ISSN 0956-8549

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FINANCIAL MARKETS GROUP DISCUSSION PAPER NO. 957

June 2026

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This draft: January 20, 2026

Abstract

We construct a firm-specific profit uncertainty index and profit shocks for Swedish firms and their employees (1997-2017) using shrinkage methods on commodity prices. Higher uncertainty decreases the likelihood of firing younger and shorter-tenured workers, while it increases the firing of more skilled workers. Furthermore, it increases the hiring of workers with sector-specific experience. These findings are consistent with a model where heterogeneous workers vary in *specialization* and *flexibility*, and uncertainty differently impacts the option value of firing and relocating workers. Our findings emphasize that estimating the effects of uncertainty on the overall level of employment of firms, without considering the different characteristics of these workers, is likely to underestimate the true impact of uncertainty shocks.

Keywords: Uncertainty, Worker Types, Hiring and Firing Decisions

JEL Codes: G30, D81, J23, J63

*We thank Manuel Arellano, Stephane Bonhome, Jan Eeckhout, Kerstin Holzheu, Marianna Kudlyak, Spyridon Lagaras, Eduardo Morales and the participants to seminars at UPF, CREI, Danish National Bank, EFA, City University (Bayes), Nottingham University, Tinbergen Institute, CEMFI, Fudan, The Labor and Finance Group, HKUST, NOVA, SAEe Symposium, SED 2024 annual conference and GRUV 2025 annual conference for useful comments and suggestions. We thank Andrea Sy and Irina-Eusignia Stanciou for excellent research assistance. Andrea Caggese acknowledges financial support from the Agencia Estatal de Investigación (AEI) grant no. PID2020-116268GB-I00 on"Firms and Households Heterogeneity, Aggregate Fluctuations, and Macroeconomic Policies", and from the Spanish Agencia Estatal de Investigación (AEI), through the Severo Ochoa Programme for Centres of Excellence in R&D (Barcelona School of Economics CEX2019-000915-S).

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1 Introduction

Economic uncertainty can have a profound impact on firm-level decisions, with broader implications for economic productivity and growth. For example, events such as the Covid-19 pandemic, the Russia-Ukraine war, or the recent escalation of U.S. import-tariff measures, imply not only likely negative economic shocks but also sharp increases in aggregate economic uncertainty.

Theoretical models predict that uncertainty shocks might have heterogeneous effects on different firm decisions. Those that imply large sunk costs or are to a certain degree irreversible, are negatively affected by uncertainty. However, investments whose future profits are convex in the uncertain outcome might increase in value, and thus be positively affected by more uncertainty.[1] This potential heterogeneity is particularly important for employment decisions. Each employee entails, from the firm's viewpoint, a bundle of real options. Hiring a new worker involves several upfront sunk costs such as screening, hiring, and training costs. Since these costs are irreversible, more uncertainty increases the option value of waiting. Moreover, workers are also similar to long-term assets of firms with options on future decisions which increase in value with uncertainty, such as firing, training, promotions, and re-locations within the firm. The value of those real options, however, depends on the profile of the worker, and therefore different types of workers are expected to be affected differently by uncertainty shocks.

Despite the potential importance of this heterogeneity in shaping the relation between uncertainty and employment fluctuations, little is known about how uncertainty shocks affect the hiring and firing of different types of workers. On the one hand, several recent papers have made significant progress in identifying exogenous variation in uncertainty and measuring their effects on capital and labour.[2] However, they do not investigate whether effects of uncertainty shocks differ depending on workers' characteristics. On the other hand, the labor literature has emphasized the importance of workers heterogeneity for wage dynamics, worker dynamics, and inequality.[3] However, it has not stud-

[1] Among the literature showing how different technology assumptions can lead to opposite predictions on the uncertainty investment relation, see Abel (1983), Caballero (1991) and Abel and Eberly (1996).

[2] See, among others, Kumar et al. (2023), Alfaro et al. (2024), Baker et al. (2020), Bloom (2009), Fernández-Villaverde et al. (2011), Bloom et al. (2018), Jurado et al. (2015), Ludvigson et al. (2021),Baker et al. (2020), Bloom et al. (2019), Gulen and Ion (2016)

[3] See, among others, Postel-Vinay and Robin (2002), Acemoglu and Autor (2011), Davis et al. (2013), Lindenlaub (2017), Bonhomme et al. (2019), Lise and Postel-Vinay (2020), Lindenlaub and Postel-Vinay

ied the effects of uncertainty shocks on heterogeneous workers.

This paper contributes to the literature in three significant ways. First, we develop a new measure of uncertainty shocks at the firm-level that can be calculated for the whole population of firms. Second, we estimate how uncertainty affects the firing and hiring decisions of firms, with special emphasis on the heterogeneous effects across worker types, e.g., by tenure, age, skills, and experience. Finally, we show that our empirical results are consistent with a model of hiring and firing decisions of different types of workers under uncertainty. The key insight of the model is that uncertainty has heterogeneous effects on workers because, depending on their characteristics, it affects differently the option values of firing and relocating them.

In our empirical analysis, we employ matched employer-employee data covering Sweden's entire population from 1990 to 2017. This comprehensive dataset enables us to precisely measure workers' characteristics and classify them into relevant categories, such as by tenure or work experience. As a result, we are able to identify how changes in uncertainty differentially affect firm decisions depending on worker characteristics.

With respect to uncertainty, we propose a novel way to construct and estimate an exogenous, firm-level uncertainty index. We use commodity price fluctuations to derive a measure of firm-specific profit uncertainty. Volatility of commodity prices is an attractive source of variation in firm-level uncertainty. The exposure of firms' profitability to different commodities is heterogeneous and often quite large. In addition, international commodity markets are large and very informationally efficient. Therefore, the fluctuations of international commodity prices are unexpected and not affected by individual firm decisions.

To estimate the uncertainty indices, we proceed in three steps. First, we start with daily prices of 20 commodities for the period 1997-2017. We then reduce the heterogeneity and dimensionality of the data by extracting seven principal components that explain 99% of the variance of the original commodity prices fluctuations. Second, we use machine-learning methods (LASSO), robust to the problem of short time-series dimension, to calculate firm-level profit exposures to each uncertainty factor. The outcome of this process is a series of estimated firm-specific coefficients (commodity betas) that represent the sensitivity of the firm's profitability to each of the seven factors. We can, therefore, con-

(2023).

sider the profitability of each firm as a portfolio of orthogonal factors with firm-specific weights. Finally, we estimate the predicted volatility of firm profits using this portfolio approach and normalize it at the firm level to obtain our firm-specific uncertainty index.

The index has three important properties: i) it measures uncertainty regarding factors that matter for firm's profitability; ii) it has a time varying, firm-specific component and does not only reflect aggregate uncertainty. This allows us to use more saturated regressions that absorb time varying sector shocks. Relatedly, the index can be calculated for the whole population of listed and non-listed firms while retaining firm-specific variation;

iii) the uncertainty shock, measured by fluctuations in this index, is exogenous to the firms' policies. We also use the commodity betas and commodity prices to compute a predicted profits shock. Its inclusion as an additional control in the regressions ensures that the uncertainty index is only capturing second-moment shocks, excluding any directional effect on profits. We also saturate our regressions with either firm-year fixed effects or a combination of firm and sector-year fixed effects.

To verify the validity of our approach, first we show that the index contains substantial within-firm variation, with 30% of its variation being within firm, net of aggregate year effects. Second, we show that a positive first moment profits shock has a positive, large, and significant effect on firm-level employment, confirming that fluctuations in profits caused by commodity price movements are important enough to affect firms' decisions. Finally, we show that, within firms, an increase in uncertainty significantly increases the time series volatility of profits.

After verifying the validity of our new uncertainty measure, we run worker-level regressions on firing decisions and firm-level regressions on hiring decisions. Our main findings are as follows. First, we document large and significant effects of first-moment shocks. An increase in profits predicted by firms' exposures to commodity prices leads to higher hiring and lower firing rates. These effects are uniform between different types of workers. Second, firm-specific uncertainty shocks have quantitatively small effects on the overall hiring and firing propensities of firms. Third, we analyse the heterogeneous effect of uncertainty shocks on different types of workers, the most important and novel set of tests in the paper. In periods of higher firm-specific uncertainty, firms are more likely to hire already experienced workers, relative to normal times. This result is consistent with less experienced workers arguably requiring higher ex-ante screening and training costs, making them less valuable in uncertain periods. Furthermore, we also find that, in normal times, older workers, as well as workers with longer tenure in the firm, are fired less frequently. However, these workers are fired more frequently conditional on an uncertainty shock, with respect to the other workers (younger workers or workers with shorter tenure). The compositional results are robust to including firm-year fixed effects, which control for any unobserved factor common to all workers in a given firm-year. Since younger and short-tenured workers are likely more flexible than older and longer-tenured ones (who are instead less flexible but likely more productive in their current tasks), these findings imply that flexibility becomes more valuable in more uncertain times. Finally, we also find that more productive worker, measured as workers with higher education, are more likely to be fired relative to less educated workers, when firms experience an increase in uncertainty.

Next, we test whether the results are really driven by firing decisions of firms rather than by voluntary separation of workers. For example, older workers might be more likely than younger ones to leave the firm voluntarily if the firm's situation becomes more uncertain. We aim to distinguish these cases by considering "voluntary exits" rather than firings as dependent variable in our analysis. We find much weaker effect of uncertainty shocks on voluntarily turnovers, reinforcing the conclusion that the results described before are generated by firing decisions of firms in the presence of exogenous changes in uncertainty.

The heterogeneous effects of uncertainty across workers can be explained through differences in workers' option values. We formalize this idea in a two-period model with heterogeneous workers and firm-level hiring and firing decisions. In the model, firms operate multiple projects, hiring workers in the first period and producing in the second. Workers differ in *specialization*, which determines their productivity in their current project, and *flexibility*, which reflects their ability to be redeployed to other projects. Flexibility is broadly interpreted as the capacity of workers to adapt to new tasks or be retrained when firms face challenges during periods of heightened uncertainty. Hiring each worker entails a positive fixed cost, representing both recruitment and training expenses. Project returns are risky and positively, but not perfectly, correlated within firms, and a firm-level uncertainty shock increases the volatility of individual project returns as well as overall firm returns. At the start of the second period, project profitability is revealed, and for unprofitable projects, firms can choose to fire workers –saving wages net of firing costs– or redeploy them to profitable projects. In this setup, expected second-period firing decisions affect workers' expected profitability and firms' ex-ante hiring decisions. Although stylized, the model features a closed-form solution and is sufficiently rich to analyze how uncertainty shocks influence the option values of hiring and firing heterogeneous workers.

The model shows that more uncertainty generates some incentives to reduce hiring, because initial hiring costs might be wasted if ex-post the project is terminated. However, uncertainty also increases the option value of firing specialised workers and relocating flexible workers. These options increase the convexity of profits and generate a positive link between uncertainty, the ex-ante value of workers, and hiring. The model shows that while the effect of uncertainty shocks on overall hiring and firing decisions is in general ambiguous, there are a set of testable predictions regarding the optimal mix of workers. First, the model predicts that the firing probability of more productive workers increases more with uncertainty than that of less productive ones. Second, uncertainty shocks increase the firing probability of specialized workers more than that of more flexible workers. Third, an increase in firm-level uncertainty increases relatively more the hiring of workers that are cheaper to hire and to train. The latter prediction is directly related to our finding that uncertainty causes firms to hire more intensely workers who are already experienced. The first one is consistent with the empirical results on skilled workers since those tend to be more productive than unskilled ones. The second prediction is supported by the data under the assumption that younger and shorter tenure workers tend to be more flexible. In the last part of the paper we provide more direct evidence of this flexibility, showing that shorter tenured workers and younger workers are more likely to change occupation within the firm. Furthermore, we provide additional direct evidence supporting the predictions of the model by showing that flexible workers, identified as those employed in more flexible occupations, are fired less often in high uncertainty periods than the other workers.

Overall, this paper is, to our knowledge, the first to propose a firm-level measure of exogenous uncertainty, and to estimate its heterogeneous effects on a matched panel of firm- and worker-level data covering a whole population of firms. On the one hand, we find that uncertainty shocks have large effects on the composition of hiring and firing, and, hence, on the employment outcomes for these workers. On the other hand, we show that our heterogeneous results can be rationalised with a trade-off between sunk costs, which drive a negative relation between uncertainty and firm decisions, and flexibility options, which instead drive a positive relation. We think this trade-off is potentially important for other types of firm decisions beyond labour. Therefore, our findings emphasize that estimating the effects of uncertainty on the overall level of investment or employment of firms, without considering the different characteristics of these investment projects or workers, is likely to underestimate the true impact of those uncertainty shocks.

***Related Literature*:** This paper is related to the literature on firm decisions under uncertainty and in particular to the recent studies that attempt to disentangle exogenous uncertainty shocks from endogenous responses to other shocks, such as Kumar et al. (2023), Alfaro et al. (2024), Baker et al. (2020) and Bloom et al. (2019).[4] Our empirical methodology to identify uncertainty shocks shares similarities with Alfaro et al. (2024), with the difference that we identify firm-level rather than sector level variation in uncertainty.[5]

However, our objective is fundamentally different from these papers. While earlier work has focused on the impact of uncertainty on the overall capital investment and employment levels in the firm, the key objective of our paper is to identify the heterogeneous employment effects of uncertainty shocks. By using a dataset with matched firms-workers data, we identify novel heterogeneous effects of uncertainty shocks on hiring and firing decisions of firms, which confirm the predictions of a stylised theoretical framework in which uncertainty affects the option value of these workers in different ways.

Given the focus on hiring and firing decisions of firms, our paper is also related to the literature on job dynamics. On the one hand, it is related to work that analyzes the dynamics of hiring and separations across firms and establishments. Among others, see for example Davis et al. (2012) and Davis et al. (2013). Consistently with the results of

[4]Earlier work on investment and labour theory under uncertainty include, among other, Bertola and Caballero (1994), Dixit and Pindyck (1995), and Abel and Eberly (1996)). Following these theoretical contributions, several papers proposed methods to identify fluctuations of uncertainty, and their real effects, using macroeconomic data (see Bloom, 2009, Fernández-Villaverde et al., 2011, Bloom et al., 2018; Jurado et al., 2015, Ludvigson et al., 2021, among others). Related work in corporate finance shows that access to debt shapes firms' precautionary responses to uncertainty (Favara and Giannetti, 2021).

[5]Alfaro et al. (2024) exploit industries' differential exposure to commodity prices shocks to identify the effects of exogenous variation in industry-level uncertainty on Compustat firms. Therefore, in their paper uncertainty is computed at the industry level using listed firms and extrapolated to all firms in the industry. In our approach, uncertainty is calculated on a firm-by-firm basis for each year and we control for industry x year fixed effects or firm x year fixed effects when we focus on within-firm firing outcomes.

this literature, we find that a positive firm-level profits shock increases employment by increasing hiring and reducing firing. In addition, we document new findings on the effects of second moment (uncertainty) shocks, which to the best of our knowledge have not been studied before in this literature.

On the other hand, it is related to the theoretical contributions on heterogeneous workers dynamics.[6] In particular, Lindenlaub (2017), Lise and Postel-Vinay (2020), Lindenlaub and Postel-Vinay (2023) develop frameworks in which workers differ in skills along several dimensions and are endogenously matched with jobs with heterogeneous skill requirements along those same dimensions. These new approaches are essential to understand how technological change interacts with the labour market to determine inequality across workers and firms. Our contribution is to show that, when firms need workers with different characteristics, fluctuations in uncertainty are likely to affect the hiring and firing rates of these workers in different ways, with potentially important distributional consequences.[7] Furthermore, we focus on specialization and flexibility as the key dimensions of workers heterogeneity. This is supported by a recent literature highlighting the importance of these dimensions, and proposing empirical strategies to measure them (e.g. see Le Barbanchon et al., 2023, Freund, 2022 and Bárány and Holzheu, 2023). Our chosen methodology to identify flexible workers is closely related to these approaches.

Our paper is also closely related to the work of Friberg and Sanctuary (2019), that uses exports, imports and currency volatility to construct a firm-level measure of exchange rate risk and studies their effect on the fraction of skilled workers in the firm. Relative to Friberg and Sanctuary (2019), we use a more comprehensive measure of uncertainty and focus on employment flows, rather than levels. We also focus on the heterogeneity of workers along several characteristics beyond their skills.

Finally, because of our focus on how firms' shocks affect workers, we are related to Guiso et al. (2005) and Friedrich et al. (2019) who, among others, document how firm shocks are partially transmitted to workers, increasing their earnings volatility. Relative to these papers, we show that not only first moment but also second moment profits shocks affect workers prospects,heterogeneously across worker types.

[6]For a review on the assortative matching literature, see Chade et al., 2017.

[7]While in general the theoretical models in the search and matching literature do not consider uncertainty shock, there are few important exceptions, such as Schaal (2017) and Den Haan et al. (2021). However these authors only consider homogeneous worker types.

2 Firm-Level Uncertainty and Empirical Framework

In this section, we explain how we construct a firm-level uncertainty index based on the exposure of the firm profits to different commodity prices. Next, we describe the data. We then provide evidence on the validity of the index. Finally, we describe the empirical framework for the main analysis in the paper.

2.1 The Construction of the Uncertainty Index

A key element of our analysis is a reliable measure of exogenous, firm-level uncertainty shocks that matter for firm decisions. This measure should have three desirable properties. First, it should affect dimensions that are relevant to the firm's profits or operations. Second, the measure should have a firm-specific component and not only reflect aggregate uncertainty. Third, the changes in the measure of uncertainty should be unexpected and exogenous to the firm's decisions.

To achieve these objectives, we construct an uncertainty index that combines the exposure of each firm's profits to commodity price fluctuations with the time-varying volatility of each commodity. The index is based on 20 daily commodity prices from 1997 to 2017. We first transform each price into an index to account for differences in units, then filter out high-frequency changes. Next, we apply principal component analysis to extract seven orthogonal factors that capture most of the variation in commodity prices. The annual average transformed price Pjt is then computed for each principal component, which can be interpreted as weighted portfolios of commodities, ranked by their explained variance (details in Section 2.2.1)

We then proceed in two steps to construct the uncertainty index. First, we estimate the directional exposure of each firm's profits to each commodity principal component. We define the profitability π_{ft} of each firm f on year t as the EBITDA of the firm on that year divided by Total Assets at the beginning of the year.[8] We then run the following specification separately for each firm:

$$\pi_{ft} = \alpha_f + \sum_{j=1}^{7} \beta_{fj} P_{jt} + \epsilon_{ft} \tag{1}$$

[8]EBITDA is earnings before interest, taxes, depreciation and amortization.

in which we estimate for each individual firm's profits, the exposure β_{fj} to price fluctuations of each of the seven portfolios indexed by j. Given the limited number of observations per firm (up to twenty years) and the potential irrelevance of some principal components to firm profits, we estimate the equation using a LASSO procedure. The regularization parameter lambda is selected via the Akaike information criterion, which is well-suited for small samples. Applying LASSO to principal components, rather than the original commodity data, is preferable because principal components are orthogonal by construction, whereas commodity prices can be highly collinear. This approach selects the most relevant components for each firm's profits and shrinks the number of coefficients used in the next stage.

In the second step of the construction of the index, we calculate –at a firm level– the predicted standard deviation of firm's profits as the square root of the sum of the product of the selected first-stage coefficients squared with the variance of their respective principal component. That is:

$$Index_{ft} = \sqrt{\sum_{\beta_{fj} \in B_f} \hat{\beta}_{fj}^2 \sigma_{jt}^2} \tag{2}$$

where the parameter σ_{jt} is the annualized standard deviation of the log monthly returns of each principal component, $\hat{\beta}_{fj}$ is the estimated beta of the first stage and B_f is the set of non-zero betas that are estimated and not discarded by the LASSO procedure for a given firm. Given that the principal components are orthogonal to each other, the profitability of the firm can be seen as if it was coming from a portfolio of orthogonal assets (factors), so the index is an unbiased predictor of the standard deviation of firm's profitability.[9] We then normalize the index to have mean zero and standard deviation 1 at the whole sample level.

We also use the estimated betas to also compute the predicted profits shock:

$$\hat{\pi}_{ft} = \hat{\alpha}_f + \sum_{\beta_{fj} \in B_f} \hat{\beta}_{fj} P_{jt} \tag{3}$$

where $\hat{\pi}_{ft}$ measures the expected effect of commodity prices on firm profits.

[9]Note that one of the advantages of using orthogonal principal components is that we can predict the standard deviation of firms profits as a portfolio of factors, rather than linearly approximating it as in Alfaro et al. (2024).

2.1.1 Sector-level uncertainty index and instrumental variable approach

As our main firm-level uncertainty index uses estimated betas as inputs, it measures the true standard deviation of profitability with some error. When we use the measure as an explanatory variable, this may lead to some attenuation bias in our regressions. However, one can achieve consistency with an instrumental variables approach that uses as IV another noisy estimate of the same underlying variable (see Arellano, 2003). For this purpose, we construct an alternative index that uses similar principles, but with a first stage constructed at the sector-year level, rather than at the firm-level. The first stage of this sector-year index follows Equation (1) but, in this case, the subindex f represents the subset of firms in a given (3-digit) sector and year. The second stage is constructed accordingly, using the estimated betas of the first stage. The source of variation of this second index is entirely different from that of our main index, however, they are both constructed on the basis of the same underlying uncertainty. Therefore, this alternative sector-year index is used in some of our specifications as an instrumental variable to reduce the effects of measurement error in the estimation.[10]

2.1.2 Index Properties

The uncertainty index is well-suited for identifying the causal effects of uncertainty shocks on firm employment decisions. First, commodity prices are set in highly liquid and informationally efficient markets, meaning that, aside from a commodity-specific risk premium, changes in prices or volatility are unexpected; otherwise, arbitrage would eliminate them.[11] Second, the index captures firm-level heterogeneity in exposure to commodity prices, allowing us to estimate its effects net of industry-year fixed effects. This heterogeneity across firms is substantial (see subsection 2.5) and proxies for an important source of uncertainty. It stems from both direct exposure (e.g., reliance on a specific input) and indirect exposure (e.g., demand from Norway, a major oil exporter and key Swedish trading partner). The indirect exposure makes the index relevant even for sectors that do not use commodities like services. While firms may hedge some fluctuations, most exhibit nonzero estimated exposures, indicating that full hedging is uncommon. Third, although

[10] In the IV regressions, the source of variation is at the 3-digit sector-year level, allowing us to control for 1-digit sector and year fixed effects.

[11] See Gorton et al. (2013) for a comprehensive analysis of commodity prices and the determinants of commodity risk premia.

$Index_{ft}$ is not directional by construction, it may correlate with first-moment shocks, so we control for the predicted profit shock $\hat{\pi}_{ft}$. Fourth, firm-level reverse causality is unlikely, as no firm in our sample is large enough to influence international commodity markets. While many firms collectively could affect prices, this concern is mitigated by Sweden's small market size and our inclusion of firm and sector-year or firm-year fixed effects. Finally, omitted variables that affect both profitability and commodity prices are unlikely to bias our results. If such factors systematically influenced commodity prices, their effect on firm profits would be captured by $\hat{\pi}_{ft}$, meaning $Index_{ft}$ would primarily reflect volatility-related uncertainty. Moreover, sector-year level omitted factors are absorbed by fixed effects, and any predictable variations would be arbitraged away. Importantly, only the unpredictable component of any omitted variable affects our results; if omitted variables predictably influenced commodity prices, arbitrage would eliminate these variations. Thus, we still capture the effects of unexpected, profit-relevant uncertainty shocks on labor outcomes, preserving our identification strategy.

2.2 Data

2.2.1 Commodity Data

To compute our uncertainty index, we use daily commodity price information for 20 commodities. Depending on the commodity, price information comes from an organized spot market (e.g., gold prices are provided by the London Bullion Market Association) or from future contracts that are spliced together to construct a continuous future price (e.g., this is the case for the Brent Crude Futures provided by Intercontinental Exchange - ICE).

We first transform each price into an index with year 1997 as a base to reduce the heterogeneity in units across commodities. Then, we filter each commodity index through a Hodrick-Prescott filter with a signal-to-noise ratio $\lambda = 500$ and retain the trend component of each price. This filtering reduces the high frequency component of commodity prices. Finally, we construct seven principal components of the transformed prices that explain 99% of the variance in the original data. Table B1 and Table B2 in the Appendix give details of the different commodities their loadings. [12]

[12]For the purpose of index construction, it is not necessary to interpret each principal component individually. What matters is that some are profit-relevant and that firms' exposures to them are heterogeneous and exogenous. first three principal components capture most of the total variation. The first principal component loads positively on all commodities, the second has positive loadings on oil and some metals

2.2.2 Firm Data

We use the PAR/Bisnode matched employer-employee data from the Swedish Companies Registration Office for universe of Swedish firms (1998-2017). The data include balance sheets and income statements of all Swedish limited liability companies, consolidated at business group-level. In the following, we use the term "firm" for standalone companies as well as for business groups.

To ensure meaningful comparisons across workers of a given firm, we limit our sample to firms with a substantial employee base and stable operations. Specifically, we include firms that: i) employ at least 50 workers, and ii) exhibit a yearly workforce growth rate between -30% and +30%. The latter criterion is likely to exclude firms that experienced a significant restructuring episode. Further, we exclude the 26% of firms for which we cannot compute the uncertainty index (see Section 2.5 below for details). Our final firm sample consists of 23,176 firm-year observations of about 3,700 unique firms. with approximately 2,000 firms per year. The mean (median) employment is 477 (107) workers. Table 1 (Panel B) reports firm-level summary statistics.

2.2.3 Worker Data

Our worker sample is the *"longitudinal integration database for health insurance and labor market studies"* (LISA) provided by Statistics Sweden (SCB). The database holds annual registers since 1990 and includes all individuals 16 years of age and older who were registered in Sweden as of December 31 for each year. The data set contains employment information such as employment status, the identity of the employer, and wages. For our sample of firms, we have approximately 8.6 million worker-year observations. We consider a worker as fired if the worker i) moves to a new firm and claims unemployment benefits in the current or in the next year or ii) if the worker becomes unemployed in the next year. We define a voluntary separation if a worker changes firms and is neither fired nor above 60. Using this classification, we observe 9.8% of the working population being fired in an average year and 7.9% moving to a different job on a voluntary basis. The average worker is 40 years old and has been with the firm for 5.2 years. Table 1 (Panel A) reports descriptive statistics of worker level data.

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and negative loadings on other commodities, and the third loads primarily on rare metals.

2.3 Empirical framework

In this Section, we describe the specifications used in the worker- and firm-level analysis. We examine how firm-level uncertainty affects firms' hiring and firing decisions across different worker types. For firing regressions, we use worker-level specifications to analyze how worker characteristics within a firm-year interact with firm-level uncertainty in determining firing probabilities. Since the population "at risk" of being hired is less clearly defined than that at risk of being fired, we use firm-level specifications for hiring regressions, focusing on how the characteristics of hired workers vary with firm-level uncertainty. To ensure consistency between these approaches, we weight the firm-level regressions by the number of workers in each firm.

2.3.1 Worker Level Regressions

For the firing regressions we use worker-level data where each observation is measured at a worker (i), firm (f), year (t) level in the following specification:

$$y_{ift} = \theta Index_{ft} + \rho\widehat{\pi}_{ft} + \lambda_f + \delta_{jt} + \epsilon_{ft} \tag{4}$$

where y_{ift} is a proxy for a worker being fired in the period between t and $t+1$. This variable is equal to 1 if a worker was working for a firm in period t, is no longer working for that firm in period $t+1$ and has perceived some unemployment benefit after leaving the firm. The parameter of interest θ measures the effect of uncertainty on aggregate firm firing.

We analyze the impact of uncertainty on workers with different characteristics. Let C_{it} be a dummy variable indicating whether a worker falls into a specific category (e.g., young, skilled, tenured). We then estimate the following specification:

$$y_{ft} = \theta Index_{ft} + \beta C_{it} Index_{ft} + \gamma C_{it} + \delta C_{it}\widehat{\pi}_{ft} + \rho\widehat{\pi}_{ft} + \lambda_{ft} + \epsilon_{ft} \tag{5}$$

where λ_{ft} are firm-year fixed effects. The coefficient of interest is β, that captures the differential effect of firm-level uncertainty on the probability of being fired for different types of workers in a given year, for a given firm. We cluster standard errors at the firm level.[13] The specification uses only within firm-year variation, as we are absorbing any

[13]The reasons to cluster at the firm level are twofold, one that we have multiple workers per firm, and

additive effects that affect all workers of a given firm in a given year. We are comparing the differential outcomes of different types of workers for a given firm across different uncertainty levels, net of any common firm-year effects.

2.3.2 Firm-Level Regressions

For the hiring regressions, we take firm-level specifications of the following form:

$$y_{ft} = \theta Index_{ft} + \rho \widehat{\pi}_{ft} + \lambda_f + \delta_{jt} + \epsilon_{ft} \tag{6}$$

In this specification, the dependent variable y_{ft} is the fraction of workers of a given type hired by the firm during the previous year, or other outcome variable related to employment or firm characteristics such as the average skill of workers or their experience. For example, y_{ft} may capture the hired workers below a certain age as a fraction of total hires or the average age of a hired worker. $Index_{ft}$ is the firm-level measure of uncertainty and $\widehat{\pi}_{ft}$ is the predicted first moment shock on profitability. We include firm fixed effects λ_f and sector-year fixed effects δ_{jt} to filter out the aggregate component of the measure of uncertainty and rely on the variation of the firm-specific component of the uncertainty measure only. We calculate standard errors robust to heteroskedasticity in all firm specifications.

The identification strategy of this specification compares the hiring policies of a given firm in periods with different levels of profit uncertainty, measured by the uncertainty index net of firm-fixed effects, sector-year fixed effects and profitability. We discuss in Section (2.1.2) how the properties of the index allow for a causal interpretation of the results of this specification.

2.4 Workers Types

We empirically link firm uncertainty to the firing and hiring of different types of workers. Worker types are associated with real options on the side of the firm. Given our focus on hiring and firing and the volatility of firm profits, we focus on options associated to the sunk costs of hiring and to the contribution of each worker to the profitability of the firm. These factors can lead to differential effects of uncertainty shocks on firms' hiring and

two to take into account that the construction of our index entails the interaction between a cross-sectional beta at the firm level and time varying commodity volatilities (See Adão et al. (2019))

firing decisions. In this section we present worker characteristics that we will use in the empirical analysis to capture different types of real options related to workers. We also provide some intuition on how they can affect hiring and firing. In Section 4 we provide an analytical framework which allows for a more formal analysis of the link between option values of workers and the effects of uncertainty on their hiring and firing.

Intuitively, greater initial hiring and training sunk costs increase the option value of waiting, and not hiring the worker in periods of higher uncertainty. This is because uncertainty raises the likelihood of being fired in the future. Conversely, any characteristic that increases a worker's ability to adapt to different conditions (e.g., her ability to deploy to different tasks) will increase the value of the worker with uncertainty. Moreover, the option to fire workers implies that those who are more productive, conditional on a positive outcome for the firm, will also have a higher ex-ante value to the firm with more uncertainty. This is because more uncertainty increases the probability of both positive and negative outcomes. The firm is then able to benefit from the higher revenues generated by these workers conditional on the positive outcome, and can reduce the losses by firing them in case of a negative outcome. Thus, more uncertainty increases the option value of more productive workers since the firing option makes profits convex in the uncertain outcome.[14]

To analyze how these "bundles of options" change with worker characteristics we focus on the following variables: i) Experience in the same sector of the firms. Workers that have worked in the past in the same sector of a given firm, are classified as "experienced". These workers likely need less screening costs and ex-ante training, and, hence, hiring them implies lower ex-ante sunk costs. ii) Age and tenure in the firm: younger and shorter tenured workers are more likely to be adaptable to different conditions, and hence relatively more efficient in exploiting new opportunities that can arise during periods of high uncertainty. In other words, older and longer tenured workers are plausibly more experienced and knowledgeable in general, but relatively less in these new opportunities compared to how productive they are in their current occupation. iii) Skill level (measured by educational attainment): Skilled workers are likely to be more productive, and perform complex tasks that greatly increase in value conditional to positive outcomes.

[14]This reasoning implicitly assumes that firing costs are not extremely large for these workers, so that they do not preclude the firing of the workers conditional on a bad outcome, which is a reasonable assumptions for Sweden.

As explained above, the ex-ante value to the firm of skilled workers should increase in periods of high uncertainty.

2.5 Properties and Validation of the Uncertainty Measure

This section describes the statistical properties of our uncertainty index, validates its link to profit uncertainty, and examines its relation to firm investment and employment.

Table 2 shows some basic firm-level index properties. The number of firm-year observations with some non-zero betas, for which we can compute the uncertainty index, is 74% of the total. Among these, about 78% of the firms have a non-zero loading on the first principal component of the commodities. The fraction of non-zero betas decreases as we go down to less important components, reaching around 65% for the last three components.[15] Moreover, the index varies substantially within firm and beyond aggregate fluctuations. After controlling for year and firm fixed effects, the index retains a residual standard deviation of 0.405.

Table 3 shows how the uncertainty index captures uncertainty shocks that are relevant to profitability. Columns 1-3 show regression results with the uncertainty index as the independent variable, and a measure of the within-firm time series variability of profits, $abs(\pi_{ft} - \pi_{it-1})$ as the dependent variable (where π_{ft} is EBITDA over total assets, as in Equation 1). Intuitively, higher values of the index should predict larger absolute variations in profitability in the future. Column 1 shows results of a simple OLS regression. In Column 2, we add firms fixed effects, and Column 3 adds also 1-digit Industry-year fixed effects. The coefficient of the index is positive and significant in all three specifications. Columns 4-6 show the results of the same regression while controlling also for the change in profits $\Delta\pi_{ft} = \pi_{ft} - \pi_{it-1}$. The coefficient of $\Delta\pi_{ft}$ is negative, indicating that negative changes in profits are on average larger than positive ones. The coefficient of the uncertainty index changes very little compared to Columns 1-3, implying that it is not simply capturing directional changes in profits. This result is important because, within firms, variations in $Index_{ft}$ are entirely driven by exogenous changes in the volatility of com-

[15]We exclude firms with zero betas because the LASSO procedure did not find a meaningful link between commodity prices and their profits. We implicitly assume that we lack enough information to estimate their commodity exposure. An alternative assumption is that these firms have no exposure and assign them an uncertainty index value of zero. However, this does not significantly affect our results, as all regressions include firm-fixed effects. Results for this approach are available upon request. After excluding these firms, the index has a mean of 0.2453 and a standard deviation of 1.07.

modity prices. In other words, these regressions confirm that increases in firm-specific, exogenous uncertainty predict larger absolute fluctuations in firm profitability.

In Table B3 in the Appendix, we use as independent variables dummies for the quintiles of $Index_{ft}$. The first quintile (20% lowest value of $Index_{ft}$) is the omitted category. Column 1 includes firm fixed effects, while Column 2 also includes sector-year fixed effects. Both specifications show that higher quintiles predict progressively larger values of the dependent variable. This monotonicity strongly supports the validity of the index.

Table B4 in the Appendix estimates Equation 6 using as dependent variables capital investment and total employment. This allows us to verify the effect of uncertainty shocks on these variables, both as a comparison with the existing literature and as a form of validation of our uncertainty measure. We run both regressions on firms with more than 50 employees which we consider more suitable for our main analysis on heterogeneous workers, as well as on a wider sample of all firms above 10 employees. Our results, in line with the recent evidence by Alfaro et al. (2024) and Kumar et al. (2023), show that uncertainty shocks tend to reduce both capital investment and total employment, regardless on whether or not we include firms smaller than 50 employees.[16]

3 Results

In this section, we present our main estimation results. While Section 3.1 focuses on worker-level specifications on firing decisions, Section 3.2 shows results on firm-level specifications regarding the hiring decisions of firms.

3.1 Effects of Uncertainty on Firing: Worker-level Regressions

When analyzing firing decisions, the population at risk of being fired is well-defined by the population of workers employed. Accordingly, we use a worker-level specification for the firing regressions. We saturate the specifications with firm-year fixed-effects. Implicitly, the likelihood of a given type of worker being fired is compared to the likelihood of other types of workers being fired in the same firm and year.

[16]Regressions in Table B4 are unweighted to allow direct comparison with the literature. In Table B5 in the Appendix, we report weighted regressions (using as weights the number of workers) for a more direct comparison with our results. The findings remain qualitatively similar but are quantitatively smaller.

Table 4 shows the results of estimating the specification in Equation 4 in which the dependent variable is equal to one if a current worker is fired over the next year.

Columns 1-3 include Sector-Year fixed effects. In column 1, we consider the benchmark uncertainty index computed at the firm-year level, $Index_{ft}$, and described in Equation 2. In Column 2, we use instead the uncertainty index at sector-level, and in Column 3, we present instrumental variable estimations in which we instrument the firm-level uncertainty measure $Index_{ft}$ with the same measure computed at the sector-year level, as discussed in Section 2.1.1. This approach allows us to reduce measurement error, as both variables measure the same underlying variation but with different measurement errors.[17] In columns 4-6, we augment the models from Columns 1-3 by also including firm fixed effects.

The directional measure of commodity price shocks ($\hat{\pi}_{it}$) has an impact on the probability of firing a worker in the more saturated specifications in columns 4 and 5. A commodity price shock that reduces profits over assets by one standard deviation increases the probability of being fired by 0.25% (the average unconditional probability of being fired is 8.6%). Conversely, in Columns 4-6 the uncertainty index has no effect on the overall probability of a worker being fired over the next year. We later show, in Table 8, that uncertainty shocks have also little effect on overall hiring rates, consistently with their small effect on overall employment mentioned in the previous section (see Table B5 in the Appendix). In contrast to uncertainty's small effects on total employment, rich patterns emerge when we condition by different worker types. In the rest of the section we explore various dimensions of worker heterogeneity to identify which groups relatively benefit or suffer from changing economic uncertainty.

Table 5 includes as explanatory variable a dummy variable *"Young"*, equal to 1 if the worker is younger than 28 years old and zero otherwise. This variable is also interacted with both the uncertainty shock and the profit shock.[18] In this table (and in the following), we keep the following configuration: In columns 1-3 we include Sector-Year and Firm fixed effects. Columns 1 and 2 consider the firm-year level uncertainty in-

[17] First-stage regressions can be found in Table B8. We report the first stage both with and without industry-year fixed effects. The sector-specific index has a positive and significant loading on the firm-level index. It also has a high predictive power on the individual index, with F-stat values between 26 and 142, depending on the specification.

[18] We choose 28 years as threshold so that we include, in the young category, workers that completed higher education (usually, students graduate before the age of 25 years) and had some working experience. Nonetheless in Appendix B, we show that the results are robust to choosing alternative age thresholds.

dex, $Index_{ft}$, while in Column 3 we present the instrumental variable estimator described above. Columns 4-6 augment the specifications in Columns 1-3 by adding firm-year fixed effects.

The results are consistent across specifications. The coefficient of the *Young* dummy indicates that young workers have a baseline probability to be fired that is around 14 percentage points higher than for older workers. This result is not surprising, since younger workers have on average shorter tenures, lower firing costs, and generally higher firing rates than more mature ones. The coefficient of the uncertainty shock captures the effect on the omitted category of older workers. In Columns and 1-2, the coefficient is positive and significant, indicating that an uncertainty shock increases the firing probability of older workers. In contrast, the interaction *"Young X Index"* is negative and significant in all specifications. Younger workers are less likely to be fired when profit uncertainty is high, relative to older workers. In absolute terms, the chances of being fired in high uncertainty periods are in fact lower for young workers. In other words, a firm reacts to an uncertainty shock by firing more old workers and retaining more young ones, relatively to normal times.

Note that the coefficient on "Young X $Index_{ft}$" is about four times larger in the IV regressions (Columns 3 and 6). As discussed in Section 2.1.1, the IV regressions address attenuation bias due to measurement error in the estimated betas used to construct the index. As expected, the IV coefficients are larger, reflecting this correction.

The coefficients in Column 3 show that a one standard deviation increase in uncertainty raises the probability of firing an older worker by 3%, while reducing it for a younger worker by 0.5%. Given a 14% baseline gap in firing probabilities, the pecking order–where young workers are more likely to be fired–persists across most uncertainty levels but is attenuated in uncertain times. Column 6 presents the most saturated IV specification. While baseline changes for older workers cannot be estimated here, the results again confirm that uncertainty weakens the firing pecking order.

Interestingly, in all specifications, the interaction with the profits shock *"Young X* $\hat{\pi}_{it}$*"* is not significant. In other words, while a negative profits shock causes the firm to increase firings across the board, the effect is homogeneous across types of workers. These results are confirmed when including both shocks together and they are robust to adding Firm-Year fixed effects (Columns 4-6).

In Table 6 we consider the variable *Tenure-short* which is equal to one for workers that have been in the firm for 0 to 2 years, and zero otherwise. Therefore, the omitted group is workers with tenure of 3 or more years. The tenure dummy is positive and significant, indicating that the probability of being fired is around 16 percentage points larger for Short-tenured workers. However, as it is the case with age, uncertainty has a compensating effect on the pecking order of tenure and firing. In all specifications, we see that an uncertainty shock reduces the probability to fire a short tenured worker. In Columns 1-3, we also find that more uncertainty increases the probability to fire a worker with longer tenure, even though the latter effect is only significant in columns 1-2. Appendix B shows that the results are robust to using alternative definitions of short-tenured workers, based on 3- and 5-year tenure thresholds.

Taken jointly, these results show that workers with the longest tenures are those with more secure jobs in normal times, but also those more negatively affected by uncertainty shocks. An increase of one standard deviation of the uncertainty index increases the likelihood of firing of a worker with 3 to 5 years of tenure by 5%, and a worker with more than 5 years of tenure by 12.3%.[19] Interestingly, also in this case, a negative profits shock increases the firing of all of workers, with no significant differences across tenure.

Table 7 considers as an explanatory variable the dummy *"Skilled"*, which is equal to 1 if the worker has college education (or higher) and zero otherwise. The coefficient indicates that more educated workers are fired less frequently on average.

Focusing on the interaction terms, we find that the interaction between skills and uncertainty is positive. More educated workers are fired more frequently after an uncertainty shock, while less educated workers are not. Referring to Column 3, an increase of one standard deviation of the uncertainty index increases the probability of being fired by 2.5 percentage points more for the skilled workers than for the unskilled ones.

3.1.1 Discussion

Taken together, we find that in periods of high uncertainty young workers are fired less and old workers are fired more often, relative to their own baseline in low uncertainty periods. Similarly, shorter-tenured workers are fired less in periods of high uncertainty, relative to their own baseline. This effect attenuates the regular pecking order of fir-

[19]These effects are calculated from a baseline probability of being fired of 6.46% and 3.46% for workers with 3-5 years and more than 5 years of tenure, respectively.

ing in firms in low uncertainty times, when younger and shorter-tenured workers tend to be fired more often. One interpretation of these results is that, in times of uncertainty, firms value the additional flexibility and options embedded in younger and recently hired workers.[20] More generally, this finding can also be seen as an attempt of the firm to diversify its capabilities (Matsusaka (2001)) or experiment in search for new lines of business (Bernardo and Chowdhry (2002)). In high-uncertainty times firms re-organize their labor force more deeply than in low-uncertainty times, maybe because the firm's employment needs are changing, making firing patterns less predictable.

We also find that skilled (more educated) workers are fired less often in normal times, but an uncertainty shock increases their firing rates more than the those of unskilled workers. Our hypothesis is that the option value of skilled workers increases more with uncertainty than that of less productive workers, thanks to the option to fire. For this option to be valuable, it needs to be exercised in equilibrium conditional on negative outcomes, which become more likely in more uncertain times. In other words, one interpretation of these findings is that firms plan to hire skilled workers even in the presence of higher uncertainty, knowing that ex-post they can exercise the firing option if the project fails, and benefit from their higher productivity if the project succeeds. In section 4, we propose a stylised model to formulate this hypothesis more formally.

3.2 Effects of Uncertainty on Hiring: Firm-Level Regressions

Table 8 shows the results of estimating Equation 6 on hiring rates. All firm-level specifications are weighted by the number of workers per firm and include firm fixed-effects as well as 1-digit industry-year fixed effects. In Column 1, the dependent variable is the number of workers hired during a year divided by total employment at the beginning of the year. We also include regressions based on the fraction of workers fired (Column 2), that can be compared with the worker-level firing regressions, as well as the fraction of net hires (hired minus fired over total employment at the beginning of the year) (Column 3), and voluntary separations (Column 4).

[20] This finding is not in contrast with the LIFO (last-in-first-out) rule in Sweden, by which firms above 10 employees, within a given job role, need always to fire the less senior worker first. That is because, to retain a valuable newly hired worker, firms can in practice circumvent the LIFO rule by using a narrow definition of the specific task to which the LIFO rule applies, or by proposing a severance package to the protected workers or the unions (Von Below and Thoursie, 2010). Firms can also fire workers outside the LIFO rule and pay an "unfair dismissal compensation" which grows with tenure (Caggese et al., 2019).

In all firing and hiring regressions, the coefficient of the profits shock $\hat{\pi}_{ft}$ is significant, and has the expected sign: A change in commodity prices that predicts higher firm-level profits is associated with a higher probability of hiring and a lower probability of firing, even after controlling for firm and sector-year fixed effects. In quantitative terms, an increase in profits of one standard deviation increases total net hiring of the firm by around 0.3% of its labor force. Moreover, the effect of the profit shock is not statistically significant for voluntary separations, highlighting that the effects in columns 1, 2 and 3 are likely to be driven by the firms' policies rather than by workers' decision.

This result, which is consistent with those in Table B4 and Table B5 , is important because it validates our empirical strategy. It is consistent with the view that firms are unable to hedge the risk represented by the fluctuations in commodity prices, and that the associated first moment shocks have a significant effect on hiring and firing decisions in the expected direction. Furthermore, Table 3 demonstrated that the uncertainty index predicts well absolute changes in profits, so it is informative of the uncertainty faced by firms.

In contrast to the predicted profit shock, we find that exogenous uncertainty shocks have insignificant effects on overall hiring and firing decisions, consistently with the firm-level regressions weighted by employment levels in Table B5. As mentioned in the introduction, uncertainty makes projects that require large initial sunk costs and/or that are irreversible less attractive, but it can be beneficial for projects with future profits that are convex in the uncertain outcome. Our stylised model in the next section shows that, when uncertainty shocks have heterogeneous effects on different types of workers, because of their different option values, their effects on overall hiring and firing are in general ambiguous. The findings in Table 8 are consistent with this ambiguous prediction and imply that such opposite effects seem to cancel each other out, for the average worker in our sample.

Table 9, investigates the effects of uncertainty shocks on the share of hired workers of different types. All regressions contain firm fixed effects. Consequently, the results of the regressions can be interpreted as the change in the relative hiring of workers of a given type relative to other years in the same firm. The variation in uncertainty is also firm-specific, net of sector-year fixed effects. Columns 1-3 consider three dimensions of heterogeneity, the average age (Column 1), the fraction of highly educated workers (Column 2) and the fraction with previous working experience in the same sector (Column 3), relative to total employment in the firm.

Columns 1 and 2 show that uncertainty shocks do not significantly affect neither the average age of workers hired nor their skill level. Conversely, column 3 shows that uncertainty shocks have significantly positive effects on the experience of the hired workers, showing that firms are significantly more likely to hire workers that already have some working experience in the same 3-digit sector. In Column 4 we add 3-digit-sector-year fixed effects and find that the uncertainty shock is still highly significant. This result addresses the concern that our findings might be driven by correlations between aggregate industry-level labour market conditions and uncertainty.

These findings are consistent with our hypothesis that experienced workers have lower sunk costs and therefore are relatively more valuable in more uncertain times. While it is plausible to assume that firms face larger ex-ante hiring and training costs for inexperienced workers, in equilibrium it must be that marginal costs and returns are equalised across workers. This means that for workers who are cheaper to hire and train, a larger proportion of those costs is related to ex-post wage payment rather than the ex-ante sunk cost. Therefore, a plausible interpretation of the results is that when uncertainty increases, the option value of firing rises more for these workers than for the other workers, thus increasing relatively more their hiring rates.

3.3 Robustness

One important question is whether uncertainty shocks only affect firms firing decisions, or also voluntary separation of workers. We analyse this in Table B6 in the Appendix, which shows the same regressions as the most saturated specifications in Tables 5 - 7, using voluntary separations rather than being fired as dependent variable. More specifically, the dependent variable is equal to one if the worker left the firm in period t and worked for a different firm in period $t+1$, without receiving any unemployment benefit between the two jobs.

Identifying the effects of uncertainty on voluntary exits is generally challenging. While our definition of firings is relatively precise and unlikely to include voluntary separation, the reverse is not true, as the latter might include some fired workers that find another job quickly without going through an unemployment spell. This might be particularly true during high uncertainty periods. If more firm-level uncertainty increases the risk of being fired, workers might anticipate this and find in advance alternative employment opportunities.

In Table B6, the OLS regressions show results that are qualitatively similar, although smaller in magnitude than for firings (Columns 1, 3 and 5). Furthermore, the IV regressions show no significant differential effects of the uncertainty index on voluntary separations by age, tenure or skill (Columns 2, 4, and 6), contrary to what we find for firings. Overall and given the above considerations, these results are consistent with uncertainty shocks primarily affecting firing decisions, rather than voluntary separations.

In the Appendix we also report additional robustness checks. In Table B7 we show selected regressions from Tables 5, 6 and 7 using the industry-level uncertainty index instead of the firm-level one. Table B9 uses alternative thresholds to define short-tenured workers, and Table B10 alternative thresholds to define young workers. All these robustness checks confirm the main results of the paper.

4 Analytical Framework

In this section we develop a model that illustrates how uncertainty affects the hiring and firing decisions of heterogeneous workers. The model is intentionally stylized, so that its main predictions can be derived in closed form, and its main objective is to explain how the effect of uncertainty on different types of option value of workers can explain our empirical results.

4.1 Technology

We consider a setting with many firms, indexed by i. Each firm operates many projects, indexed by j, that require heterogeneous workers. Since in the empirical analysis we control for both time-variant and time-invariant firm characteristics, in the model we abstract from firm ex-ante heterogeneity, and we assume all firms to be symmetric, while ex-post they are hit by idiosyncratic shocks.

There are two periods, $t \in \{0, 1\}$. Workers need to be hired in period 0 for each project, and output is produced in period 1. A worker is described by characteristics $\{v, v^f\}$. v measures their productivity in the project, and we interpret it as the degree to which workers are *specialized* in their current tasks, where specialization increases their efficiency in performing them. For each worker, v is strictly larger than v^f, and is drawn from a distribution bounded between 0 and a positive upper bound $\overline{v}$:

Assumption 1. $v \in [0, \overline{v}]$, $v^f \in [0, v)$.

v^f represents the productivity of the workers when they are relocated to a different project. We interpret it as more broadly representing the ability of workers to be assigned to different tasks or re-trained if necessary, when the firm faces new challenges during periods of high uncertainty. Relocated workers are less productive than in their initial project, so that the ratio $\frac{v^f}{v}$, which measures the degree to which workers are *flexible*, is between 0 and 1. We keep the model as stylised as possible by assuming that all workers within a given project need to have the same characteristics $\{v, v^f\}$. Furthermore, they are assigned a set of tasks that have same ex-ante profitability, and for each worker these tasks are independent on the tasks of the other workers. These assumptions are not essential for the results but they simplify considerably the analysis, allowing us to obtain closed form results.

While all workers within a given project have the same values $\{v, v^f\}$, different projects require different workers characteristics. In this section we describe the optimal decisions regarding a generic project j in a generic firm i, while in Section 4.7 we will make explicit assumptions on the distribution of workers across projects.

At the start of period 0, the project's profitability is affected by an idiosyncratic random variable, $\theta_{i,j}$. The firm then decides the number of workers in this project, denoted with $n_{i,j}$, to maximise total expected profits $\Pi_{i,j}$:

$$\max_{n_{i,j}} \Pi_{i,j}\left(\theta_{i,j}, v_{i,j}, v^f_{i,j}\right) = \max_{n_{i,j}} E(\pi_{i,j})n_{i,j} - Mn_{i,j} \tag{7}$$

Where $\left\{v_{i,j}, v^f_{i,j}\right\}$ are the skills of the workers assigned to this project. In period 0, one worker costs $M > 0$ to hire and train, and the profits she is expected to generate for the project are $E(\pi_{i,j})$. In period 1 her realised profits are:

$$\pi_{i,j} = \frac{\mu_{i,j}}{(1-\gamma)n^{\gamma}_{i,j}} - w \tag{8}$$

Where w is the wage paid to the worker, assumed to be exogenous and equal for all workers.[21] The term at the denominator, with $0 < \gamma < 1$, reflects that the larger is the number of workers, the lower is their productivity, because of decreasing returns. Since workers have independent tasks, ex post, if a worker is fired, the productivity of the other workers is not affected. In equilibrium, it implies the firing and relocation decisions are symmetrical across workers in a given project.

The term $\mu_{i,j}$ at the numerator is:

$$\mu_{i,j} \equiv \theta_{i,j} + P_{i,j} \tag{9}$$

Where $\theta_{i,j}$ is uniformly distributed in $\left[\underline{\theta}, \overline{\theta}\right]$, and:

Assumption 2. *i)* $\underline{\theta} = -\overline{v}$ *and ii)* $\underline{\theta} + \underline{v} + \underline{v}A^E > 0$

At the beginning of period 0, the shock $\theta_{i,j}$ can be interpreted as exogenous idiosyncratic factors that affect the ability of the project to generate revenues. It is useful to generate heterogeneity across projects with similar workers, and derive testable predictions. Assumption 2 imposes two regularity conditions. 2.*i* ensures that a failing project with lowest value of θ does not generate any revenues, even when employing the most productive workers. 2.*ii* ensures that all projects considered have positive expected revenues under both the firing and the no firing regime.

$P_{i,j}$ is a profits shock realised in period 1, which depends on whether or not the project is successful, as well as on workers' characteristics:

$$\begin{aligned} P_{i,j} &= v_{i,j}(1 + A^G) \text{ with probability } s \text{ (the project is successful)} \\ P_{i,j} &= v_{i,j}(1 + 0) + R_{i,j} \text{ with probability } 1 - s \text{ (the project fails)} \end{aligned} \tag{10}$$

Where $R_{i,j} \geq 0$ is the return from relocation (described below). The stochastic return of the project A takes the value A^G conditional on success and zero conditional on failure. This structure captures a key assumption in the model. On the one hand, higher specialization $v_{i,j}$ implies workers are on average more productive both on success and failure. On the other hand, the absolute level of profits they generate is more sensitive to

[21] This assumption is for simplicity, and without loss of generality. We could allow for wage bargaining and it would not affect the model's predictions as long as wages only partially absorb unexpected shocks to demand or productivity. Empirically, wages tend to be sticky and revenue shocks are mainly absorbed by fluctuations in firms profits. For example Guiso et al. (2005) estimate how wages of heterogeneous workers absorb firm shocks. On average, only around 15% of firm's idiosyncratic shocks are absorbed by workers' wages.

the success of the project.[22]

Projects returns are uncorrelated across firms but partially correlated within firm. This is formalised by assuming that the success probability s is:

$$s = prob(x_{ij} > \underline{x}) \text{ where } x_{i,j} = \epsilon^P_{i,j} + \epsilon_i. \tag{11}$$

$\underline{x}$ is an exogenous positive threshold. $\epsilon^P_{i,j}$ is a project specific shock and ϵ_i is a firm specific shock, both uniformly distributed between 0 and $\overline{\epsilon^P}$ and 0 and $\overline{\epsilon}$, respectively. Given symmetry, ex-ante the expected success probability is identical across all firms and projects. Ex post, firms with higher realization of ϵ_i will have an higher fraction of successful projects. From now on, we will for simplicity omit the subscripts i, j.

Relocation option

R is the return from relocation. In period 1, if the project fails, the firm has the option to relocate the workers to a different project that was ex post successful. The workers no longer generate v in their current project, but can generate $v^f(1 + A^G)$ in the relocated project.[23] Assumption 1 and Condition 10 imply that workers are never relocated from successful projects. Instead, they might be relocated from failed ones. Therefore, there exists a threshold flexibility value $v^f_R \equiv \frac{v}{1+A^G}$, such that workers are relocated from failed projects when $v^f \geq v^f_R(v)$, and not relocated when $v^f < v^f_R(v)$. Therefore:

$$R = \max\left[0, v^f\left(1 + A^G\right) - v\right] \tag{12}$$

Firing option

A worker can be fired in period 1, before production takes place, by paying the firing cost $F \geq 0$. We allow firings to happen in equilibrium by assuming $F < w$, that is, firing a worker saves at least part of the wage costs of the project. Define $\tilde{\pi}$ as ex post profits from Equation 8 after the relocation decision. Hence:

$$\text{Fire if: } \tilde{\pi} < -F \tag{13}$$

[22]That is, consider for simplicity a project with no relocation value ($R_{i,j} = 0$). The percentage increase in profitability from failure to success is equal to $1 + A^G$, and therefore independent from specialization $v_{i,j}$. But this also implies that the absolute increase in profits $v_{i,j}A^G$ is instead increasing in specialization.

[23]Notice that we do not explicitly model the role of the workers that are relocated to these projects from unsuccessful ones. To model explicitly their contribution to the profits function 8 would make the analysis more complicated but leave all results unaffected.

In other words, a worker is fired when her project receives a bad shock ($A = 0$) and profits, even considering the relocation option, are below $-F$.

Mean preserving uncertainty shocks

The variance of A can be shown to be equal to:

$$\sigma_A^2 = (1 - s^2)A^E \text{ with } A^E \equiv sA^G \tag{14}$$

In the empirical section we estimate the effect of firm-level uncertainty shocks while controlling for the first moment shocks. Given the distributional assumption 11, this is equivalent in our model to a mean-preserving uncertainty shock that increases σ_A^2 by a decreasing in s and an increases A^G thus keeping the expected return A^E constant.[24] In other words, more uncertainty reduces the probability of success, but increases revenues conditional on success.[25] This specific type of stochastic process is not essential for the analysis, and assuming a symmetric process would slightly complicate the analysis but leave the main qualitative results unaffected.[26]

4.1.1 Option to fire and workers productivity

Before analysing in details the solution of the model, and the conditions under which workers are fired or relocated, we want to highlight one important feature in driving some of the results derived below. The maximization Problem 7 implies the firm chooses n so to equalise expected marginal profitability with marginal cost of workers.

Consider a project in which workers are not relocated and not fired, and assume for simplicity that $\theta = 0$. In this case, the marginal cost is $M + w$, and marginal profits conditional on success and failure are equal to $MPL^{succ} = \frac{v(1+A^G)}{n^\gamma}$ and $MPL^{fail} = \frac{v}{n^\gamma}$,

[24]Since in the data the shock is firm specific, this is equivalent to assuming that the decrease in s is caused by an increase in $\bar{\epsilon}$.

[25]Implicit in our assumptions, human capital risk in the form of the obsolescence of a worker's skills are absorbed by the firm unless a worker is fired. Similar intuitions can be found in Berk and Walden (2017). Moreover, ideally we would like to model A as a shock with a continuous probability density function, where an increase in uncertainty is an increase in the variance of the shock around the same mean. In this case, more uncertainty would increase both the probability of very low outcomes, during which workers are fired, but would also increase expected productivity conditional on not firing the worker. We chose a much simpler stochastic process for A in order to keep the analysis simple and obtain results in closed form. Nonetheless, assuming a continuous probability density function would not change the main qualitative predictions of the model.

[26]Intuitively, if the return of the project is symmetrically distributed, a mean preserving uncertainty shock, by increasing the density of the tails of the distribution, would increase the probability of low outcomes under which the worker is fired, but would also increase expected profits when the worker is not fired, which is what also happen with our chosen stochastic process.

respectively. Therefore: $\frac{MPL^{succ}}{MPL^{fail}} = 1 + A^G$. In other words, when firing is not an option, uncertainty affects similarly workers with different productivity, and the ratio $\frac{MPL^{succ}}{MPL^{fail}}$ does not depend on workers productivity v .

Consider now the same project but assume workers are fired conditional on failure. In this case the marginal cost is M.[27] Marginal profits in case of success and failure are $\frac{v(1+A^G)}{n^\gamma} - w$ and $-F$, respectively, so that $\frac{MPL^{succ}}{MPL^{fail}} = \frac{v(1+A^G)}{Fn^\gamma} - \frac{w}{F}$. Now the firing option, by putting a floor on losses in case of failure, generates an asymmetry in which workers' productivity only matters conditional on success. Such asymmetry implies that $\frac{MPL^{succ}}{MPL^{fail}}$ is different for workers with different productivity, the more so the higher is uncertainty. Since the option value of firing is proportional to $\frac{MPL^{succ}}{MPL^{fail}}$, this result implies that in our framework workers productivity interacts with uncertainty when the option to fire is present, so that the value of this option increases in uncertainty, the more so for more productive workers.

4.2 Hiring decisions

First, it is useful to define $w' \equiv w - F$ as wages net of firing costs. Expected profits from a worker in period 0 can be written as:

$$E(\pi) = \frac{E^+(\mu)}{(1-\gamma)n^\gamma} - w'p^+ - F \tag{15}$$

$E^+(\mu)$ is the expected value of μ conditional on a given firing policy, and p^+ is the probability of not firing the worker. Note that hiring and firing policies are co-determined. Expected profits affect hiring that, in turn, affects the firing policy, that feeds back into expected profits. To determine hiring and firing policies we first guess a given firing policy, which determines $E^+(\mu)$ and p^+. Substituting $E(\pi)$ in Equation 7 and solving we obtain the associated hiring policy n^* and expected profits Π^*:

$$n^* = \left[\frac{E^+(\mu)}{w'p^+ + M + F}\right]^{\frac{1}{\gamma}} \quad \text{and} \quad \Pi^* = \frac{\gamma}{1-\gamma}\frac{E^+(\mu)^{\frac{1}{\gamma}}}{(w'p^+ + M + F)^{\frac{1-\gamma}{\gamma}}} \tag{16}$$

[27] We only include the certain cost. The wage is an uncertain cost, only paid conditional on success, and is therefore subtracted by the marginal profits in case of success

4.3 Firing policy

Workers are always profitable, and never fired, when the project is successful. Therefore, there are two possible firing policies. i) Fire workers when the project fails. ii) Do not fire workers when the project fails. We define the $firing$ policy as time-consistent if, given the ex-ante hiring conditional on this policy, ex-post the firm has no incentive to deviate and will fire workers when the project fails. A time consistent $firing$ policy is optimal if ex ante is more profitable than the *no firing* policy, so when $\Pi^{firing} > \Pi^{nofiring}$, which can be written as:

$$\frac{s(\theta+v)+vA^E}{\theta+v+vA^E+(1-s)R} > \left[\frac{w+M-(1-s)(w-F)}{w+M}\right]^{1-\gamma} \tag{17}$$

Where A^E is the expected value of A (see 14) and R are the relocation returns (see 12).[28]

The term in square brackets on the right hand side of 17 is the ratio between the expected marginal cost of one worker under the *Firing* policy at the numerator, and under the *No firing* policy at the denominator. The numerator is reduced by the option value of firing the worker and saving $w-F$, which happens with probability $1-s$. Therefore more uncertainty (a reduction in s) reduces the relative marginal cost of the firing policy, the more so the larger is $w-F$, which is the gain from exercising the firing option, and the less so the larger is hiring cost M, which increases the option value of waiting.

The term on the left hand side of 17 is the ratio between the marginal return of one worker under the *Firing* policy relative to the *No firing* policy. More uncertainty reduces success probability s at the numerator. Furthermore, it also increases the expected relocation returns $(1-s)R$ at the denominator as long as $R>0$, which means workers are sufficiently flexible to be relocated when the project fails.

4.4 Uncertainty and firing – non-relocated workers

In period 1, the firm relocates all workers in failing projects in which $\frac{v^f}{v} > \frac{1}{1+A^G}$. We consider first projects with specialised workers, with low value of flexibility $\frac{v^f}{v}$, that are not relocated if their project fails:

Proposition 1. *For specialised workers, there exist an internal threshold value* $\theta^{fire}(v) > \underline{\theta}$ *such*

[28] We focus on the set of parameters such that optimal firing policies are always time consistent.

that the firing policy is optimal for those failing projects with $\theta \in [\underline{\theta}, \theta^{fire}(v)]$, and the no firing policy is optimal for the failing projects in $\theta \in (\theta^{fire}(v), \overline{\theta}]$

Proof: see Appendix A. The intuition is straightforward. Projects with higher value of θ generate more revenues when the project fails, and this reduces the incentives to fire the workers. Assumption 2 ensures that the threshold θ^{fire} is within the support for θ.

We now focus on the effects of mean preserving changes in uncertainty σ_A^2. Proposition 1 implies that, in order to analyse the effect of uncertainty on firings, it is sufficient to analyse its effects on the threshold level θ^{fire}, where an increase in θ^{fire} means the firm fires workers in a larger share of projects, so firings increase in equilibrium. We can prove the following propositions:

Proposition 2. *A second moment uncertainty shock increases firings of non relocated workers:* $\frac{\partial \theta^{fire}(v)}{\partial \sigma_A^2} > 0$

Proposition 3. *A second moment uncertainty shock increases relatively more the firings of more productive specialised workers:* $\frac{\partial \theta^{fire}(v)/\partial \sigma_A^2}{\partial v} > 0$

For a formal proof of Propositions 2 and 3, see Appendix A. The intuition behind these results is articulated in Section 4.1.1, with the key insight being that the value of the option to fire increases with uncertainty. Therefore, the firm finds it optimal to select the firing equilibrium for a larger fraction of projects, and this effect is stronger the more productive workers are.

4.5 Uncertainty and firing – relocated workers

Workers for whom $\frac{v^f}{v} > \frac{1}{1+A^G}$ are relocated if the project is unsuccessful, because $R > 0$. We can prove the following proposition:

Proposition 4. *Consider a group of specialised workers S and flexible workers F, such that: i) specialised workers are weakly more productive, $v_S \geq v_F$, and flexible workers are closer to the relocation threshold, so that $\frac{1}{1+A^G} > \frac{v_F^f}{v_F} > \frac{v_S^f}{v_S}$. An uncertainty shock increases the firings of the flexible workers relatively less than the firings of specialised workers.*

An increase in uncertainty increases A^G, and lowers the relocation threshold $\frac{1}{1+A^G}$. Therefore, for the limit case of $v_S = v_F$, Proposition 4 follows simply from the fact that flexible workers are more likely to be relocated the higher is uncertainty. For the case in which $v_S > v_F$, flexible workers that are not relocated are less likely to be fired than the specialised workers, because of Proposition 3.

4.6 Uncertainty and hiring decisions

Firing regime

Consider projects with $\theta \in [\underline{\theta}, \theta^{fire}(v))$, in which workers are fired conditional on failure, so that $E^{+}(\mu) = s(\theta + v) + vA^{E}$ and $p^{+} = s$. We substitute these values in 16. The effect of an increase in mean preserving uncertainty on hiring under the "firing regime" is:

$$-\frac{\partial n}{\partial s} > 0 \text{ if } \frac{vA^{E}}{\theta + v} > \frac{M+F}{w-F} \tag{18}$$

A positive value of $-\frac{\partial n}{\partial s}$ implies that hiring increases with uncertainty. Condition 18 clarifies that this is more likely to happen when vA^{E}, which is the part of expected return of the project that is risky, is large relative to the safe part $\theta + v$. Furthermore, it is also more likely to happen when the expected gain from the firing option, $(w - F)$, is large relative to overall hiring and firing costs $M + F$.

No firing regime

Consider now projects with $\theta \in [\theta^{fire}(v), \overline{\theta}]$, in which workers are not fired. For these firms, $E^{+}(\mu) = \theta + v(1 + A^{E}) + (1-s)R$ and $p^{+} = 1$, which yields:

$$n^{*} = \left[\frac{\theta + v(1+A^{E}) + (1-s)R}{w+M}\right]^{\frac{1}{\gamma}} \tag{19}$$

For specialised workers that are not relocated when the project fails, then $R = 0$, and the optimal hiring n^{*} is unaffected by uncertainty. For flexible workers, $R > 0$, and an increase in uncertainty increases the term $(1-s)R$ (as explained in the previous section), and increases hiring n^{*}.

In terms of testable implications, notice that, both in the *Firing* and *No firing* regime, $-\frac{\partial n}{\partial s}$ is larger the smaller are hiring/training costs M:

Proposition 5. An increase in firm level uncertainty increases relatively more the hiring of workers that are cheaper to hire and train.

4.7 Links to empirical results

In the previous section, we derived a set of propositions conditional to workers' abilities v, v^f. In this section, we map these propositions into testable predictions that we link to the empirical results discussed earlier. To achieve this, we need to specify how workers are distributed across projects, and how workers' abilities v, v^f relate to observable workers' characteristics. To do so, we make the following additional assumptions.

Assumption 3. *There are many ex-ante identical firms. Within a given firm, there exist a continuum of project types uniformly distributed across* $v \in [0, \overline{v}]$ *and* $v^f \in [0, v)$

This assumption simply states that there is an equal measure of projects for any given possible combination of $\{v, v^f\}$ within their defined support. [29]

Assumption 4. *Flexibility* $\frac{v^f}{v}$ *is negatively correlated with* v *across workers of different age and tenure.*

The intuition for this assumption is that workers become more productive by specialising in a given job. Therefore, as long as flexibility and productivity are not too positively correlated, older and longer-tenured workers are on average relatively more productive and less flexible than younger and shorter-tenured workers, respectively.

Assumption 5. *Skilled workers have on average higher productivity* v *than the complementary sample of unskilled workers.*

We identify skilled workers with those with more years of education.

4.7.1 Model's Predictions and empirical evidence

In this section, we derive predictions on the effect of a mean preserving increase in uncertainty. Since we assume that, within firms, project's profits are positively correlated (see Equation 11), it follows that such shock can be measured with a firm-level increase in volatility of profits, for given average expected profits, which is the strategy we follow in the empirical section of the paper.

Skilled workers

[29] As mentioned before, the assumption of ex-ante identical firm is not restrictive since in the empirical analysis we control for both time-variant and time-invariant firm characteristics.

By Assumption 5, skilled workers have higher productivity v than unskilled ones. If these workers are not relocated, then Proposition 3 and Assumption 3 imply that the share of projects in which non-relocated workers are fired increases with uncertainty, and such an increase is larger for more productive workers. This prediction is consistent with our empirical finding that skilled workers are fired more intensely during high uncertain periods, relative to unskilled workers. [30]

Age and tenure

Assumption 4 implies a trade-off between productivity v and flexibility $\frac{v^f}{v}$ along the age and tenure dimension of workers. Higher relative flexibility $\frac{v^f}{v}$ implies that younger and shorter-tenured workers are more likely to be relocated in failing projects, the more so the higher is uncertainty (see Proposition 4). Conversely, lower productivity implies that they are relatively less likely to be fired as uncertainty increases if they are not relocated (see Propositions 3). Both effects contribute to the prediction that an uncertainty shock increases the firing of specialized workers (older, longer-tenured) more than the firing of flexible workers (younger, shorter-tenured), which is strongly consistent with what we find in the data.

Experience

Proposition 5 implies that an increase in firm level uncertainty increases relatively more the hiring of workers that are cheaper to hire and train, which is consistent with our empirical findings when we classify workers with respect to hiring/training costs by considering their previous work experience in the same sector. We argue that workers which are already experienced in a sector are cheaper to hire and to train.

Effects on overall hiring and firing levels

While in the previous sections we could derive predictions on the effects of uncertainty on the *firing* of skilled and younger workers, the effects on the *hiring* of these workers are generally ambiguous. Skilled workers are more productive, and Condition 18 implies that higher v either strengthens or weakens the relation between uncertainty and hiring, depending on whether the variable θ is positive or negative. Regarding the age of new hires, the discussion in Section 4.6 implies that with more uncertainty firms value more

[30] If skilled workers in the relocation region were significantly more flexible than unskilled ones, this would weaken or eventually reverse the model's prediction. Thus, our findings suggest that skilled workers are not markedly more flexible and that their higher productivity drives the positive link between uncertainty and firing.

the potentially higher flexibility of younger hires, but also value less their potential need for larger training costs, and it is uncertain which effect might prevail. These considerations help to explain why we find that uncertainty does not differentially affect hiring by age or skill (see Table 9).

Furthermore, the effect of uncertainty on total hiring and firing is in general ambiguous. For firing, we show that higher uncertainty raises the probability of firing conditional on no relocation, but lowers the relocation threshold v_R^f, thus reducing firing for some worker types. For total hiring, condition 18 implies an ambiguous overall effect, as discussed in section 4.6. This aligns with the empirical finding that first-moment profit shocks affect hiring and firing strongly, while second-moment uncertainty shocks do not (see Table 8). Summing up, while the effect of uncertainty shocks on overall hiring and firing is in general ambiguous, many heterogeneous effects across different types of workers are not, and these define clear unambiguous predictions that align with the empirical findings.

5 Flexibility and the effects of uncertainty shocks.

In Section 3, we showed that firm-level uncertainty shocks cause firms to increase the firing of older and longer tenured workers and reduce those of younger and shorter tenured workers. One plausible explanation of this finding, formalized in our model, is that uncertainty increases the option value of more flexible workers.[31] In this section, we test this hypothesis directly, using a proxy for workers flexibility.

We define a "relocation" as an internal horizontal job change. That is, a worker moving to a different 3-digit occupation within the same firm. To isolate strictly horizontal movements (given that occupational codes reflect both horizontal and vertical-hierarchical dimensions) we require the absolute change in next-year pay to be below 10%.

We define a worker as "flexible" in that she can be relocated more easily. Our main measure of flexibility is purely based on a worker's occupation. For each 3-digit occupation, we calculate the average fraction of workers who are relocated. We define a worker as "flexible" if she is in the top tercile based on that occupational flexibility measure.

[31] Kim and Kung (2017) develop a similar result for fixed capital using how specific tangible assets can be reused within and across industries. Tate and Yang (2021) also show how more diversified firms redeploy workers internally more efficiently.

Table 10 estimates Equation 5 including the flexibility indicator $Flex$. The coefficient of $Flex$ is negative and significant, indicating that flexible workers are 1.6% less likely to be fired on average than the complementary group. Importantly, these two groups of workers are affected differently by uncertainty shock. Non-flexible workers are more likely to be fired when uncertainty increases (the coefficient of $Index_{ft}$ is positive) while flexible ones are less likely to be fired (the coefficient of the interaction $Flex\ X\ Index_{ft}$ is negative). Furthermore, Table B12 in the Appendix shows that younger and shorter tenured workers are also more flexible, that is, are on average more likely to be relocated to different occupations in the same firms than the complementary groups of older and longer tenured workers. Taken together, these results support our hypothesis that workers flexibility affects their option value and explain the heterogeneous effects of uncertainty shocks on firms firing decisions that we find in the data.

Finally, in the appendix, we also consider an alternative flexibility measure based on both individual and job-related characteristics. We proceed in three steps. First, we regress the relocation dummy on tenure (as a categorical variable) interacted with 3-digit occupation dummies, along with age, gender, number of children, marital status and a set of educational dummies. Second, we predict the likelihood of a relocation for each worker-year. Third, we classify a worker as flexible if she belongs to the top tercile in the predicted relocation probability. Results, presented in the Appendix in Table B11, confirm all the main findings.

6 Conclusion

We provide new evidence on the heterogeneous effects of uncertainty shocks by investigating the consequences of firm-level profit uncertainty on the probability of being fired and hired across different types of workers. This is a relevant empirical question for two reasons. First, depending on the nature of adjustment costs, the theoretical literature on uncertainty and investment yields ambiguous results with respect to whether uncertainty increases or decreases investment. Second, different types of workers may have different real options embedded in their employment relationships. While uncertainty may depreciate the attributes of certain workers to the firm, it may make other workers more valuable.

We start by introducing a firm-specific index of profit uncertainty for a broad set of non-listed firms, constructed from annual accounting data and high-frequency commodity prices. We use principal component analysis and LASSO to identify each firm's key exposures. The resulting index is firm-specific, capturing uncertainty beyond aggregate or industry shocks. It is also non-directional and uncorrelated with profit changes. We can therefore control in our regressions for industry specific time effects as well as for directional profit changes. As the index relies only on annual profits and standard commodity price series, it is easily applicable in other settings.

We then focus on the heterogeneous effects of the index across workers in firm-level hiring regressions and worker-level firing regressions. The latter allow us to compare different types of workers within the same sector-year or firm-year. The results show very little effect of profit uncertainty on aggregate hiring or firing rates. However, they show important heterogeneous effects. In relative terms, workers who are younger, less skilled, and less tenured benefit from lower firing rates when uncertainty is high. Moreover, more experienced workers are more likely to be hired in periods of high uncertainty. Our empirical results are consistent with a model of hiring and firing decisions of different types of workers under uncertainty, in which workers have embedded firing and relocation options. Higher uncertainty makes firms more likely to choose a firing equilibrium in which they hire more workers of the types that contribute to increasing the volatility of profits, because the firing and relocation options put a lower bound to losses in case of failure.

A broader interpretation of our theoretical and empirical findings is that high uncertainty is associated with a restructuring of the labor force. We find that uncertainty acts against the normal pecking order of workers when it comes to being fired. In general, older, higher-tenured and more skilled workers face a lower risk of being fired. However, periods of high firm-specific uncertainty act as equalizers, in which the firm fires across the board of worker characteristics. This highlights the role of high uncertainty periods as creative destruction phases, in which firms place more weight on the future options embedded in each employment relationship and reduce the role of firing costs and other heterogeneous adjustment costs. It also reflects how the diversification and experimentation efforts of firms during uncertain periods are reflected in their employment decisions. Note that, according to our non-directional uncertainty measure, firing is not higher in high uncertainty periods, so the re-balancing of the workforce occurs through the adjustment of the firing rates across different types of workers. Our paper is the first to highlight this role of high uncertainty periods as a moment for firms to adjust their workforce composition, by differently hiring and firing different types of workers.

Overall, our paper emphasizes the heterogeneity of the effect of firm-level profit uncertainty among different types of workers. While more established workers are negatively affected by uncertainty, others, with higher embedded options, benefit from it. These results are important within the realm of labour and finance, but their implications go beyond workers. A nice property of using workers data is that it is relatively easy to sort workers according to their embedded options (e.g., the option to be relocated, to be fired in the future or to be trained). Firing is also a well-defined form of investment with some upfront costs (severance and disruption costs) and some future rewards (stop paying wages, loss of real options). Our results therefore help us to understand the role of uncertainty and optionality for broader classes of investment, in which it is harder to sort different projects according to their embedded options.

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Tables

Table 1: Descriptive Statistics (Administrative employer-employee matched data)

Panel A: Worker-level

	Obs.	Mean	St.Dev.	p10	p25	p50	p75	p90
Male	8,633,534	0.561	0.496	0.000	0.000	1.000	1.000	1.000
Age	8,633,534	39.949	12.252	24.000	30.000	39.000	50.000	57.000
%hired	8,633,534	0.201	0.401	0.000	0.000	0.000	0.000	1.000
%fired	8,633,534	0.098	0.298	0.000	0.000	0.000	0.000	0.000
%voluntary turnovers	8,632,732	0.079	0.269	0.000	0.000	0.000	0.000	0.000
%any separation	8,632,732	0.184	0.387	0.000	0.000	0.000	0.000	1.000
Tenure (years)	8,633,534	5.222	4.175	1.000	2.000	4.000	8.000	11.000
Tenure (short)	8,633,534	0.201	0.401	0.000	0.000	0.000	0.000	1.000
Young	8,633,534	0.159	0.366	0.000	0.000	0.000	0.000	1.000
Skilled	8,633,534	0.212	0.409	0.000	0.000	0.000	0.000	1.000
Education (index)	8,617,070	2.476	0.985	1.000	2.000	2.000	3.000	4.000
$Index_{ft}$	8,633,534	-0.000	1.000	-0.631	-0.554	-0.358	0.091	1.032
$\hat{\pi}_{ft}$	8,633,534	0.002	0.095	-0.048	-0.018	-0.003	0.017	0.060

Panel B: Firm-level

	Obs.	Mean	St.Dev.	p10	p25	p50	p75	p90
$Index_{ft}$	23,176	0.000	1.000	-0.737	-0.626	-0.362	0.198	1.211
$\hat{\pi}_{ft}$	23,176	0.000	0.002	-0.001	-0.000	0.000	0.000	0.001
$abs(\pi_{ft+1} - \pi_{ft})$	21,839	0.063	0.102	0.002	0.010	0.031	0.073	0.149
%hired	23,176	0.203	0.137	0.065	0.109	0.167	0.267	0.387
%fired	23,176	0.104	0.087	0.028	0.048	0.081	0.129	0.211
%net hired	23,176	0.099	0.104	-0.005	0.035	0.082	0.153	0.234
%voluntary	23,176	0.097	0.096	0.027	0.044	0.072	0.121	0.187
Age (hired)	23,105	33.57	5.66	26.43	30.00	33.67	36.76	40.28
Skilled (hired)	23,104	0.171	0.194	0.000	0.000	0.108	0.250	0.462
Experienced (3d) (hired)	23,105	0.433	0.217	0.154	0.275	0.432	0.571	0.714
Experienced (4d) (hired)	23,105	0.402	0.219	0.125	0.241	0.400	0.543	0.686
CapEx	21,495	0.086	0.168	-0.094	0.001	0.076	0.173	0.293
Firm age	23,176	11.448	5.296	4.000	8.000	12.000	16.000	18.000
Employees	23,176	477.20	1132.82	56.00	68.00	107.00	269.00	1114.00

Number of observations in thousands. Index is normalized to have a zero mean and a standard deviation one at a firm level. This table reports descriptive statistics of the main variables used in the worker-level analysis. Panel A examines the worker level data. Panel B shows summary at the firm level. Detailed definitions and explanations of all variables is provided in the Appendix.

Table 2: Descriptive Statistics (Uncertainty Index)

	Mean	St.Dev.	p25	p75	mean abs(beta)	% zero
First component beta	-0.009	0.053	-0.019	0.004	0.026	22.8%
Second component beta	0.007	0.223	-0.010	0.014	0.033	27.7%
Third component beta	0.014	0.086	-0.008	0.029	0.043	28.4%
Fourth component beta	0.020	0.133	-0.009	0.046	0.066	31.2%
Fifth component beta	-0.015	0.125	-0.034	0.009	0.059	35.7%
Sixth component beta	0.001	0.235	-0.036	0.030	0.030	36.2%
Seventh component beta	0.031	0.176	-0.009	0.070	0.098	33.2%
$Index_{ft}$	0.243	1.070	-0.427	0.455	–	–
$Index_{ft}$ net of year and firm effects	0.000	0.405	-0.171	0.152	–	–
Obs (non zero)	23,176					
Obs (all)	31,408					

We report summary statistics of the different profit exposures to each of the principal components of the commodity basket. These correspond to β_{fj} of expression (1). Mean abs(beta) refers to the average of the absolute value of each beta. Obs(non zero) shows the number of firms for which at least one principal component has non-zero loadings in the LASSO regression. Obs(all) shows the total number of firm/regressions.

Table 3: Predictive Power of the Index

	$abs(\pi_{ft+1} - \pi_{ft})$					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$Index_{ft}$	3.802***	2.578***	2.979***	3.767***	2.549***	2.953***
	(0.323)	(0.493)	(0.626)	(0.339)	(0.528)	(0.661)
$\pi_{ft+1} - \pi_{ft}$				-0.139**	-0.129*	-0.114*
				(0.064)	(0.069)	(0.068)
Obs	21,839	21,839	21,839	21,839	21,839	21,839
R-squared	0.130	0.221	0.265	0.153	0.243	0.281
Firm FE	No	Yes	Yes	No	Yes	Yes
Industry-Year FE	No	No	Yes	No	No	Yes

***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$. Standard errors in parentheses.
We regress the uncertainty index $Index_{ft}$ on the absolute value of the year-on-year profit changes, $abs(\pi_{ft+1} - \pi_{ft})$. Columns (4)–(6) additionally include the change in profits as a regressor.

Table 4: Uncertainty Shocks and Firing, Baseline estimation

	Fired					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$Index_{ft}$	0.007***		0.034	0.001		0.034
	(0.002)		(0.043)	(0.001)		(0.043)
$\hat{\pi}_{it}$	-0.010	-0.006	-0.016	-0.025**	-0.025**	-0.016
	(0.012)	(0.012)	(0.014)	(0.010)	(0.010)	(0.014)
$Index_{Ind,I(f)t}$		0.004**			0.001	
		(0.002)			(0.001)	
Obs	8,633,534	8,633,534	8,633,534	8,633,534	8,633,534	8,633,534
R-squared	0.006	0.006		0.037	0.037	
Year-Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	Yes	Yes	Yes
Estimator	OLS	OLS	IV	OLS	OLS	IV

***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$. Standard errors in parentheses. The dependent variable equals one if the worker leaves the firm in period t and receives unemployment benefits, and zero otherwise. $Index_{ft}$ denotes firm-level uncertainty; $\hat{\pi}ft$ is the firm-level profit shock; $IndexInd, I(f)t$ is the 3-digit industry uncertainty index. Sources: SCB LISA, UC AB, Bolagsverket.

Table 5: Uncertainty Shocks and Firing, Young versus Old

	Fired					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$Index_{ft}$	0.002***	0.002***	0.029			
	(0.001)	(0.001)	(0.039)			
Young X $Index_{ft}$	-0.008***	-0.008***	-0.034***	-0.008***	-0.008***	-0.036***
	(0.001)	(0.001)	(0.005)	(0.001)	(0.001)	(0.005)
$\hat{\pi}_{ft}$	-0.027**		-0.023			
	(0.011)		(0.014)			
Young X $\hat{\pi}_{ft}$	-0.004		0.013	-0.003		0.014
	(0.009)		(0.016)	(0.009)		(0.017)
Young	0.147***	0.147***	0.147***	0.146***	0.146***	0.146***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	
Obs	8,633,534	8,633,534	8,633,534	8,633,534	8,633,534	8,633,534
R-squared	0.066	0.066		0.072	0.072	0.030
Year-Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	No	No	No
Firm-year FE	No	No	No	Yes	Yes	Yes
Estimator	OLS	OLS	IV	OLS	OLS	IV

***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$. Standard errors in parentheses.
The dependent variable equals one if the worker leaves the firm in period t and receives unemployment benefits, and zero otherwise. *Young* is a dummy equal to one if the worker is under 28. $Index_{ft}$ denotes firm-level uncertainty; $\hat{\pi}ft$ is the firm-level profit shock; $IndexInd, I(f)t$ is the 3-digit industry uncertainty index. Sources: SCB LISA, UC AB, Bolagsverket.

Table 6: Uncertainty Shocks and Firing, Tenure Profile

	Fired					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$Index_{ft}$	0.002***	0.003***	0.053			
	(0.001)	(0.001)	(0.048)			
Tenure (short) X $Index_{ft}$	-0.008***	-0.008***	-0.031***	-0.007***	-0.007***	-0.031***
	(0.001)	(0.001)	(0.008)	(0.001)	(0.001)	(0.008)
$\hat{\pi}_{ft}$	-0.028**		-0.018			
	(0.011)		(0.016)			
Tenure (short) X $\hat{\pi}_{ft}$	0.008		0.024	0.005		0.022
	(0.010)		(0.015)	(0.010)		(0.014)
Tenure (short)	0.164***	0.164***	0.164***	0.165***	0.165***	0.165***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Obs	8,633,534	8,633,534	8,633,534	8,633,534	8,633,534	8,633,534
R-squared	0.082	0.082		0.089	0.089	0.048
Year-Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	No	No	No
Firm-year FE	No	No	No	Yes	Yes	Yes
Estimator	OLS	OLS	IV	OLS	OLS	IV

***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$. Standard errors in parentheses.
The dependent variable equals one if the worker leaves the firm in period t and receives unemployment benefits, and zero otherwise. $Tenure\ (short)$ is a dummy equal to one if the worker has been at the firm for less than three years. $Index_{ft}$ denotes firm-level uncertainty; $\hat{\pi}ft$ is the firm-level profit shock; $IndexInd, I(f)t$ is the 3-digit industry uncertainty index. Sources: SCB LISA, UC AB, Bolagsverket.

Table 7: Uncertainty Shocks and Firing, Skilled versus Unskilled

	Fired					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$Index_{ft}$	0.000	0.000	0.030			
	(0.001)	(0.001)	(0.044)			
Skilled X $Index_{ft}$	0.002**	0.003**	0.024**	0.003***	0.003***	0.027***
	(0.001)	(0.001)	(0.009)	(0.001)	(0.001)	(0.010)
$\hat{\pi}_{ft}$	-0.027***		-0.014			
	(0.010)		(0.016)			
Skilled X $\hat{\pi}_{ft}$	0.007		-0.010	-0.003		-0.019
	(0.006)		(0.013)	(0.006)		(0.013)
Skilled	-0.035***	-0.035***	-0.034***	-0.034***	-0.034***	-0.033***
	(0.002)	(0.002)		(0.001)	(0.001)	(0.002)
Obs	8,633,534	8,633,534	8,633,534	8,633,534	8,633,534	8,633,534
R-squared	0.038	0.038		0.044	0.044	0.001
Year-Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	No	No	No
Firm-year FE	No	No	No	Yes	Yes	Yes
Estimator	OLS	OLS	IV	OLS	OLS	IV

***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$. Standard errors in parentheses.
The dependent variable is binary variable equal to one if the worker leaves the firm in period t and receives unemployment benefits afterwards, and zero otherwise. Among the regressors, *Skilled* is a dummy variable equal to one if the worker has college education (or higher). $Index_{ft}$ is the firm-level uncertainty index. $\hat{\pi}_{ft}$ is the firm-level profits shock. $Index_{Ind,I(f)t}$ is the 3-digit industry uncertainty index. Sources: SCB LISA, UC AB, Bolagsverket.

Table 8: Firm-level hiring and firing

	% hired	**% fired**	**% net hired**	**% volunt.**
	(1)	**(2)**	**(3)**	**(4)**
$Index_{ft}$	0.003	0.001	0.002	-0.001
	(0.002)	(0.001)	(0.002)	(0.002)
$\hat{\pi}_{ft}$	1.800**	-1.363***	3.163***	-0.769
	(0.833)	(0.457)	(1.050)	(0.690)
Obs	23,176	23,176	23,176	23,176
R-squared	0.746	0.773	0.531	0.471
Year-Ind. FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$. Standard errors in parentheses.
Estimates are at the Firm level, using weighed OLS (weights are the total number of employees for each firm). Employment variables correspond to period t+1 and are scaled using total number of employees in period t. Among the regressors, $Index_{ft}$ is the firm-level uncertainty index. $\hat{\pi}_{ft}$ is the firm-level profits shock. Sources: SCB LISA, UC AB, Bolagsverket.

Table 9: Firm-level hiring and firing

	Age (hired)	Highly educ. (hired)	Experience (hired)	Experience (hired)
	(1)	(2)	(3)	(4)
$Index_{ft}$	0.104	0.002	0.009***	0.008**
	(0.065)	(0.002)	(0.003)	(0.003)
$\hat{\pi}_{ft}$	-41.596	1.539**	-2.106*	-2.023*
	(28.116)	(0.772)	(1.108)	(1.153)
Obs	23,105	23,104	23,105	23,105
R-squared	0.680	0.846	0.609	0.623
Year-Ind. FE	1-digit	1-digit	1-digit	3-digit
Firm FE	Yes	Yes	Yes	Yes

***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$. Standard errors in parentheses.
Estimates are at the Firm level, using weighed OLS (weights are the total number of employees for each firm). Dependent variables are the average age (column 1), the average n. of years of education (column 2), the average fraction of workers with experience in a firm in the same 3-digit sector (columns 3 and 4) of workers hired in period t+1. Among the regressors, $Index_{ft}$ is the firm-level uncertainty index. $\hat{\pi}_{ft}$ is the firm-level profits shock. Sources: SCB LISA, UC AB, Bolagsverket.

Table 10: Uncertainty Shocks and Firing, Flexible versus Non-flexible Workers

	Fired					
	(1)	(2)	(3)	(4)	(5)	(6)
$Index_{ft}$	0.002***	0.002***	0.064			
	(0.001)	(0.001)	(0.050)			
Flex X $Index_{ft}$	-0.003***	-0.003***	-0.008**	-0.004***	-0.004***	-0.010***
	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)	(0.004)
$\hat{\pi}_{ft}$	-0.034***		-0.029**			
	(0.009)		(0.014)			
Flex X $\hat{\pi}_{ft}$	-0.002		-0.004	-0.021**		-0.018
	(0.012)		(0.014)	(0.010)		(0.012)
Flex	-0.016***	-0.016***	-0.016***	-0.017***	-0.017***	-0.017***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Obs	7,142,036	7,142,036	7,142,036	7,142,036	7,142,036	7,142,036
R-squared	0.036	0.036		0.044	0.044	0.001
Year-Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	No	No	No
Firm-year FE	No	No	No	Yes	Yes	Yes
Estimator	OLS	OLS	IV	OLS	OLS	IV

***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$. Standard errors in parentheses.
The dependent variable is binary variable equal to one if the worker leaves the firm in period t and receives unemployment benefits afterwards, and zero otherwise. Among the regressors, Flex is a dummy variable equal to one if the worker is in the top tercile of our occupational flexibility measure. $Index_{ft}$ is the firm-level uncertainty index. $\hat{\pi}_{ft}$ is the firm-level profits shock. $Index_{Ind,I(f)t}$ is the 3-digit industry uncertainty index. Sources: SCB LISA, UC AB, Bolagsverket.