an underestimate since workers making an EE transition need not register with the public employment services.

Figure 1: Histogram of 2023 layoff rates



Notes: This figure presents a histogram of 2023 firm layoff rates for firms with more than 10 workers.

Figure 2: Persistence in layoff rates



Notes: This figure presents a bin scatter of a firm's layoff rate in 2023 on its layoff rate in 2022 for firms with more than 10 workers in 2023.

characteristics are also quite predictive of layoff rates, with an R-squared of 0.36. (We leverage this fact later in our experimental design). However, even on top of these characteristics, the layoff rate last year is a powerful predictor of the layoff rate, increasing the R-squared to 0.56. In other words, there is substantial heterogeneity in layoff rates, conditional on detailed observable characteristics of firms. Even among observably similar firms, last year's layoff rate is a good predictor of this year's layoff rate. Together, these results suggest that persistent variation in layoff rates across firms may be best thought of as differences in churn, potentially, for example, driven by a firm's choice of "personnel policy" (as hypothesized by Burgess et al. (2000)).

Next we regress the firm layoff rate on different lags of the layoff rate.

$$\delta_{it} = \beta \delta_{i,t-\tau} + \epsilon_{it} \tag{2}$$

We estimate equation 2 for $\tau = 1, 2, 3, 4, 5$. Table 2 shows these results. The layoff rate 5 years ago remains a strong predictor of the layoff rate this year, with a 1 percentage point higher layoff rate 5 years ago predicting a 0.47 ppt higher layoff rate this year, with an r-squared of 0.28. Together, these tables show that heterogeneity in layoff rates is not just driven by idiosyncratic shocks, with different firms laying workers off in different years.

Table 1: Predictors of Layoff Rates

	(1) Layoff Rate$_t$	(2) Layoff Rate$_t$	(3) Layoff Rate$_t$	(4) Layoff Rate$_t$	(5) Layoff Rate$_t$
Layoff Rate$_{t-1}$	0.64***	0.84***			0.56***
	(0.0028)	(0.012)			(0.0019)
Growth Rate$_t$			-0.056***	-0.039***	-0.037***
			(0.0081)	(0.00071)	(0.00059)
Growth Rate$_{t-1}$			0.000023	0.000035	0.000022
			(0.000023)	(0.000025)	(0.000021)
Constant	0.031***	0.0075***	0.082***	0.088***	0.040***
	(0.00020)	(0.00054)	(0.00021)	(0.00024)	(0.00026)
Firm size-wage -NACE 6-year FEs				Yes	Yes
>100 workers		Yes			
R^2	0.39	0.75	0.024	0.36	0.56
N	383589	39990	346633	203804	203804

Notes: This table presents predictors of firm layoff level. Column 1 regresses layoff rates on lagged firm layoff rates. The Growth Rate is the firm-level growth rate. NACE 6 denotes six-digit industry codes. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2: Predictors of Layoff Rates

	(1) Layoff Rate$_t$	(2) Layoff Rate$_t$	(3) Layoff Rate$_t$	(4) Layoff Rate$_t$	(5) Layoff Rate$_t$
Layoff Rate$_{t-1}$	0.64***				
	(0.0028)				
Layoff Rate$_{t-2}$		0.57***			
		(0.0030)			
Layoff Rate$_{t-3}$			0.52***		
			(0.0030)		
Layoff Rate$_{t-4}$				0.51***	
				(0.0032)	
Layoff Rate$_{t-5}$					0.47***
					(0.0033)
Constant	0.031***	0.033***	0.034***	0.033***	0.033***
	(0.00020)	(0.00022)	(0.00023)	(0.00023)	(0.00025)
R^2	0.39	0.34	0.31	0.30	0.28
N	383589	348633	314178	280456	247979

Notes: This table shows regressions of firm level layoff rates on different lags of the layoff rate. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

3.3 Disentangling worker selection from firm effects

We have shown significant heterogeneity in firm layoff rates that is highly persistent. But the extent to which this is driven by firm or worker effects matters. If the heterogeneity in firm layoff rates is driven by worker selection, then workers would not be able to reduce their exposure to layoff risk by applying to low layoff rate firms. To disentangle these forces, we compare workers who moved to a high layoff rate firm with those who moved to a low layoff rate firm. This allows us to estimate an event study-style design and control for time-invariant worker characteristics.

Specifically, we look at workers who started a new job between 2013 and 2019 (using data from 2010 to 2024). The year the worker begins a new job for the first time in 2013 or later is assigned event time $\tau = 0$. We restrict to workers who did not move jobs in the three-year pre-period and do not treat subsequent job moves as events. This means that each worker is only treated once. We also require the new job to have been the result of an EE transition (employment to employment). Otherwise, workers who move to higher layoff rate firms may be those who left their previous job involuntarily—they may be experiencing a time-varying negative worker effect. We define ΔLayoff Rate$_i$ as the layoff rate at the worker's new firm minus the layoff rate at the worker's old firm. Both layoff rates are calculated on the pre period, so this measure is time invariant and set before the worker was employed at the new firm, avoiding introducing any mechanical correlation between the new firm's layoff rate and the layoff probability of the worker in the post period.

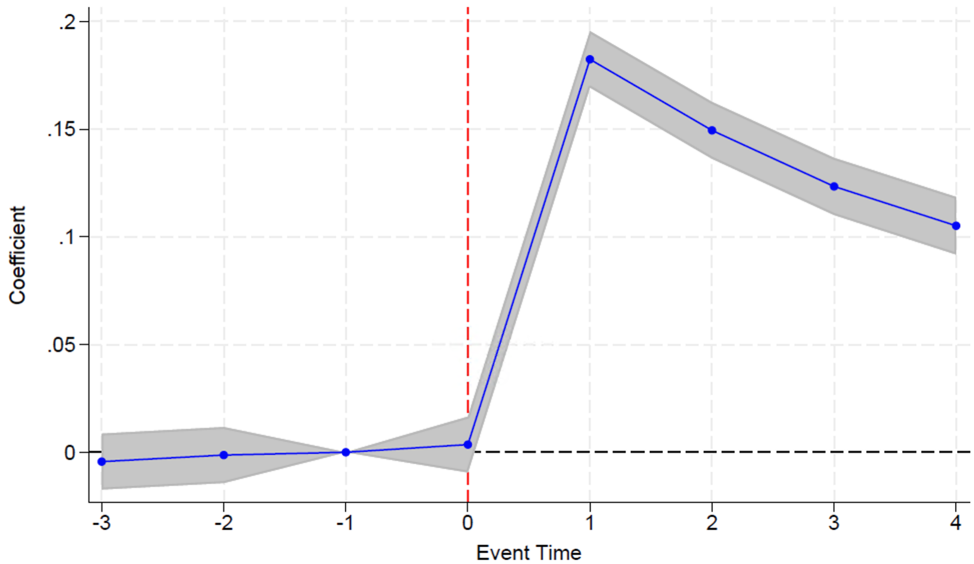
We estimate the following equation:

$$\text{Laid off}_{it} = \sum_{\tau=-3}^{4} \beta_\tau I_{i\tau} \Delta\text{Layoff Rate}_i + \alpha_i + \gamma_t + \varepsilon_{it} \tag{3}$$

The estimates of β_τ are shown in Figure 3. Upon starting at a firm with a 1 ppt higher past layoff rate, workers become 0.18 percentage points more likely to be laid off. This suggests that differences in layoff rates across firms are not all driven by worker selection. Rather, the firm at which a worker is employed does affect their risk of job loss. The coefficient being less than 1 reflects two forces: the presence of worker effects, and the time-varying nature of firm effects. To understand the role of worker versus firm effects, note that a 1 ppt higher ΔLayoff Rate$_i$ is associated with a 0.36 ppt higher layoff rate in $\tau = 1$. Under a simple model of additive worker and firm effects, this suggests that about half of the variation in layoff rates is explained by a firm effect and the other half, worker effects. We can benchmark these against the AKM (Abowd et al., 2004) literature, which has focused on understanding the role of firm effects in wages. Card et al. (2018) summarizes this literature as follows: "typical finding that about 20% of the variance of wages is attributable to stable firm wage effects." Our results suggest slightly larger firm effects in layoff rates. While worker fixed effects control for time-invariant differences between the workers who start jobs at high layoff rate firms, it is still possible that our results are biased by time-varying worker effects. Reassuringly, the flat pre-trend allow us to rule out stories which involve a worker becoming progressively less reliable or lower quality, and then moving to a firm that tends to hire less reliable workers. We also estimate a split-sample AKM-style model for layoff rates in Appendix A.5, and find similar results: firm effects are roughly as important as worker effects in explaining the variance of layoffs.

To summarize the evidence from this section, we find substantial heterogeneity in layoff rates across firms, even among observably similar firms. We find that this heterogeneity is persistent and that moving to a historically higher layoff rate firm increases a worker's risk of being laid off. In other words, there is a firm effect in layoff rates, and workers could hypothetically influence their exposure to layoff risk by working at a historically lower layoff rate firm. A worker may care primarily about their future layoff risk, but this is difficult to contract over. In practice, a firm's reputation as a risky or safe employer may form from its past decisions. In the next section, we use these insights to design a survey to understand workers information about layoff rates across firms and how this information affects their job search decisions.

Figure 3: Effect of moving to a higher layoff rate firm on layoff risk



Notes: This figure plots coefficients of the effect of moving to a new job with a 1 ppt higher layoff rate (in the pre period) than one's old job. The coefficient can be thought of as compared to someone who moves to a firm with the same layoff rate, as only workers who make an EE transition in $\tau = 0$ are included. 95% confidence intervals are shown.

4 Survey Design

The previous section shows that layoff rates vary across firms and that workers *could* theoretically lower their exposure to layoff risk by working at firms with lower historical layoff risk. In this section, we use a survey to ask whether workers know which firms had high past layoff rates, whether workers value working at such a firm, and whether they believe working at such a firm lowers their exposure to layoff risk.

4.1 Setting and implementation

We partner with the PES in Lower Austria to field our surveys among unemployed individuals. The PES is the government agency responsible for managing unemployment benefits and labor market programs in Lower Austria, Austria's second most populous state. The recipients of the survey include the population of registered unemployed in the state of Lower Austria on October 31, 2024. We intentionally target unemployed individuals with our survey. Our intent is to understand how information about layoff rates across different firms affects worker search behavior, and unemployed workers are much more likely to be searching for jobs than for employed workers. Our intervention is not designed to shift *whether* an individual is searching, so it is desirable for a large share of the target population to already be searching for jobs. The PES distributed the survey invitation emails in 2024, with a soft launch of Survey 1 on November 8 and a full launch on November 12, followed by Survey 2 two weeks later. Between October 31 and when the survey is received or completed, some participants may become employed. Among those who start the survey, 16% report being employed or having accepted a job at the time of participation. They are not part of our main sample. To encourage participation, respondents entered a raffle of 100 vouchers worth €80 each, conditional on completing both surveys.[5] The set up allows us to link the survey responses to administrative records in the AMDB through PES identifiers.

4.2 Survey 1: Measuring beliefs about layoffs at own firm

One of the primary goals of the survey is to measure the extent to which workers know which firms had high or low layoff rates in the past. To do this, we ask unemployed individuals several questions about layoffs last year at the firm they used to work at before they became unemployed. Note that the survey intentionally asks about the share of workers laid off *in the previous year*. In the previous section, we showed that working at a firm with lower past layoffs in the past reduces a worker's exposure to layoff risk. While a worker may care most about their future employment risk, future employment risk is difficult to observe, and past firm behavior provides an economically important and theoretically observable measure of employment risk. Asking about the past also allows us to construct an empirical benchmark in the administrative data so we can evaluate the accuracy of worker beliefs. Knowledge about a firm at which the participant recently worked likely provides an upper bound on how much workers know about layoff rates across different firms when searching for jobs.

We ask four different versions of this question. Participants are randomized to answer two versions of the question. Each version of the question has different benefits and limitations, so asking in several ways provides a more robust measure of the extent of any misperceptions and allows us to validate the questions by comparing the responses of the same individual across different questions. Additionally, 20% of participants are given a monetary incentive for correctness. Previous work has generally found limited effects of incentivizing accurate belief elicitation on responses (Haaland et al., 2023). Incentivizing a subsample allows us to verify this in our setting. The beginning of the survey also includes a precise definition of what is considered a layoff in the survey and an example of how to calculate the percent of workers laid off. Participants are then asked a "percent test" question. This provides an attention and quality check and allows us to condition our assessment of beliefs on those who

[5] For 20% of respondents, we incentivize correctness when asking participants their beliefs about the firm they used to work at. The incentive comes in the form of an additional raffle entry if their responses meet an accuracy threshold.

understand the question. In practice, 72% of the respondents pass the "percent test."

Version 1 elicits the layoff rate as a number: "The average company laid off 11% of employees in the last year. Think about the company/employer you worked for before becoming unemployed. What percentage of employees do you think were laid off in 2023?" We anchor participants to the average layoff rate to provide a sense of a reasonable layoff rate—we are primarily interested in measuring whether participants know how a firm's layoff rate compares to that of other firms. The key benefits of this elicitation are (1) that we can measure how close participants are even when they are not correct, (2) that it is well defined for all firms, and (3) that it allows us to estimate the relationship between measured layoffs and perceived layoffs in a way that can be used to estimate the model. A disadvantage of this elicitation may be that workers find calculating precise shares difficult. We also elicit participant's confidence in their responses for version 1.

Version 2 elicits the layoff rate in a simpler way: "Think about the company that you were working at before you became unemployed. In 2023, how do you think the share of employees laid off at your former employer's layoff rate compared to that of other companies with XX-XX employees?" and participants can select either "higher layoff rate than most companies" or "lower layoff rate than most companies." This question is easy to understand and has a direct empirical analog of the median. Workers are asked earlier how many employees their former employer had. This question asks them to compare that firm to other similarly-sized firms. For firms with less than 10 workers, the median is 0.[6] Since the question is not well defined for such firms, participants who reported that their firm employed 10 people or fewer are not given this question. The advantage of this elicitation is that it is easy to understand and measures a simple moment of the distribution of firms. Additionally, restricting to similarly sized firms is useful because it may be difficult for workers to consider firms that are very different from their firm. A disadvantage of this elicitation is that it is not defined for all workers, and it provides a very coarse measure of the extent of misperceptions.

Version 3 elicits the decile of the layoff rate: "Consider your former employer alongside nine other randomly selected companies (with XX-XX employees). We have lined up the companies from the lowest layoff rate to highest layoff rate in 2023. Where do you think your company/employer would fall? Please select the appropriate company." Participants are shown icons for 10 companies ordered from lowest to highest layoff rate and click on one to respond. We additionally ask respondents a comprehension question. We condition our analysis of this question on correctly answering the comprehension question. By eliciting the decile, this version of the question provides the most direct measure of workers' knowledge of

[6] This is not because small firms have lower layoff rates on average, but rather that large firms are less likely to have exactly 0 layoffs due to the law of large numbers.

their firm's position on the distribution of firms. This is important because even if workers correctly know the layoff rate at their firm, they could be very wrong about where that firm falls on the distribution. That is, they may be wrong about whether their firm is a "good" or "bad" firm. An obvious disadvantage of this question is that eliciting beliefs about distributions is difficult and participants may not understand this question.[7] Additionally, for firms with 40 workers or fewer, a layoff rate of 0 falls in more than one decile, so the question is not well defined. For that reason, this question is conditioned on workers reporting working at a firm with more than 40 workers and asked for similarly sized firms.

Version 4 elicits the layoff rate relative to a second firm that the respondent used to work at. We ask workers who say they had another job prior to their most recent job: "Which company do you think laid off a larger share of its employees in 2023?" They can choose either the last company they worked at or the second-to-last company they worked at. This question is relatively easy to understand and relates to the key question of whether workers can tell which firms laid off a higher share of workers than other firms. However, it is only well-defined for workers who have had multiple jobs before.

Together, these four questions provide a rich picture of worker beliefs about the layoff rates at the firms they used to work at and allow us to construct empirical benchmarks to which we can compare workers beliefs.

4.3 Survey 1: Measuring WTP for job with lower historical layoffs

The next section of the survey asks whether worker beliefs about layoff rates matter. While the previous year's firm-level layoffs are highly predictive of next year's layoffs, workers may not know this. Or, they may have private information about their ability or fit at different types of firms. Workers may also believe that other job characteristics are correlated with a firm's layoff behavior. To understand whether and why workers value accurate information about a firm's historical layoffs, we conduct (1) a hypothetical choice experiment and (2) an information provision experiment within the survey.

We use hypothetical choice experiments to elicit workers value for jobs at firms with lower past layoffs. Specifically, we ask workers to make repeated choices between two hypothetical jobs varying the compensation and the share of workers the firm laid off in the previous year. We tell participants to assume the jobs are otherwise identical. This elicitation is similar to that used in papers valuing various workplace amenities, which allows us to compare WTP estimates from this exercise to WTP for other job attributes from other papers. While the choices participants make here are all hypothetical, previous work on job attributes finds that

[7] In practice, we find 46% of respondents correctly answer the comprehension question.

responses correlate strongly with real-world choices (Maestas et al., 2023; Mas and Pallais, 2017).

In particular, we ask them to choose between two jobs, A and B. Job A laid off 10% of its employees last year and job B laid off 15% of its employees last year. We start by setting the compensation for A to the participant's target compensation, and the compensation for job B to 10% higher. If the participant chooses A, we gradually increase the salary for job B until the participant switches. If the participant chooses B, we gradually decrease the salary for job B until the participant switches to choosing job A. Importantly, we tell participants to "assume that Job A and Job B are identical in every way other than pay and the layoff rate."

4.4 Survey 1: Experimentally providing information about layoffs

The hypothetical choice experiment allows us to establish whether workers value past layoffs. However, it does not allow us to understand how information about past layoffs affects workers' beliefs about their future risk of job loss. It also does not tell us whether this information would affect worker search behavior. Workers may value working at a firm with lower layoff rates, but it may not affect their choices,[8] for example, if unemployed workers simply always take the first job they are offered. To understand the effects of perceived layoff rates on job search, we implement an information provision experiment. The experimental design will allow us to ask whether workers believe past firm behavior predicts their future risk.

The ideal experiment would provide workers with the previous year's layoff rate for every firm they could consider working at. Since we cannot provide information about specific firms, we leverage the fact that highly observable firm characteristics are correlated with layoff risk. We randomize participants into one of three treatment arms. The first arm compares large firms to small firms. The second arm compares firms in the worker's most recent industry to firms in the industry that workers from their industry mostly commonly transition into. The third arm compares workers in the participant's most recent industry to temp agency workers who were previously employed by firms in the same industry.[9] Within each arm, workers are randomized to treatment or control (see Table A2 for balance). We describe the rest of the design using size as an example for the rest of this section.

[8]Indeed, in most random search models of the labor market, workers accept all jobs with values that exceed the value of unemployment. At their indifference point, where the value of the job equals unemployment, workers do not care what the risk of separation is, because the worker is indifferent between being in that job and being unemployed. So an unemployed worker's decision of whether to accept a job is not impacted by the separation rate, even if they prefer jobs with lower layoff rates.

[9]Those who have never worked for a firm before or who select "other" for industry are sorted into the size arm.

We provide information about the layoff rate at small firms in 2023 and elicit beliefs about the layoff rate at large firms in 2023 (whether we anchor small or large is random). Anchoring all workers to one of the traits allows us to treat beliefs about the differences across firms rather than changing workers' beliefs about the levels of layoff rates. Beliefs about the level of layoffs could also affect job search, for example, through discouragement effects, which we are not trying to capture. We then provide the treated group with the correct layoff rate for large firms. We then ask them to recall the information we provided and whether they over or underestimated the layoff rate at large firms (control participants are asked to recall the anchor). This allows us to record whether they processed the information provided. It will also allow us to rule out that respondents are reporting the numbers back to us when we ask about their personal risk.

We also explain to participants that the information provided is calculated on workers similar to them, in that it is calculated on workers hired out of unemployment. This may make the information more relevant to workers. Layoff rates for workers hired out of unemployment are generally higher.

Outcomes We next elicit their beliefs about the probability they will lose their job within a year if they were to start working at a small firm and at a large firm. This question allows us to test whether a firm's past layoffs affect workers beliefs about their future risk. While the previous year's firm-level layoffs are highly predictive of next year's layoffs, workers may not know this. Or, they may believe they have private information about their ability or fit at different types of firms.

Next, we elicit several job search behaviors. The order of these questions is randomized. We ask how many applications they plan to submit to large and small firms in the next weeks. We also offer them tips to tailor their resumes to small firms or to large firms. Choosing information for one type of firm requires them to forgo information about the other type of firm, so the choice is costly.[10] The information they select is provided upon completion of the survey. We also ask whether they would like to be redirected to job postings at small firms or job postings at large firms. They are redirected upon completion of the survey. Again, while they can choose neither, they cannot choose both types of jobs.

4.5 Survey 2: Follow up

We survey workers again two weeks later. The second survey allows us to re-elicit workers' beliefs about the probability they would be laid off within a year if they went to a small and

[10]They can choose to receive no information.

a large firm. This allows us to test whether the information was memorable. Though our intervention is light touch, valuable information should be memorable. We also ask workers about the applications they have submitted in the two weeks since the first survey and about any job offers they have received.

5 Survey Results

5.1 Sample description

The survey was successfully sent to 37,962 people. Of those, 3,159 completed at least 95% of the survey. Table A1 compares those who completed at least 95% percent of the survey to the population of unemployed in Lower Austria on October 31, 2024. Respondents are broadly similar to the overall population on observable characteristics. We analyze 2 primary samples that we pre-registered. The first sample excludes employed individuals, those who complete the survey too quickly and those who have low German proficiency as recorded by the PES. The second "high quality" sample additionally excludes those who do not correctly answer a question testing their comprehension of percentages and those who do not correctly actively recall the anchor. We successfully match 99% of unemployed workers who have previously had a job to their previous firm in the administrative data.

5.2 Descriptive evidence of misperceptions

Only 26% of people are within 5 percentage points of the empirical benchmark. Among all respondents, 75% overestimate their previous firm's layoff rate. This may be explained by the fact that we survey a population of unemployed workers, who, by definition, had a negative experience. It is also worth noting that 65% of people are very or somewhat confident in their estimate. This is notable for two reasons. First, it suggests that a substantial share of respondents (35%) do not even think they know this information, suggesting substantial misperceptions. Second, it suggests that a substantial share of respondents believe they know more about the layoff rate at the firm than they do.

Among all respondents, 52% correctly identify whether their firm is above or below the median and 50% of respondents are correct about which of two firms they formerly worked at had higher layoff rates, no better than if they guessed randomly.

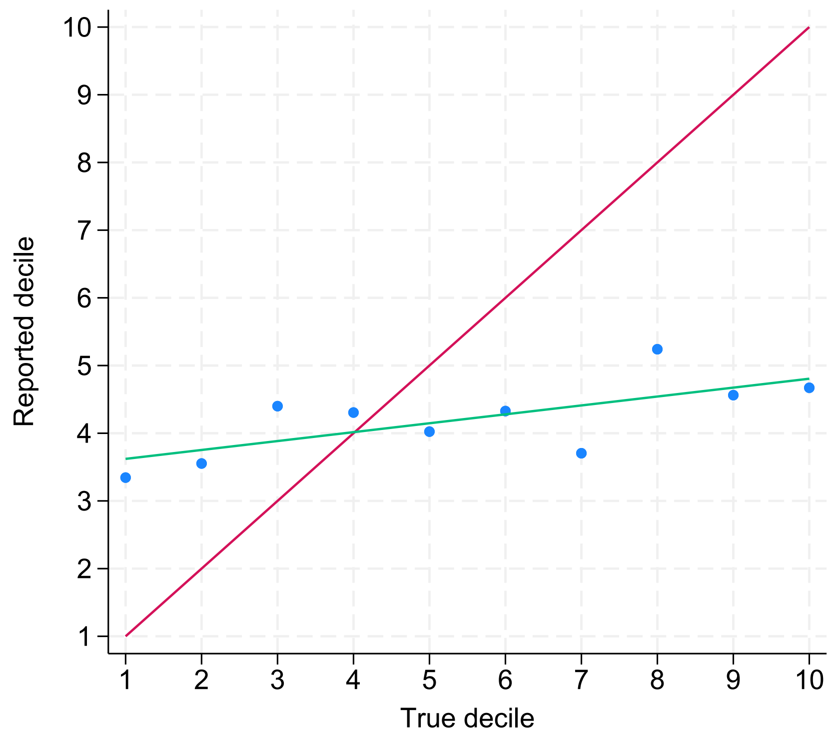
Figure 4 plots perceived decile of the firm against the decile of the firm calculated in the administrative data. Respondents respond relatively similarly across deciles. In particular, note that respondents in the top two riskiest deciles believe they are around median.

Tables 3 and 4 regress empirical benchmarks on survey responses. In all columns, responses exactly matching the empirical benchmark would produce a coefficient of 1. In practice, for every measure, the coefficients are far below 1. Note, however, that coefficients are positive and statistically distinguishable from zero in the case of the numerical measure and the decile measure, suggesting some, albeit limited, knowledge of the layoff rate. Table 3 shows the regression output for layoff rate beliefs elicited as a number. The first column shows the baseline specification—a 1 ppt higher layoff rate corresponds to 0.14 ppt higher beliefs. Column 2 restricts to participants for whom we incentivized correctness. This only increases the coefficient to 0.18, consistent with Haaland et al. (2023). Column 3 restricts to participants who correctly answer a question where they have to calculate a percentage. Column 4 instruments for the empirical layoff rate with the layoff rate last year as a measurement error correction. Our survey question is about the actual share laid off in that year, rather than something about the underlying or persistent layoff rate, so this is not our preferred specification, but it is nonetheless a useful diagnostic.

What if the layoff rate among workers similar to you is more relevant to workers? Perhaps they only know the layoff rate among people similar to them because that is more relevant. We chose to design the survey based on the layoff rate overall because it is difficult to know which groups of people workers perceive as most similar to them and because any potential policies would likely focus on firm layoff rates overall. Nonetheless, to understand whether our results are masking more accurate beliefs for workers similar to you, we construct several alternative measures of the layoff rate. Specifically, we construct the layoff rate for four age-gender bins and for workers hired out of unemployment. Then, we assign workers to *whichever layoff rate their belief is closest to* (requiring them to be in the correct age-gender bin), since some workers may have answered the original question correctly. Mechanically, this can only increase worker accuracy since we only benchmark them to a different layoff rate if it helps them. Even this conservative exercise only increases this coefficient to 0.25.

Table 4 shows results for the other measures of misperceptions: beliefs about what decile the firm falls in (columns 1 and 2), beliefs about whether your firm is above or below median (column 3), and beliefs about which of two firms has a higher layoff rate (column 4). Column 2 restricts to those who pass a comprehension test for the decile question. Workers' lack of knowledge about whether their firm is above or below median is particularly striking, since that question is relatively easy to understand and the bins are very coarse. While limited attention or effort may look like inaccurate beliefs, the very inaccurate beliefs combined with the percent and comprehension checks and incentives for attention suggest that this is not driving our results. The results from the information provision experiment also help validate our findings from this section. In the experiment, limited attention and effort would have the reverse effect, attenuating the effect of information on beliefs.

Figure 4: Beliefs about decile of layoff rate



Notes: This figure plots respondent beliefs about what decile in the distribution of layoff rates their previous firm was in against the empirical benchmark. The red line is the 45° line.

5.3 Willingness to pay

Here we show the willingness to pay estimates from our stated choice experiment. We take a midpoint approach to analyzing the data. Each choice is associated with a wage premium between the two jobs. We set an individual's WTP to be the midpoint between the premium at their switching point and the premium at their previous option. We exclude participants who do not make any switch. We find that the median participant is willing to pay 11% of wages for a job at a firm that laid off 10% of its employees last year, compared to a job that laid off 15% of its employees last year. This corresponds to a WTP of 2.2% of salary for a 1 percentage point lower layoff rate last year. Figure 5 plots the distribution of WTPs estimates.

We can contrast this estimate against valuations of other job characteristics from the literature. Among college seniors surveyed just before labor-market entry, Wiswall and Zafar (2018) estimate willingness to pay of 2.8% for a 1 percentage point decline in the probability

Table 3: Beliefs about own firm

	(1) Rate Belief	(2) Rate Belief (incentivized)	(3) Rate Belief (percent test)	(4) Rate Belief (IV)	(5) Rate Belief
Rate	0.14***	0.18**	0.19***	0.14**	
	(0.050)	(0.082)	(0.064)	(0.060)	
Closest Rate					0.25***
					(0.061)
Constant	0.18***	0.16***	0.17***	0.18***	0.18***
	(0.0067)	(0.014)	(0.0073)	(0.0078)	(0.0066)
N	1132	216	902	1089	1132

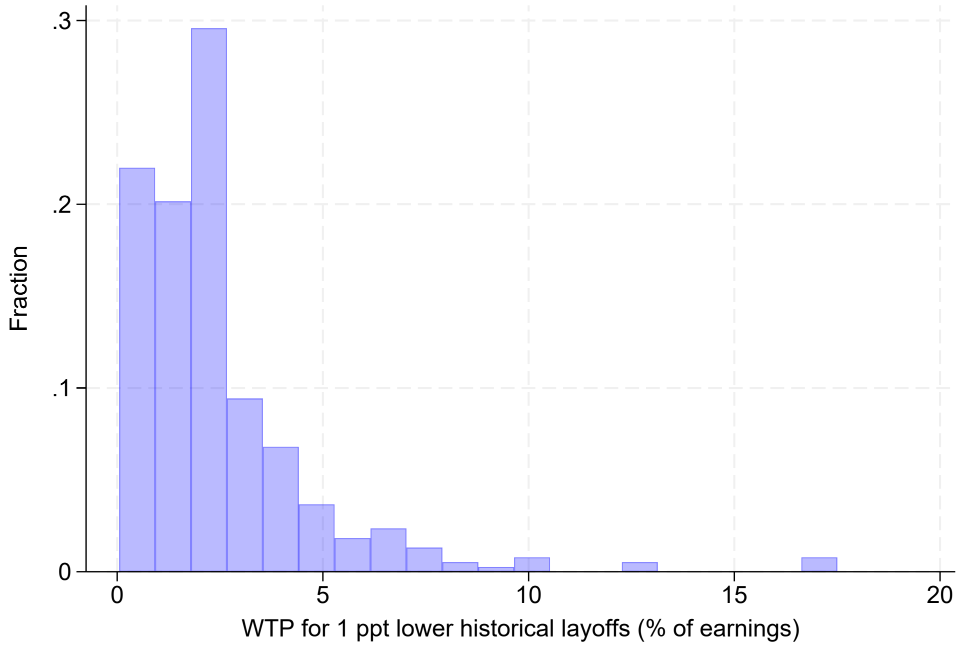
Notes: This table shows regressions of worker beliefs about the layoff rate (collected in the survey) on the layoff rate calculated in the administrative data. Rate refers to the layoff rate as a number (and rate belief would be the participant's belief about the layoff rate). Incentivized (column 2) refers to a subset of participants who are incentivized. Percent test (column 3) is a subset who correctly answer a question asking them to calculate a layoff rate. Column 4 instruments for the layoff rate with the layoff rate last year. Column 5 regresses beliefs on the layoff rate the participant's belief is closest to, out of a set of reasonable layoff rates. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Beliefs about own firm

	(1) Decile Belief	(2) Decile Belief (decile test)	(3) Median Belief	(4) Two Firms Belief
Decile	0.13***	0.17***		
	(0.039)	(0.063)		
Median			0.069	
			(0.044)	
Compare Two Firms				-0.0054
				(0.049)
Constant	3.51***	3.29***	0.43***	0.39***
	(0.26)	(0.40)	(0.035)	(0.035)
N	470	214	556	400

Notes: This table shows regressions of worker beliefs about measures of the layoff rate (collected in the survey) on the same measure of the layoff rate calculated in the administrative data. Decile is the decile of the layoff rate of the firm (and decile belief is the worker's belief about the decile). Median is an indicator for whether the firm is above median. Compare two firms is an indicator for which of two firms had a higher layoff rate. Decile test is a subset of participants who correctly answer a comprehension questions about deciles. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 5: Willingness to pay for 1 ppt lower past layoffs



Notes: This figure plots a histogram of worker WTP for lower past layoffs. Specifically, WTP is the percent of salary a worker would give up to work at a firm that laid off 1 percentage point fewer employees last year.

of being fired. By contrast, we are estimating the WTP for *previous layoffs*, not for a direct change in the risk of being fired. Using nationally representative stated-choice data, Maestas et al. (2023) report average compensating differentials of about 9% of wages for flexible scheduling and 4% for the option to work from home. Field-experimental evidence from Mas and Pallais (2017) shows that workers are willing to pay 20% of wages to avoid employer-set schedules.

5.4 Experimental Evidence

The information provision experiment allows us to study the relationship between information about past layoffs at firms and worker beliefs about personal risk exposure. We specify the regression in terms of the treated trait. For example, if a respondent is anchored to the layoff rate at small firms and then asked and treated with information about the layoff rate at large firms, Posterior_{ij} is respondent i's posterior belief about the probability they would lose their job in the next 12 months if they were to start a job at a large firm. We index the treatment trait they are assigned to (large, small, temp, non temp, the industry of interest) with j. Gap_{ij} is the information provided about type j firms minus participant i's prior about type

j firms, Prior_{ij}. Treat_{ij} indicates whether the individual was treated. We can estimate the effect of believing a type of firm had higher previous layoffs on personal employment risk with the following regression:

$$\text{Posterior}_{ij} = \beta_0 + \beta_1 \text{Gap}_{ij} + \beta_2 \text{Treat}_{ij} + \beta_3 \text{Treat}_{ij} \times \text{Gap}_{ij} + X_{ij} + \varepsilon_{ij} \tag{4}$$

where the coefficient of interest is β_3. X_{ij} indicates controls for the prior and the trait arm they are assigned to. We control for the trait (size, industry, or temp agencies) since some workers can only be assigned the size arm and treatment is assigned conditional on the trait. Table 5 shows the estimated coefficients. Column 1 uses full sample of respondents who we match to the administrative data, column 2 uses the "high quality" sample, column 3 uses those who complete survey 2 and who are in the "high quality" sample. Taking the estimate from the "high quality" sample, we find that learning a type of firm laid off 1 percentage point more of its workers in 2023, makes participants believe that they would be 0.43 percentage points more likely to be laid off if they were to start a job at that type of firm. This suggests that workers believe past layoffs are predictive of future employment risk. If participants simply repeated the information provided back as their posteriors the coefficients would be 1. There are several reasons the coefficients may be less than 1. First, participants may (correctly) believe that the past is an imperfect predictor of the future. Second, participants may have private information about their ability at different types of firms or about the particular types of, say, large firms they would get a job at. In principle, participants imperfectly recalling the information would also attenuate the coefficient of interest. However, since column 2 (the "high quality" sample) conditions on those who correctly recall the anchor exactly, imperfect recall does not explain why the coefficients are significantly less than one. Rather, we believe it reflects participant beliefs that their personal risk of losing their job is a different economic object than past layoffs at a given type of firm. Remarkably, the coefficients are consistent with our estimates of the effect of moving to a higher layoff rate firm from Figure 3. That is, workers correctly believe that going to a previously higher layoff rate firm raises their layoff risk, *but* that the pass-through from past firm layoff to personal risk is less than 1. The magnitude of the coefficient is also similar at a little less than 0.5.

Column 4 uses posteriors collected in Survey 2. Of the 1,591 participants in column 2, 1,247 complete survey 2. The retention rate for survey 2 is 78%. We find no evidence of differential attrition by treatment group (see Appendix Table A3). While the coefficient in Column 4 is somewhat attenuated, as would be predicted by imperfect memory of the information provided, the information is still clearly affecting participant beliefs about their layoff risk. Learning that a type of firm had a 1 ppt higher layoff rate in 2023 causes workers to believe they would be 0.27 ppt more likely to be laid off if they were to work at that job—two weeks after learning the information. This is surprising given how light-touch our intervention is, but it is consistent with the severity of the misperceptions and the information being valuable. It is worth noting that 44% of workers are making direction errors (e.g. believing that large firms have higher layoff rates than small firms, when the opposite is true) rather than magnitude errors. Direction errors may be a particularly salient type of misperception. The survey 2 results support the interpretation that the initial belief update was not merely a result of participants repeating back information but rather that the information causes participants to meaningfully change their beliefs.

Table 5: Belief Updating

	(1) Posterior 1	(2) Posterior 1	(3) Posterior 1	(4) Posterior 2
Treat X Gap	0.34***	0.43***	0.47***	0.27**
	(0.065)	(0.089)	(0.10)	(0.11)
Treat	2.38**	3.13**	4.17***	0.13
	(1.07)	(1.25)	(1.45)	(1.51)
Gap	0.36***	0.29**	0.31**	0.70***
	(0.12)	(0.14)	(0.16)	(0.16)
Prior	0.87***	0.79***	0.82***	1.02***
	(0.12)	(0.15)	(0.17)	(0.17)
Constant	11.7***	11.7***	10.6***	21.9***
	(2.18)	(2.59)	(2.85)	(3.01)
N	2345	1591	1247	1247
Quality Restriction	No	Yes	Yes	Yes
Completed Both Surveys	No	No	Yes	Yes

Notes: This table shows the effect of the treatment on worker beliefs about their risk of layoff. The first row of coefficients (Treat X Gap) shows the effect of learning that a certain type of firm had 1 percentage point higher layoffs last year on a worker's belief that they will be laid off within 12 months if they were to start a job at that type of firm. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Employment risk beliefs and job search behavior Having shifted beliefs, we can use the treatment as an instrument to study the relationship between employment risk beliefs and job search behavior. We estimate the following model with two stage least squares. The first stage is

$$\text{Posterior}_{ij} = C_j + \beta_{1j}\text{Gap}_{ij} + \beta_{2j}\text{Treat}_{ij} \times \text{Gap}_{ij} + X_{ij} + \varepsilon_{ij} \tag{5}$$

and the second stage is

$$Y_{ij} = c_j + \alpha_j \widehat{\text{Posterior}}_{ij} + \beta'_{1j}\text{Gap}_{ij} + X_{ij} + \varepsilon_{ij} \tag{6}$$

Note that the first stage here excludes a main effect for $Treat_{ij}$ to ensure positive weights in the estimation of treatment effects in the second stage (Vilfort and Zhang, 2024). In this way, the first stage differs from equation 4 used to estimate the effect of treatment on beliefs. X_{ij} includes controls for the prior and the trait arm the participant was assigned to. This IV analysis also assumes the exclusion restriction that the treatment only affects job search behavior and intentions by changing participant beliefs about their probability of job loss at that type of firm. Our primary job search outcomes are those elicited at the end of survey 1: requesting tips to target their resume to the treated type of job, requesting links to jobs in the treated type of job, and planned applications to firms of that type. Table 6 shows the results. To aid in interpretation, we present treatment effects of a 10 ppt change in beliefs about layoff probability. The average misperception is 10.2 ppt, so these effects approximate a case in which the average participant believes the historical averages are perfectly predictive of future layoff rates and which beliefs are fully corrected.

We find that believing they are 10 percentage points more likely to be laid off in a job causes a participant to be 9 percentage points less likely to request tips to tailor their resume to that type of job and 6 percentage points less likely to choose to receive filtered job postings for that type of job. That is, learning one type of firm is riskier relative to another type of firm causes workers to seek fewer resources and job openings at that type of firm. This requires them to forgo job postings and tips for the other type job.

The rest of our outcomes are about worker application plans. Learning the firm is riskier also causes them to direct their application plans toward safer firms. The same change in beliefs causes a participant to plan to submit 0.6 fewer applications to that type of firm (a 26% decline) and 9 percentage points less likely to plan to submit *any* applications to that type of firm. We also show effects on the share of applications to that firm and on the inverse hyperbolic sine of applications to that firm. Across these outcomes, we generally estimate a 0.1 to 0.2 standard deviation decline in the outcome.

We present results on symmetry in Appendix A.4. The effects are generally symmetric, with participants who learned a type of firm was safer than they thought shifting search effort towards that type of firm and those learning a type of firm was riskier shifting away from that type of firm. The point estimates tend to be slightly larger for those who learn a type of firm was safer, but the difference is not statistically significant. In the case of applications, this is likely explained by the fact that there is more scope to increase intended applications than reduce applications from a low baseline.

While these effects are sizable, it is important to note that employment at different types of firms is downstream of these outcomes, and large effects in search effort or intentions generally map on to smaller effects on realized outcomes. However, it is also worth noting that information about broad firm characteristics are different from firm-specific layoff rates. On the one hand, firm traits bundle other characteristics (changing industries changes many other things about a job). On the other hand, workers may perceive the layoff rates of firm traits as more persistent over time (relative to the layoff rates of specific firms), and thus may perceive last year's layoff rate as a more useful piece of information. To understand how workers value information about firm characteristics relative to firms, at the very end of the second survey, we asked workers "Suppose the Public Employment Service (AMS) could provide information on the share of employees laid off at *X*. How useful would you find this information?" where *X* is either specific employers you are considering applying to or one of the three experimental arms (firms of different sizes, industries, temp agencies vs not). On average, 75% say they would find the information size/industry/temp agencies somewhat or very useful, whereas 85% of people say they would find information about specific firms somewhat or very useful (and the latter group is more likely to say they find the information very useful). This suggests that the effects of firm characteristic level information on behavior may understate the effects of firm-specific information.

Table 6: Beliefs about layoff rates affect search intentions

	(1) Resume Tips	(2) Link to Jobs	(3) Planned Number of Apps	(4) Planned Any Apps	(5) Planned Share Apps	(6) IHS Apps
Posterior (10 ppt)	-9.62**	-7.33*	-0.59*	-9.25**	-3.87	-0.20**
	(4.09)	(4.15)	(0.33)	(4.58)	(3.34)	(0.097)
N	1388	1388	1388	1388	1388	1388
Control Mean	20.7	27.6	2.34	64.1	39.3	1.13
First Stage F-stat	16.5	16.5	16.5	16.5	16.5	16.5

Notes: This table shows the 2SLS estimates of the effect of posterior beliefs about the layoff rate at a type of firm on interest in jobs at that type of firm. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All regressions include controls for gap, prior, and trait.

The results in this section show workers value information about the layoff rate at a firm. Specifically workers believe that past firm layoffs are predictive of their own future layoffs and learning that certain types of firms have had historically lower layoffs causes workers to direct their job search away from such firms. This behavioral response suggests that the misperceptions we document have real consequences for how workers allocate their search effort across firms.

5.5 Discussion

The findings from this section reveal an information friction in labor markets that has not been previously documented. While workers demonstrate a clear preference for employment security—they are willing to sacrifice over 2% of compensation to work at firms with 1 percentage point lower historical layoff rates—they lack the information necessary to act on these preferences effectively. The magnitude of the misperceptions we document is large. Workers perform no better than random chance when identifying whether their former employer had above- or below-median layoff rates, and those from the highest-risk firms believe they are at fairly typical firms.

Our experimental results demonstrate that these information frictions have important consequences. First, workers corrrectly believe that information about firms' past behavior is highly predictive of their future job loss risk. Second, workers direct their search intentions and effort towards firms they believe to provide lower job loss risk. This is true even in our intervention, which provides information about very broad firm characteristics.

6 Model

The previous sections establish that workers have imperfect information about layoff rates across firms and that this lack of information distorts workers' job search behavior. It does not allow us to speak to the effects of imperfect information on compensating differentials or aggregate separation rates, as these are equilibrium objects. In this section, we develop a model of job search where workers have imperfect information about firm layoff rates to shed light on the general equilibrium effects of imperfect information about layoff rates.

We set up the model to match certain important moments of the data. First, we find a negative compensating differential in the data. Second, most employment is concentrated at low layoff rate firms, even though workers have poor information. The key to matching both of these moments is that our model features heterogeneous firm productivity and that layoff rates are negative correlated with firm productivity. Under incomplete information, productive firms will increase the wage to boost their likelihood of successfully recruiting workers. Since these productive firms are more likely to have low layoff rates, this leads to a negative compensating differential for layoff risk. The theoretical literature attempting to explain small or wrong-signed compensating differentials has taken the approach of showing how imperfect competition can distort compensating differentials (Bonhomme and Jolivet, 2009; Hwang et al., 1998; Lamadon et al., 2022; Lavetti, 2023). Our model shows how imperfect information can flatten and even reverse the compensating differential, even in a model that produces the "correct" compensating differential with full information.

We use the model to explore two counterfactuals: partial and full information. Layoff risk is fundamentally uncertain. This means that even providing workers with the best information possible would not be full information. We consider the counterfactual that workers perfectly know the layoff rate last year, and that the layoff rate perfectly matches the worker's layoff risk. This partial information counterfactual only modestly increases the compensating differential. This finding may be important for other amenities, where information frictions are likely less severe, but information is still unlikely to be perfect.

We also explore the effects on the average separation rate. The effect of information on the average layoff rate is theoretically ambiguous in our model. There are two main forces. First, higher signal precision improves a worker's information about which jobs are desirable. Second, better information forces high layoff rate firms to pay relatively more in equilibrium, attracting workers. In the full information benchmark, workers are fully compensated for layoff risk and are indifferent across jobs, which can increase the average layoff rate. (The intuition is similar to how a minimum wage can increase the employment of a monopsonist). However, some firms may no longer find it profitable to exist at the new wage they have to pay and may exit (while low layoff rate firms may now enter, since they have to pay a lower wage), which can decrease the average layoff rate. Quantitatively, we find that partial information and full information both decrease the average separation rate relative to the benchmark, but full information increases the average layoff rate relative to partial information.

We first present the model, then we describe how we estimate and calibrate parameters, and, finally, we present the main calibration and compare it to two counterfactuals.

6.1 Environment

Time is discrete and all agents discount the future at rate β. There is a unit measure of firms and of workers. Unemployed workers receive a random job offer with odds λ that they may accept or reject. There is no on-the-job search. Employed workers are laid off from firm j with probability δ_j. This layoff rate is exogenous, fixed, and idiosyncratic to the firm. After being laid off, workers incur a cost C and return to unemployment. Workers are only heterogeneous in their beliefs about firm layoff rates, which influence whether they accept or reject a job offer. Firms vary not only in their layoff rate δ_j but also in their productivity level z_j. Firms choose what wage w_j to post and cannot renegotiate with workers based on their beliefs.

6.2 Unemployed Worker Problem

To set up the unemployed worker's problem, we must first describe the employed worker's value function.

$$V(w_j, \delta_j) = w_j + \beta(1-\delta_j)V(w_j, \delta_j) + \beta\delta_j V_U - \beta\delta_j C^{11} \tag{7}$$

A worker employed at a firm with wage w_j receives their wage and then next period with odds $1-\delta_j$ remains at the firm. With odds δ_j they are laid off and re-enter unemployment. If they are laid off they incur cost C. Workers prefer low layoff rates for two reasons. First, because being laid off lowers lifetime earnings, and, second, because they incur cost C. But the cost C is necessary for the layoff rate to affect the unemployed workers choice of whether to accept a job. Otherwise, if workers were paid their reservation wage they would be indifferent between unemployment and employment and therefore δ would not affect whether a worker accepts a job.[12] C can be microfounded with many forces that cause workers to dislike being laid off, including the idea that workers spend a fixed minimum time in unemployed before finding another job, some penalty in job search if employers discriminate against workers with gaps in their resumes, some psychological cost of being laid off, foregone on-the-job wage growth, or risk aversion. Some positive cost C is also consistent with the empirical literature which often finds negative effects of job loss in excess of the loss in earnings (Charles and Stephens, 2004; Del Bono et al., 2012).

In the standard wage posting model without on-the-job search, the unemployed worker would accept any job offering a wage which is at least the flow value of unemployment b. This results in every firm offering the same wage, b (Rothschild/Diamond critique). Because we have introduced a cost to being laid off, the worker will not accept a job which they know has a positive layoff rate that just pays b because the worker risks paying C.

The unemployed worker receives flow value b and then with probability λ draws a random job offer from the distribution of posted contracts. If a worker matches with a job offer from firm j, worker i observes w_j and receives a noisy signal s_{ij} about δ_j and forms beliefs about δ_j. In the belief formation process, we assume workers know the true distribution of δ_j. Given

[11] We can rearrange this expression: $V(w_j, \delta_j) = \frac{w_j + \beta\delta_j V_U - \beta\delta_j C}{1-\beta(1-\delta_j)}$.

[12] Intuitively, in equilibrium, wages will equal b, the flow value of unemployment. At $w = b$, workers are indifferent between being employed and unemployed, so they do not care about the probability they become unemployed again. They will not accept any $w < b$, no matter how low the layoff rate, because they would rather be unemployed. They will gladly accept $w > b$, but firms have no reason to offer this, regardless of their layoff rate, because workers will accept any job that pays b.

that our survey anchors participants to the true layoff rate mean, our survey can be thought of as identifying limited information rather than biased beliefs. We assume workers treat the offered wage as uninformative in forming beliefs about the layoff rate. This is reasonable, given the very limited information they have overall about δ in our survey.

If the workers had perfect information, there would be a unique wage $w^*(\delta_j)$ at which the worker would be willing to accept a job with layoff rate δ_j. Since workers do not have perfect knowledge of firm layoff rates, they will accept the job if its expected value given their signal s_{ij} exceeds the value of being unemployed, $\mathbb{E}[V(w_j, \delta_j)|s_{ij}] > V_U$. This implies that there is some cutoff $s^*(w_j)$ such that the worker will accept the job if $s_{ij} < s^*(w_j)$.

Since workers have the same layoff belief *process*, and there are infinitely many firms, the value of unemployment is the same for all workers.

$$V_U = b + \beta\lambda \int \max\{\mathbb{E}[V(w_j, \delta_j)|s_{ij}], V_U\} dF(w_j, \delta_j) + \beta(1-\lambda)V_U \tag{8}$$

6.3 Firm Problem

Firm j posts exactly one vacancy per period. Firm size is determined by the share of matched unemployed workers who accept an offer each period. The firm has a fixed productivity z_j and a fixed layoff rate δ_j. They choose a wage w to post to maximize the vacancy's steady state profits.

$$\pi_j = \max_w (z_j - w) l(w, \delta_j) \tag{9}$$

Steady state labor per vacancy is given by

$$l(w, \delta_j) = \frac{u\lambda A(w, \delta_j)}{\delta_j} \tag{10}$$

where $A(w, \delta_j)$ is probability the unemployed worker accepts the job offer. From the unemployed worker's problem, we know that there is exists a cutoff $s^*(w)$ where the worker will accept the job if their signal is less than the cutoff. This means that $A(w, \delta_j) = Pr(s_{ij} < s^*(w_j)|\delta_j)$.

With perfect information about δ, firms of a given δ will post the same w, regardless of their z_i. They post the worker's reservation wage for that δ_i. This is because $A(w, \delta_j) = 0$ if $w \leq w^*(\delta_j)$ and is 1 otherwise, so all firms will offer exactly $w^*(\delta_j)$. This is another form of the Diamond paradox. There is still dispersion in wages across firms with different layoff rates. With no information about δ, all firms offer the same reservation wage.

With imperfect information, the firm's optimal wage is pinned down by the first order condition. We can write this FOC as follows.

$$\frac{z_j - w}{w} = \frac{A(w,\delta_j)}{A_w(w,\delta_j)}\frac{1}{w} = \frac{1}{\varepsilon_l} \tag{11}$$

This takes a familiar form: the markdown equals the inverse labor supply elasticity. Here, the curvature of the labor supply curve is governed by the acceptance probability. That is, with imperfect information, the posted wage will be increasing in z. Increasing the posted wage will result in more workers accepting the job offer, but at the cost of a higher wage. More productive firms value having an additional worker more highly, so they offer a higher wage than their less productive counterparts. In this way, we find that imperfect information offers another "solution" to the Diamond paradox.

How a given firm's wage and size change with information depends on how the acceptance function changes with information. Figure 6 provides a concrete example. The plots visualize the acceptance probability $A(w, \delta_j)$ as a function of the w. The plot fixes the layoff rate of the firm to $\delta = 0.06$. Each line shows a different value of the extent of information frictions. The blue line shows a very low level of information, the orange line shows a moderate level of partial information, and the green line shows full information. Specifically, "increasing information" refers to increasing the precision of the signal s_{ij} the worker draws about a firm's layoff rate. The plot shows several features.

First, notice that the acceptance function is relatively steep with respect to the wage when information is very low or very high. Recall that with no information or perfect information that labor supply is perfectly elastic. In the middle, labor supply slopes upward.

Second, we note that whether or not a firm of a given layoff rate increases in size as information increases, depends on its productivity. Each line has a star. The star denotes the firm's optimal choice of wage w^* for that level of information. Rearranging equation 11, the stars mark where $A(w, \delta) = (z - w)A_w(w, \delta)$.

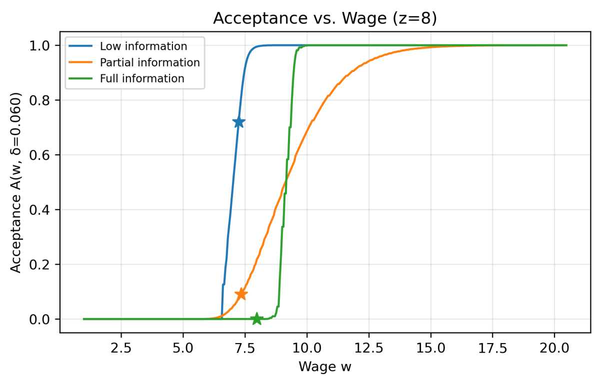
In panel A, $z = 8$. Paying workers any wage above 8 would be unprofitable. The firm has a relatively high acceptance probability with low information. This firm would have to pay more to maintain the same acceptance rate as information increases.[13] This firm becomes very small and then exits. The required wage with full information would make it unprofitable

Panel B shows a firm of the same layoff rate, but with a higher productivity $z = 13$. The three lines are identical, but the firm's optimal choices change. This firm is more productive, so it is larger to begin with, with low levels of information. Partial information increases

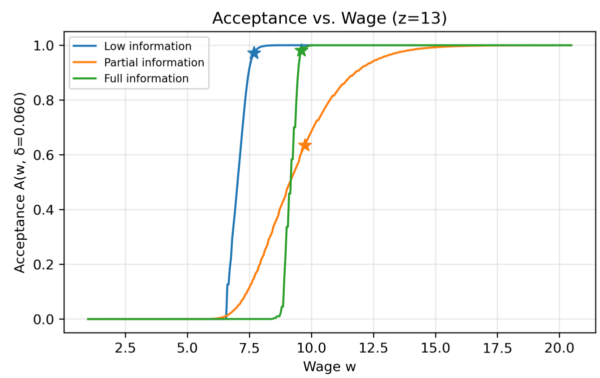
[13] This is a function of its layoff rate, which we have fixed. The wage a lower layoff rate firm would have to pay would be different.

the wage the firm pay and reduces the acceptance rate from near 1 to about 0.6. Then, full information *increases* the acceptance rate. With full information, labor supply is perfectly elastic, so firms either pay the minimum wage needed so all workers accept or they choose a wage so all workers reject. Workers are fully compensated for layoff risk and are therefore indifferent between jobs at all firms that exist. The firm in panel B is productive enough to pay the wage required so all workers accept. These two firms have the same layoff rate, but one grows and one shrinks. This exemplifies the mechanism through which information can increase or decrease the average layoff rate.

Figure 6: Effect of information on firm size



(A) Low z (z = 8)



(B) High z (z = 13)

Notes: Both panels plot the acceptance probability $A(w, \delta)$ against the wage. Each line is a different n, where n is the precision of worker signals. The equilibrium V_u is changing with n. Panel (a) marks the firm's choice of wage w^* for a firm of productivity $z = 8$. Panel (b) marks the firm's choice of wage w^* for a firm of productivity $z = 13$.

6.4 Steady state unemployment and employment

Steady-state unemployment is determined by the average layoff rates among employed workers and the share of jobs that are accepted by unemployed workers.

$$1 = u + \int l(w(z_j, \delta_j), \delta_j) dF(w_j, \delta_j) = u + u\lambda \int \frac{A(w_j, \delta_j)}{\delta_j} dF(w_j, \delta_j)$$

$$\implies u = \frac{1}{1 + \lambda \int \frac{A(w_j, \delta_j)}{\delta_j} dF(w_j, \delta_j)} \tag{12}$$

6.5 Equilibrium

A stationary equilibrium of the model consists of a vector $(u, F(w, \delta), l(w, \delta), w(z, \delta), A(w, \delta))$ such that: (i) workers decide whether to accept jobs to maximize utility, given their beliefs, signals, and the offer distribution $F(w, \delta)$ (ii) firms choose wages to maximize profits, given $l(w, \delta; u)$ (iii) the offer distribution is consistent with firm wage policies (iv) unemployment satisfies stationary equation (12).

6.6 Efficiency

The full-information version of the model is not necessarily efficient. The worker will accept any job with value $V > V_u$. However, their privately optimal cutoff is not necessarily the socially optimal cutoff. The planner may prefer that the worker wait to match into a better job.[14] If b is set optimally, full information will increase welfare. However, if it is not, increasing information can increase or decrease welfare (theory of the second best).

7 Quantitative Exercise

Next, we calibrate and estimate the model to match several important moments of the data. Each period corresponds to one quarter. We calibrate $\beta = 0.99$ and can normalize the flow value of unemployment b to 1. We cannot directly use the distribution of layoff rates to estimate the underlying distribution of δ_i in the model because some firms will find it unprofitable to exist and will post wages that workers will not accept. This force is important because we want to study how changing the information workers have changes which firms exist. So we simulate the employment-weighted distribution of annual firm layoff rates and match this to the analogous empirical moment. We parameterize the distribution of δ as a Beta(x,y) distribution and calibrate parameters x and y. We can then calibrate the precision of the signal in the belief formation process n, given the true (unweighted) distribution of layoff rates, which workers take as their prior. We specify worker signals s_{ij} as being drawn from a Beta distribution $s|\delta \sim \text{Beta}(n\delta, n(1-\delta))$. As n increases, the worker receives a more precise signal of δ. We choose n to match the coefficient from the regression of beliefs on layoff rates. We later vary n in our counterfactuals to understand how the equilibrium changes with the precision of worker signals. We calculate workers' Bayesian posteriors numerically.

Given all other parameters of the model, we choose C such that the worker willingness-to-pay for a 1ppt lower layoff rate equals the median worker willingness-to-pay calculated from

[14] If b reflects leisure or home production, any inefficiency will come from the workers not waiting long enough. That is, the planner prefers the worker to wait longer for a better job rather than take any job that exceeds the value of unemployment. (If b includes unemployment benefits, then workers may wait too long or not long enough.)

our survey (2.2%). From equation 7, we have that the value of a job is

$$V(w, \delta) = \frac{w + \beta\delta V_U - \beta\delta C}{1 - \beta(1 - \delta)} \tag{13}$$

If a worker is willing-to-pay ν for 1pp lower layoff rate, they are indifferent between the LHS and RHS:

$$\frac{(1 - \nu)w + \beta(\delta - 0.01)V_U - \beta(\delta - 0.01)C}{1 - \beta(1 - (\delta - 0.01))} = \frac{w + \beta\delta V_U - \beta\delta C}{1 - \beta(1 - \delta)} \tag{14}$$

We can re-arrange for C.

$$C = V_U + \frac{w(\nu(1 - \beta(1 - \delta)) - 0.01\beta)}{0.01\beta(1 - \beta)} \tag{15}$$

Next, we need the joint distribution of δ_i and z_i. While we cannot observe z_i in the data, we do observe wages. In our model, any variation in wages for a given layoff rate is driven by one of two forces: the extent of imperfect information (the belief process) or the variation in z given δ. Having pinned down the belief process, additional variation in wages comes from variation in z. Additionally, variation in δ across values of z governs the compensating differential. In our model, a negative correlation between wages and layoff rates (which we find in the data) can only be explained by a negative correlation between z and δ (i.e. less productive firms have higher layoff rates), since, all else equal, firms have to pay more to compensate workers for the higher layoff rate. We parameterize the distribution of z as Normal(μ, σ^2), and estimate the mean μ and standard deviation σ. The Gaussian copula of the joint distribution of z and δ is ρ. Finally, given other parameters, the arrival rate of jobs λ maps onto the unemployment rate. We calculate our moments using 2018 AMDB data, because we do not have wage data after 2018. The distribution of layoff rates was very similar in 2018 as in 2023, and we assume worker information has not changed meaningfully between those two years. We describe how we calculate the moments in detail in Appendix B.1.

Table 7 shows our preferred parameter values. Table 8 shows the model fit. This calibration matches certain important moments of the data well. We always match our survey moments. Given all other parameters, we can always estimate C, the cost of being laid off, and n, the signal precision, to match our empirical willingness-to-pay measure and our survey measures of misperceptions. In particular, we also match the correlation of layoff rates and log(wages). To calculate the correlation in the data, we residualize out worker effects from log wages and residualize out industry and state fixed effects from both. This correlation maps onto the compensating differential. Since it is negative in the data, this is a key moment to match. In our model, a negative correlation between wages and layoff rates can only be explained by a negative correlation between z and δ (i.e., less productive firms have higher layoff rates), since, all else equal, firms have to pay more to compensate for the higher layoff rate. Importantly, while we do control for observable determinants of wages (such as industry and place) when generating our empirical moments, we are assuming that there is no other variation in wages driven by forces outside the model, such as unobserved amenities. We also match the employment weighted average layoff rate, and unemployment rate. Our model variances are generally smaller than in the data. This is not surprising since there are limited sources of heterogeneity in our model. On the other hand, the empirical variances may be too high due to measurement error.

Table 7: Model Parameters

Parameter	**Value**
Mean of z (μ)	6
SD(z) (σ)	4
Mean of δ	0.047
Var(δ)	0.0015
ρ between δ_j and z_j	-0.7
Belief precision (n)	6.1
Job arrival rate (λ)	0.6
Discount factor (β)	0.99
b (normalized)	1.0

Table 8: Model Fit

Moment	**Model**	**Data**
Coefficient of belief on truth	0.19	0.19
WTP (%)	2.2	2.2
Corr(δ, $\log w$)	-0.25	-0.22
Mean δ	0.049	0.05
Var(δ)	0.002	0.008
Var($\log w$)	0.004	0.008
Var($\log w \mid \delta$)	0.003	0.007
Unemployment rate (%)	7.4	7.1

7.1 Counterfactuals

We vary n to show how the compensating differential and aggregate separation rates vary with worker information about layoff rates. As n increases, the signal precision (information) increases. We consider our baseline model and two counterfactuals. First, we consider a partial information counterfactual, because, in reality, future layoff rates are not perfectly predictable. In particular we choose n consistent with perfectly knowing the layoff rate of the firm last year ($n = 69.8$). Second, we consider the full information counterfactual, which is theoretically interesting, though less realistic.

Figure 7 plots the acceptance probability against the layoff rate for each of the three cases and Table 9 reports compensating differentials, average layoff rates, and unemployment rates for each case. We define the compensating differential as the % change in wages associated with a 1ppt increase in the layoff rate (employment weighted). Whether or not a worker decides to accept a job depends on the wage posted (which firms are endogenously changing across the three counterfactuals), the information that workers have about the layoff rate (the signal and the signal precision n), and the value of unemployment.

The baseline model produces a compensating differential of -0.37%. In our calibration, the correlation of layoff rates and productivity is negative—unproductive firms have higher layoff rates. Because of this, the compensating differential is negative at low levels of information. Intuitively, unproductive firms post lower wages as they profit less off of workers, and when information is very poor, workers are not very responsive to the high layoff rates. In other words, they hardly need to be compensated. The acceptance probability is downward sloping in the layoff rate, but with a fairly flat slope.

Partial information substantially shifts workers into safer jobs, but with minimal effect on recovering the compensating differential. The acceptance probability increases for low layoff rate jobs and decreases for high layoff rate jobs. This is because workers have better information about layoffs. This increased information also means that higher layoff rate firms now must have relatively higher wages relative to low layoff rate firms to maintain the same acceptance rate. They can choose to do this, or they can choose to wait (longer) for workers who get a signal that they are a low layoff rate firm and shrink in size. They mostly choose to wait longer: the compensating differential only goes from -0.37% to 0.25%. The shift in the acceptance function shifts employment toward lower layoff rate firms, decreasing the average layoff rate from 4.9% to 4.4%. This decreases unemployment from 7.43% to 6.41%, because small decreases in the average layoff rate have larger effects on how long an individual stays employed in a job. (Unemployment does not decrease because of an increase in the overall acceptance rate, which goes down slightly).

The full information counterfactual fully restores the compensating differential[15] while pushing layoff rates back up slightly (relative to partial information). The acceptance function

[15]The full compensating differential is not equal to the willingness-to-pay measure we use to calibrate the survey. This is because the WTP depends on both the cost of being laid off C and the cost in terms of lifetime earnings. The lifetime earnings cost depends on the distribution of offered wages, which adjusts in equilibrium.

steepens substantially. Now, firms must fully compensate workers for their layoff rate because workers fully observe the layoff rate. This also means that each firm either has an acceptance rate of 0 or 1. Low layoff rate firms have a higher average acceptance probability because they are more likely to find it profitable to pay the necessary wage both because they are more productive and also because the necessary wage is lower.[16] The average layoff rate is lower than the baseline, but interestingly, slightly higher than the partial information counterfactual. This is because with partial information, high layoff rate firms could choose to post a lower wage and wait around for someone willing to take their job. Now, firms can either post a wage that everyone accepts or no one accepts. This will result in any of those high layoff rate firms that are profitable enough to exist growing—workers are now indifferent between that job and any other.

Unemployment falls further relative to the partial equilibrium counterfactual even though the layoff rate has gone up slightly because the overall acceptance rate increased. Since some firms grow and some firms exit, whether the overall average acceptance rate increases again depends on what share of firms can afford to exist under imperfect versus full information.

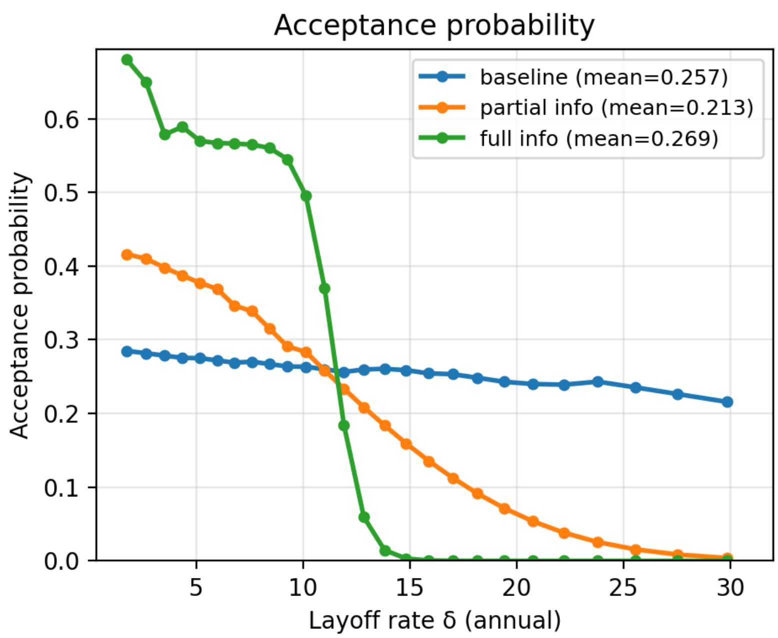
Table 9: Counterfactual Equilibrium Objects

Version	**Compensating differential**	**Average layoff rate**	**Unemployment Rate**
Baseline	−0.37%	4.9%	7.43%
Partial Info	0.25%	4.4%	6.41%
Full Info	3.35%	4.5%	5.33%

Notes: This table shows the equilibrium objects for three calibrations of the model: the baseline (to match the data), the partial information counterfactual (as if workers perfectly knew last year's layoff rate), and the full information counterfactual. The compensating differential and average layoff rate are employment-weighted.

[16]The acceptance probability is not 1 even for the lowest layoff rate firms because some firms are not productive enough to pay the required wage.

Figure 7: Acceptance Probability



Notes: This figure plots the worker acceptance probability against the annual firm layoff rate for three calibrations of the model: the baseline (to match the data), the partial information counterfactual (as if workers perfectly knew last year's layoff rate), and the full information counterfactual. The legend includes the mean acceptance rate for each series.

8 Conclusion

This paper provides new evidence on the extent and consequences of imperfect information about employment risk. Using unique linked administrative and survey data from Austria, we document several key findings.

First, we establish that employment risk varies substantially and persistently across firms, creating meaningful opportunities for workers to influence their layoff exposure through firm choice. Our analysis of administrative data shows that firm layoff rates exhibit strong persistence over time and reflect genuine firm effects rather than simply worker sorting. This persistence means that historical layoff rates provide valuable information about future job loss risk.

Second, despite this predictive value, we find that workers have remarkably poor information about layoff rates across firms. Even when asked about their most recent employer (where their knowledge should be greatest) workers perform no better than random chance in identifying whether the firm had above- or below-median layoff rates.

Third, our experimental evidence demonstrates that these information frictions matter for worker behavior. Workers are willing to sacrifice substantial compensation for lower employment risk, with the median participant giving up 2.2% of wages to work at a firm with a 1 percentage point lower historical layoff rate. When provided with accurate information about firm layoff histories, workers systematically redirect their search intentions toward safer employers. Finally, to quantify the equilibrium implications of these information frictions, we develop and calibrate a search model where workers have imperfect information about firm layoff rates. The calibration suggests that the misperceptions are large enough to reverse the compensating wage differential and raise unemployment by 1 percentage point, by shifting workers towards high risk firms.

The results in this paper also have additional implications. Workers' ability to observe employment risk also matters for the extent to which firms choose to offer insurance over employment risk. A classic question in economics asks why do firms lay off workers instead of cutting wages? Our results offer one potential explanation: firms do not benefit from offering ex-ante employment insurance, because workers do not observe the level of employment risk associated with a firm. It is difficult to enforce or verify a given layoff risk. By contrast, it is easier to enforce downward nominal wage rigidity as a form of wage insurance.

This work leaves open several directions for future research. Importantly, in our model, we fix layoff rates exogenously. If firm layoff behavior responds to worker behavior, imperfect information would also distort the firm's choice of layoff rates. Future research studying the empirical mapping between worker behavior and firm layoff decisions is key to quantifying such a force. This would also have implications for the optimal design of information provision policies and experience rating schemes. Testing the effects of providing workers with firm-specific (rather than trait-level) information would also be useful for policy design.

More broadly, our results suggest that transparency about past layoffs could be an important dimension of labor market policy. As workers increasingly rely on online platforms to navigate the job search process, there are substantial opportunities for governments to provide information about firms to workers during the job search process. Understanding what information workers value and do not have, and understanding the consequences of providing that information is key to designing policy.

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Appendix

A Results

A.1 Selection into Survey Completion

This table compares the characteristics of those who opened the survey to those who did not. They are broadly similar. Those who started the survey are slightly more likely to be women and slightly older.

Table A1: Sample Characteristics

	Did not start	Started	Total	Test (p-value)
N	37,382 (92.2%)	3,155 (7.8%)	40,537 (100.0%)	
Austrian	0.736 (0.441)	0.760 (0.427)	0.737 (0.440)	0.003
Woman	0.483 (0.500)	0.536 (0.499)	0.487 (0.500)	< 0.001
Age	39.614 (12.820)	42.412 (12.384)	39.831 (12.808)	< 0.001
Marginally employed	0.082 (0.274)	0.077 (0.266)	0.081 (0.273)	0.320
Married	0.355 (0.479)	0.377 (0.485)	0.357 (0.479)	0.013

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A.2 Balance

Table A2 shows the treated and control groups are balanced across a broad range of observable characteristics.

A.3 Survey 2 attrition

To verify that there is no differential attrition of treated versus control participants, we estimate the following equation.

$$\text{Completed Survey } 2_i = \beta_0 + \beta_1 \text{Treat}_i + \gamma_j + \varepsilon_{ij} \tag{A1}$$

Table A3 shows the coefficient estimates. The estimated effect of treatment on completing survey 2 is statistically indistinguishable from 0 and quantitatively small. The 95% confidence interval for the coefficient on Treat is (-0.057, 0.0239).

Table A2: Balance

Variable	Control	Treated	Total	Test (p-value)
N	1,798 (50.0%)	1,801 (50.0%)	3,599 (100.0%)	
Austrian	0.756	0.755	0.756	0.930
	(0.429)	(0.430)	(0.430)	
Woman	0.549	0.531	0.540	0.261
	(0.498)	(0.499)	(0.498)	
Age	42.490	42.540	42.515	0.903
	(12.349)	(12.465)	(12.406)	
Marginally Employed	0.077	0.080	0.078	0.721
	(0.266)	(0.271)	(0.269)	
Married	0.384	0.385	0.385	0.977
	(0.487)	(0.487)	(0.487)	
German Native	0.664	0.665	0.664	0.944
	(0.473)	(0.472)	(0.472)	

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3: Survey 2 attrition

	(1) Completed Survey 2
Treat	-0.017
	(0.021)
Industry	0
	(.)
Size	-0.037
	(0.025)
Temp	-0.022
	(0.031)
Constant	0.82***
	(0.023)
N	1591

Notes: This table tests for differential attrition by treatment status. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A.4 Symmetry of experimental results

We estimate the 2SLS specification to understand the effect of beliefs about layoff risk on job search outcomes, interacted with an indicator for whether the gap (information provided - participant prior) was positive. If it was positive, the layoff rate exceeded the prior–i.e. the participant learned a type of firm was riskier. The coefficient on the interaction is generally small in magnitude relative to the coefficient on the main effect, suggesting the effects are symmetric. Define $D_{ij} \equiv \mathbf{1}\{\text{Gap}_{ij} > 0\}$. The results are in Table A4. The first stages are given by

$$\text{Posterior}_{ij} = C_j + \beta_1 \, \text{Gap}_{ij} + \beta_2 \left(\text{Treat}_{ij} \times \text{Gap}_{ij}\right) + X_{ij} + u_{ij} \tag{A2}$$

$$\left(\text{Posterior}_{ij} \times D_{ij}\right) = C_j + \gamma_1 \, \text{Gap}_{ij} + \gamma_2 \left(\text{Treat}_{ij} \times \text{Gap}_{ij}\right) + X_{ij} + v_{ij}. \tag{A3}$$

And the second stage is:

$$Y_{ij} = c_j + \alpha_0 \, \widehat{\text{Posterior}}_{ij} + \alpha_1 \left(\widehat{\text{Posterior}_{ij} \times} D_{ij}\right) + \beta_{1j}' \, \text{Gap}_{ij} + X_{ij} + \varepsilon_{ij}. \tag{A4}$$

Table A4: Symmetry by direction of updating

	(1) Resume Tips	(2) Link to Jobs	(3) Planned Number of Apps	(4) Planned Any Apps	(5) Planned Share Apps	(6) IHS Apps
Posterior (10 ppt)	-12.4**	-7.31	-0.70	-9.77	-3.33	-0.24*
	(5.92)	(5.60)	(0.46)	(6.05)	(4.39)	(0.13)
Posterior (10 ppt) × $1(Gap > 0)$	1.77	-1.89	0.16	-0.42	-1.17	0.035
	(3.87)	(3.66)	(0.29)	(4.11)	(2.96)	(0.087)
N	1388	1388	1388	1388	1388	1388

Notes: This table shows the 2SLS estimates of the effect of posterior beliefs about the layoff rate at a type of firm on interest in jobs at that type of firm. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All regressions include controls for gap, prior, and trait.

A.5 Layoff Rate AKM

To understand the role of time-invariant firm effects in layoffs, we can also estimate a fixed effects model in the tradition of the wage AKM (Abowd et al., 1999) literature. We define $\text{Laid off}_{ijt} = 1$ if worker i was employed by firm j at the start of year t and laid off from firm j in time t and 0 if worker i was employed by firm j at the start of year t. We regress this indicator on worker fixed effects, firm, fixed effects, and year fixed effects.

$$\text{Laid off}_{ijt} = \alpha_i + \psi_j + \delta_t + \varepsilon_{ijt} \tag{A5}$$

We then decompose the variance into the part explained by each component and the residual component.

$$Var(\text{Laid off}_{ijt}) = Var(\alpha_i) + Var(\psi_j) + Var(\delta_t) + Var(\varepsilon_{ijt}) + \\ 2Cov(\alpha_i, \psi_j) + 2Cov(\alpha_i, \delta_t) + 2Cov(\psi_i, \delta_t) \quad \text{(A6)}$$

Table A5 shows the variance decomposition. Of the total variance, 31% is explained by worker fixed effects, 20% is explained by firm fixed effects, there is a -15% negative contribution of sorting, and 62% is residual variance. Of course, there is much higher unexplained variance $Var(\varepsilon_{ijt})$ in layoff indicators than in wages. Even if latent layoff probability was fully driven by worker effects, the realization of whether a worker is laid off in any given year is a random variable, so not all of the variance would be explained by worker fixed effects. These results are broadly in line with the results from movers analysis in 3, showing a substantial contribution of firm effects in layoff rates.

Table A5: Variance decomposition

Component	Value	Share of total (%)
Var(Laid off$_{ijt}$) (Total)	0.0517	100
Var(α_i)	0.0158	31
Var(ψ_j)	0.0102	20
Var(δ_t)	0.0000	0
Var(ε_{ijt})	0.0322	62
2 Cov(α_i, ψ_j)	-0.0078	-15
2 Cov(α_i, δ_t)	0.0000	0
2 Cov(ψ_j, δ_t)	0.0000	0

Notes: "Share of total" is each component divided by Var(Laid off$_{ijt}$); covariance terms may be negative, so shares need not all be positive. Shares may not sum to 100% due to rounding.

Because layoffs are not extremely common, one may also worry about measurement error increasing the variance of estimated fixed effects. To address this, we use two split samples. First, we split observations from each firm into two samples. This allows us to estimate firm FEs on each sample and estimate the covariance of the fixed effects in each sample. Then, we split observations from each worker into two samples, and estimate the covariance of the fixed effects in each sample. We restrict to firms with at least 50 workers to have enough observations to estimate firm effects. Then we restrict to sample of workers that have enough observations to be split. Of course this introduces sample selection, where the firm effects at smaller firms may be different than those at larger firms. (This also likely helps correct firm measurement error on its own). We re-estimate the naive AKM on this sample for comparison. We find similar estimates of the share of the variance explained by firm and worker fixed effects.

The variance of firm effects for this sample, naively estimated is 0.0033. The naive variance of worker effects is 0.0071. The split sample estimates are 0.0033 for the estimate of firm effects and .0042 for the estimate of worker effects. We also get a very similar estimates of the split sample covariance. Encouragingly, the split sample produces a similar number for the share of the explained variance explained by firm effects. It also suggests that, for layoff rates, measurement error is likely to contribute to the overestimate of worker effects. Table A5 shows the split sample estimates alongside the naive estimates, for the same sample.

Table A6: Variance decomposition

Component	Value	Split-sample value	Share of total (%)
Var(Laid off$_{ijt}$) (Total)	0.0266		100
Var(α_i)	0.0071	0.0042	26
Var(ψ_j)	0.0033	0.0033	12
Var(δ_t)	0.0000		0
Var(ε_{ijt})	0.0181		68
$2\,\mathrm{Cov}(\alpha_i, \psi_j)$	-0.0022	-0.0022	-8
$2\,\mathrm{Cov}(\alpha_i, \delta_t)$	0.0000		0
$2\,\mathrm{Cov}(\psi_j, \delta_t)$	0.0000		0

Notes: "Share of total" is each **naive** value (not split sample) divided by Var(Laid off$_{ijt}$); covariance terms may be negative, so shares need not all be positive. Shares may not sum to 100% due to rounding.

An important feature of this exercise is that we estimate time-invariant firm effects. While firm layoff rates are persistent, they become less persistent as you go further back in time. It seems likely that firm effects have an important time-varying component.

B Quantitative Exercise

B.1 Calculating Moments

This section describes the calculation of moments used in the quantitative exercise in section 7. For the following moments, we first need a measure of firm level layoff rates and firm-level wages. We use 2018 wages and layoff rates. We regress log(wages) and the layoff rate on 6 digit industry-state fixed effects and use the residuals. We use the residuals in every measure below. Since factors like industry-specific wage premia are not modeled, removing this component of wages is useful.

Corr(δ, $\log w$) We estimate the correlation between firm layoff rates and average firm wages. Since the relationship between wages and layoff rates is a key object in our model, and disciplines the choice of a negative correlation between the layoff rate and firm productivity, we also show robustness to this by estimating the relationship between the AKM firm wage premia and the layoff rate. We estimate a fairly similar correlation: -0.19 instead of -0.22. It is worth noting that other job attributes could be correlated with layoff rates and wages and be driving this negative correlation.

Mean δ The weighted mean of 2018 layoff rates of firms with more than 10 workers. This uses raw rather than residual layoff rates.

Var(δ) The weighted mean of 2018 layoff rates of firms with more than 10 workers. This uses raw rather than residual layoff rates.

Var($\log w$) The variance of the residual log(wages), employment weighted and restricted to firms of more than 10 workers. We do a method of moments correction for measurement error.

Var($\log w \mid \delta$) We regress log(wages) on percentile of 2018 layoff rates along with industry-state fixed effects, and take the variance of the residuals. This is weighted by employment and restricted to firms larger than 10.

B.2 Quantitative Exercise Assumptions

Functional form of the beliefs process We specify worker signals s_{ij} as being drawn from a Beta distribution $s|\delta \sim \text{Beta}(n\delta, n(1-\delta))$. As n increases, the worker receives a more precise signal of δ. We choose n to match the coefficient from the regression of beliefs on layoff rates. Let α be the coefficient of beliefs on the truth. We set $n = \frac{(x+y+2)\alpha-1}{1-\alpha}$, where x and y are the parameters of the Beta(x,y) distribution of layoff rates.