Employment beta and the risk relevance of restructuring

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Abstract

The systematic risk of a firm is important but challenging to assess, and it is often estimated using stock returns or cash flows. This study investigates whether the timing of labor outflows is informative about systematic risk. In expectation of demand shocks, firms reduce labor. Demand shocks may be firm-specific or economy-wide, but only economy-wide shocks will manifest macroeconomic employment changes. Accordingly, observing whether a firm reduces labor in concert with, or independently of, macroeconomic employment changes can indicate its sensitivity to aggregate demand shocks and therefore systematic risk. Using restructuring, a transitory accrual, to indicate firm-level labor outflows, tests indicate that firms reducing labor in conjunction with the aggregate economy have higher levels of stock return-based measures of systematic risk and realize lower firm and aggregate growth subsequent to labor outflows, consistent with demand shock realization. These results highlight the informativeness of labor flows and transitory accruals in systematic risk assessment.

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1. Introduction

The systematic risk of a firm depends on the projects that the firm undertakes. Determining the projects' exposure to undiversifiable macroeconomic shocks can be challenging. However, by observing when the firm is investing in or divesting from their projects, outsiders may be able to assess management's demand expectations. If the firm is expecting a negative demand shock, it will reduce its inputs to production. This demand shock may be either idiosyncratic or economy-wide, so observing a reduction alone is inadequate for risk assessment. Instead, the reduction in inputs needs to be considered in context of the macroeconomy. If the firm reduces its inputs in conjunction with the macroeconomy, then likely the firm is exposed to macroeconomic demand shocks. If the firm adjusts inputs independently of the macroeconomy, then the firm is likely exposed to idiosyncratic demand shocks. Relative to conventional stock return-based approaches, observing reductions in inputs lies closer to observing firm fundamentals, in tune with arguments for using cash flow betas or managerial characteristics (Ball et al., 2022; Ellahie, 2021; Schoar et al., 2024).

This study focuses on a single, but critically important, input to production: labor. This is for several reasons. Labor is a universal input to production with increasing importance as the U.S. transitions to a more services-based economy. There are long-standing quarterly time-series data on macroeconomic labor usage, i.e., employment.[1] The interpretation of employment declines as macroeconomic demand shocks is well-grounded (Brainard and Cutler, 1993; Chodorow-Reich and Wieland, 2020; Gali, 1999; Hamermesh and Pfann, 1996).[2] Finally, the lack of information available about firm human capital resources has

[1]While market portfolio-based measures can be constructed from returns or accounting data as a proxy for macroeconomic data, these proxies largely omit broad cross-sections of the economy, including private firms and public assets, and therefore are unlikely to be representative of the macroeconomy (Ball et al., 2022).

[2]I disucss the potential role of supply and technology shocks affecting macroeconomic employment in section 6.3.

raised interest in the potential usefulness of such information (Banks et al., 2022; Batish et al., 2021; Edmans, 2011).

Generally, labor investments are not capitalized and therefore changes in their value are difficult to observe. However, when layoffs and employee relocation generate expected separation costs, they are accrued in a restructuring liability and related expense (Financial Accounting Standards Board, ASC 420-10-05-1), indicating firm labor divestment. For firms that depend on labor as a significant input to production, this likely is a substantial fraction of the restructuring expense (Jennings et al., 1998). Because the expense is recorded when restructuring terms are communicated to employees, it provides a timely indication of the decision to reduce labor investment as compared to changes in labor expenses or headcount. Because the expense is denominated in monetary units, and not employees, restructuring expense is increasing in the cost to replace the labor terminated (Ghaly et al., 2017). Because of adjustment costs in labor markets, firms do not accrue the expense lightly (Anderson et al., 2003; Banker et al., 2013). As a part of special items, restructuring is responsive to economy-wide news and the firm's economic circumstances, and is related to GDP and job destruction (Abdalla and Carabias, 2022; Hann et al., 2021; John et al., 1992). These characteristics suggest the possibility that, in context of macroeconomic information, restructuring expenses are risk relevant.

Validation tests confirm prior conclusions that restructuring coincides with labor reduction (Brickley and Van Drunen, 1990; John et al., 1992). Using a sample of firms that incurred restructuring expenses between 2001 and 2020, inclusive, I find a positive correlation between annual restructuring expense and firm employee growth.[3] Tobit regressions confirm the relation. Further tests document a systematic labor-related component to restructuring expense, meaning that, on average, aggregate restructuring expenses move in

[3]Higher restructuring expenses are more negative amounts in the data.

concert with aggregate labor growth. This systematic labor-related component of restructuring is present even in samples with higher labor adjustment costs, as measured by union membership and unemployment, meaning that the aggregate labor-related component of restructuring is important across a wide variety of firms.

However, firms may divest labor in expectation of idiosyncratic or macroeconomic demand shocks, and therefore restructuring alone is inadequate for systematic risk assessment. Instead, the restructuring should be considered in context of the macroeconomic environment. If the macroeconomic signals indicate expectations of a macroeconomic demand shock when the firm is restructuring, that is likely affecting the firm. If the firm restructures when there is no indication of a macroeconomic demand shock, the restructuring suggests an idiosyncratic demand shock.

Following this logic, I construct the employment beta, β_i^{EMPL}, following the familiar capital asset pricing model formula. Specifically, β_i^{EMPL} is the coefficient from a time-series Tobit regression of firm restructuring expense on macroeconomic labor growth. Higher β_i^{EMPL} indicates more exposure to aggregate demand shocks manifesting in macroeconomic employment changes. Employment beta correlates with measures of firm dependence on labor as a factor of production, i.e., labor leverage and the conventional return-based measure of systematic risk.

As an initial test, I calculate firm return-based market betas using the the Fama-French-Carhart four-factor model (Carhart, 1997; Fama and French, 1993), and regress them on employment beta, β_i^{EMPL}. The measures are positively correlated. To ensure that the information in restructuring is not reflected in operating earnings, I also construct an operating earnings-based alternative to β_i^{EMPL}. I regress operating earnings on macroeconomic labor growth, and the coefficient is the earnings-based alternative measure, β_i^{OI}. Results show that neither operating earnings nor labor leverage substitutes for the information provided by restructuring charges.

The main test estimates the Fama-French-Carhart four-factor model by portfolio, based on employment beta, β_i^{EMPL}. Market betas increase monotonically over the quintiles of β_i^{EMPL}, supporting the conclusion that the timing of labor divestment can provide systematic risk-relevant information. Results are consistent when estimating market betas by β_i^{EMPL} portfolio conditional on the operating earnings-based measure or estimating market betas using out-of-sample returns.

Additional tests investigate differences in post-restructuring outcomes for firms with higher employment betas. If systematically risky firms reduce labor in expectation of a firm, and therefore macroeconomic, demand shock, then there should be evidence of firm and macroeconomic demand shocks subsequent to these firms' restructuring activities. Consistent with this notion, firms with higher employment betas have lower revenue and expense growth over the two years starting in the year of restructuring relative to other firms. Further, when firms with higher β_i^{EMPL} incur restructuring expense, aggregate sales and GDP growth is lower thereafter, consistent with the realization of aggregate demand shocks after firms with high β_i^{EMPL} reduce labor.

I also investigate whether firms that divest labor in response to expected macroeconomic demand shocks are more likely to reverse restructuring charges. Hutton et al. (2012) show that firm managers have less information about the aggregate economy versus analysts, and Kim et al. (2016) show that managers reduce voluntary disclosure during times of aggregate uncertainty. Because aggregate demand shocks put managers at an information disadvantage, those managers may be more likely to mis-estimate restructuring and subsequently need to reverse charges. I find that reversals are increasing with the sensitivity of restructuring to aggregate demand shock, consistent with this notion.

Two extensions reinforce the overall findings. The first extension uses a separate macroeconomic measure of demand shock expectations, VIX, as an alternative to macroeconomic employment growth. A second extension calculates employment beta at the industry level, and uses only firms that do not report restructuring expense during the sample period to test whether an industry employment beta is informative when the firm-level measure is incalculable.

This study aims to contribute in three ways. First, it introduces the possibility that labor flows can provide systematic risk information. To my knowledge, this is the first study to specifically investigate how observing the timing of management's labor divestment decisions in the context of aggregate labor flows can be informative about firm exposure to macroeconomic shocks. This indicates the types of activities that systematically risky firms are required to engage in as a result of exposure to aggregate shocks. Also, this may provide an alternative method for assessing systematic risk, either in conjunction with earnings and returns, or as an alternative for firms where earnings and returns are not available or reliable.

This study also contributes to the literature on transitory accruals and specifically restructuring expense. Generally accepted accounting principles (GAAP) require the inclusion of restructuring expense in operating earnings, but this expense is often excluded from non-GAAP earnings, earnings used in compensation calucations, street earnings, and operating earnings measures provided by third parties, including Computstat (Bradshaw and Sloan, 2002; Dechow et al., 1994; Laurion, 2020). Restructuring expenses are criticized for reducing matching and the value relevance of earnings, and for being easy to manipulate (Bens and Johnston, 2009; Elliott and Hanna, 1996; Fairfield et al., 2009; Moehrle, 2002). As a counterpoint to this literature, this study provides evidence of the risk relevance of restructuring and its usefulness in valuation.

Finally, this study sheds light on the value of reporting human capital investments in the financial statements. The Financial Accounting Standards Board has proposed a new standard requiring the disaggregation of income statement items into more granular categories, including employee compensation (Financial Accounting Standards Board, 2023). Further, the SEC has issued human capital disclosure requirements as part of amended Item 101 of Regulation S-K. The importance of disclosure about human capital investment remains a key issue (Banks et al., 2022). This study is one of the first to highlight how even limited reporting regarding human capital investment can be risk-relevant, underscoring the call for further disclosure about this intangible asset and a deeper understanding of the risk-relevance of financial statement information (Barth, 2015).

The remainder of this paper is organized as follows. Section 2 provides a discussion of the research related to systematic risk, labor disinvestment, restructuring charges, and the hypothesis tested in this study. Section 3 describes the research design and measurement. Section 4 describes the data, section 5 provides the results of the tests, and section 6 provides additional analyses. Section 7 concludes the study.

2. Related literature and hypothesis

Labor is a factor of production that generates output for the firm to sell. The firm adjusts labor investment based on changes in product demand expectations (Gali, 1999; Hamermesh and Pfann, 1996). This study proposes that the timing of labor adjustments can be informative about firm risk.

There may be several reasons why a firm expects a demand shock. This study considers two collectively exhaustive categories of reasons: idiosyncratic and systematic. Idiosyncratic reasons are relevant to the firm specifically, but not to the broader market. Product demand shocks caused by the firm's product design, for example, fall into this category. These generate risk to the firm, but are diversifiable, as the same risk does not affect all firms in the same way at the same time. Systematic demand shocks, on the other hand, affect a broad cross-section of firms in the same way, and therefore are undiversifiable and have a significant effect on firm valuation. A demand shock created by interest rate changes is an example of a systematic shock.

If the demand shock is economy-wide, many firms will reduce their labor, resulting in changes in macroeconomic employment (Gali, 1999). If an individual firm reduces its labor in simultaneity with the aggregate market, it is likely also affected by the aggregate demand shock and therefore exposed to systematic risk. All other things being equal, the more the firm is affected by the aggregate shock, the more the firm will make adjustments to its labor.[4]

In this way, the timing and degree of labor adjustments at a firm can signal its exposure to systematic risk. If the firm adjusts labor in concert with the aggregate market, the firm is exposed to aggregate demand shocks and carries systematic risk. If the firm adjusts labor independently of the aggregate market, then it is less systematically risky. This leads to the main hypothesis of this study:

Hypothesis 1 *Firms that reduce labor when macroeconomic employment growth is lower carry more systematic risk than firms that reduce labor independently of macroeconomic employment growth.*

[4]There is a debate in the economics literature regarding the degree to which cyclical shocks and sectoral shocks cause macroeconomic employment changes. Lilien (1982) challenges traditional Keynesian explanations of unemployment by introducing the sectoral shift hypothesis. However, the degree to which the sectoral shift hypothesis describes macroeconomic employment changes may be limited, as broad market shocks cause employment growth dispersion resembling sectoral shocks (Abraham and Katz, 1986). Brainard and Cutler (1993) indicates that time-series deviations in employment are better described by macroeconomic shocks. More recently, Chodorow-Reich and Wieland (2020) shows that the effect of sectoral employment shift is conditional on aggregate downturns in the economy. Regardless, this study does not aim to contribute to this debate. As long as either a) cyclical demand shocks are the dominant reason for declines in employment, or b) sectoral demand shocks causing substantial macroeconomic employment declines are not simultaneously offset by demand growth in other sectors, either type of demand shock is undiversifiable.

Firms that reduce labor when macroeconomic employment growth is lower may not carry more systematic risk than other firms. Firms may not adjust labor as quickly as demand shocks would suggest (Fay and Medoff, 1985). One reason is that firms face labor adjustment costs (Anderson et al., 2003; Banker et al., 2013; Golden et al., 2020; Hamermesh and Pfann, 1996). Laying off employees requires dealing with regulatory, reputational, and morale-related issues, and therefore firms may delay or forgo labor divestments in light of aggregate demand shocks. Firms may instead carry higher inventories or cash to weather the downward change in demand (Ghaly et al., 2017; Topel, 1982). Accordingly, whether changes in labor assets provide information about systematic risk becomes an empirical question.

This study focuses on restructuring expense as an indication of labor disinvestment. Restructuring costs are related to exit and disposal activities, and include a) one-time involuntary termination benefits, b) costs to terminate a contract that is not a lease, and c) other associated costs, such as costs to relocate employees or close facilities (Financial Accounting Standards Board, ASC 420-10-05-1). A restructuring liability and related expense are recorded at fair value when the restructuring is probable and when the firm has communicated the termination benefits to affected employees. Restructuring expense does not include inventory write-downs, impairments of long-lived assets, or costs associated with retiring long-lived assets. Restructuring costs are not recognized in expense over the period that the restructuring occurs but instead when the obligations related to the restructuring are created.[5]

Because it is a quarterly accrual, restructuring provides a timely indication of manage-

[5]The rules related to restructuring expense changed slightly over the sample period. In 2003, EITF 94-3 was superseded by SFAS 146. The standards were largely similar; the main difference was that SFAS 146 required recognition of the restructuring liability when the liability is incurred, versus when management commits to a restructuring plan (Financial Accounting Standards Board, 2010). In 2018, ASC 842 modified the scope of restructuring from including only contracts that are not capital leases to contracts that are not leases (PwC, 2023).

ment's expectation of the effect of the demand shock on the firm; restructuring expense also matches the frequency of macroeconomic employment information. Because it is denominated in dollars, and not employees, restructuring expense is correlated with the value of employees relocated or terminated, reflecting the difficulty of replacing them (Ghaly et al., 2017). Restructuring expenses are substantial, amounting to 80% of pre-restructuring income according to Dechow et al. (1994), and restructuring contains severance a vast majority (88%) of the time (Lin, 2006). The analysis in John et al. (1992) finds that restructuring results in a 5% workforce reduction and lower labor costs. The study also finds that firms often restructure for exogenous reasons, such as the state of the economy. As part of special items, restructuring increases during bad macroeconomic news events, in the aggregate is predictive of changes in GDP (Abdalla and Carabias, 2022), and is informative about aggregate job creation and destruction (Hann et al., 2021).

While restructuring has potential to be informative about labor divestment, it may fail to inform, for a few reasons. I acknowledge that restructuring expense entails more than labor costs, and therefore is a noisy signal of labor divestment. Further, restructuring has been criticized as an expense subject to managerial manipulation (Bens and Johnston, 2009; Elliott and Hanna, 1996; Moehrle, 2002). Specifically, Bens and Johnston (2009) finds that firms overstate restructuring expenses as part of "big bath" manipulations, but that the introduction of EITF No. 94-3 and higher SEC scrutiny moderate this manipulation. Also, restructuring expense is a signal only of labor divestment, not of investment. GAAP does not allow firms to use restructuring expense to indicate hiring efforts in expectation of positive demand shocks. Therefore the signal provided by restructuring expense is one-sided, limiting the scope of information that it can communicate about changes in the labor assets of the firm.

There are several papers discussing alternatives to returns-based measures for assessing systematic risk. Closest to this paper are studies that investigate the usefulness of betas constructed from earnings. Early studies, including Ball and Brown (1969) and Gonedes (1973), demonstrate that earnings can provide information about systematic risk by calculating and demonstrating the association between earnings betas and future returns. However, Ismail and Kim (1989) suggest that earnings betas provide a subset of the information that cash flow betas provide, perhaps because earnings are less objective and difficult to understand. More recently, Ellahie (2021) constructs multiple earnings betas using 11 different measures of earnings, finding that expected earnings can provide a more effective measure of expected return relative to using firm and market returns. Ball et al. (2022) investigate the association between aggregate productivity and firm operating earnings, finding that the association indicates systematic risk. This study emphasizes the importance of using macroeconomic measures that reflect the wider economy and not just public companies. While these studies have developed the foundation for earnings as an indicator of systematic risk, they do not consider how specific expenses, such as restructuring, can provide information about systematic risk. Their focus on persistent earnings omits restructuring specifically.

More closely related to labor, Kuehn et al. (2017) show that firms with sensitivity to labor market tightness are higher risk. Investors require higher compensation for investing in firms with more exposure to fluctuations in the labor market. Other papers investigate labor leverage: the notion that having large and inflexible labor creates operations that function similarly to financial leverage and increase the risk of the firm (Donangelo et al., 2019; Lev, 1974; Levhari and Weiss, 1974; Rosett, 2001, 2003). Schoar et al. (2024) show how managers can affect systematic risk by changing the projects the firm undertakes. My study differs from these in that it does not suggest that reliance on labor generates risk. The type or quantity of labor used by the firm is not the source of exposure to macroeconomic shocks. Instead, I use the timing of labor flows out of the company as a signal to assess whether the firm is expecting to be affected by an aggregate demand shock.

3. Research Design and Measurement

3.1. Restructuring as a human-capital related expense

Restructuring expense is defined by GAAP to include costs related to divestment in labor assets, and many studies, including Abdalla and Carabias (2022), Hann et al. (2021), John et al. (1992), and Lin (2006), support its use as a signal of firm labor divestment. However, the novelty of using restructuring in systematic risk assessment prompts validation. Accordingly, this study tests the correlation of restructuring expense with other signals of labor disinvestment.[6]

The most direct test is whether restructuring expenses increase when the firm has lower employee growth. If restructuring generates more costs (is more negative) as the number of employees terminated increases, then the expense should be positively correlated with change in firm employees. Firms are required to report their number of employees annually along with their financial statements, which also include restructuring expense. I measure restructuring expense, $restr_{i,t}$, as annual restructuring expense divided by total assets as of the beginning of the annual period, where i indicates firm and t indicates quarter. The change in employees is the difference between the number of employees as of the end of fiscal year y and year $y-1$ as a fraction of total assets as of the end of year $y-1$.

It is also important that restructuring expense displays a systematic component. Specif-

[6]This study uses restructuring expense instead of employee growth for a few reasons. First, restructuring expense is reported as a dollar value, and therefore it is increasing in the value of the human capital that is terminated (Ghaly et al., 2017). Second, restructuring is reported quarterly and therefore provides greater frequency of observation that matches macroeconomic measures. Finally, restructuring expense is an important component of income and its value relevance is of interest to accountants and standard setters.

ically, do restructuring charges fluctuate with macroeconomic employment? If so, then the sample of firms for which we can observe restructuring is exposed to aggregate shocks affecting macroeconomic employment. This is important because publicly listed firms comprise only a fraction of macroeconomic employment. The wider breadth of firms encompassed by macroeconomic employment can provide better information about changes in the macroeconomy, but such changes may not be relevant to the sample we observe (Ball et al., 2022). I measure shocks to macroeconomic employment as seasonally adjusted quarterly macroeconomic employment growth, $EMPL_t$, which is the percent change in employment from the same calendar quarter a year ago for all workers in the non-farm business sector. I use quarterly observations from the Bureau of Labor Statistics (BLS) to match the frequency of restructuring observations and the non-farm business sector to provide a sample that is representative of the changes in labor growth across the U.S. economy.

I test the association between macroeconomic employment growth and restructuring expense in the regression:

$$restr = \alpha_i + \beta_1 \times EMPL_t + \varepsilon, \tag{1}$$

where $EMPL_t$ is defined above. The measure of restructuring, $restr$, is one of two variables. The first is $restr_{i,t}$ as defined above and is measured quarterly on a rolling four-quarter basis. In this case, I regress a variable with both time-series and cross-sectional variation on a variable with only time-series variation, and therefore I cluster t-statistics by firm and year because standard errors will be correlated in the cross-section and in the time-series. I estimate the relation using Tobit regression. The latent variable of interest is the firm's change in human capital investment. Restructuring only allows us to observe divestment, and therefore the observable data is censored with an upper bound of zero. Tobit regression accounts for this censoring of the data.

Second, I construct an aggregate measure of restructuring expense, $AGGrestr_t$, which is the cross-sectional quarterly mean of $restr_{i,t}$. The aggregate measure of restructuring, $AGGrestr_t$, is assessed at the same frequency as aggregate labor market growth, $EMPL_t$. Because of the large number of firms included in calculating the aggregate restructuring measure, the aggregate variable is not censored at zero, and therefore I use conventional OLS regression to estimate Equation (1) using this measure. Because restructuring expenses are correlated across the year, I incorporate Newey-West standard errors with lags for four observations.

It is well documented that adjustment costs can affect firm labor investment decisions (Chen et al., 2011; Golden et al., 2020; Topel, 1982). If the systematic component of restructuring is not sufficiently large, adjustment costs will render it unobservable. To assess the degree to which adjustment costs affect the systematic component of restructuring, I divide the sample by adjustment cost. Following Chen et al. (2011) and Golden et al. (2020), I use industry unemployment and employee union membership as observable variation in labor adjustment costs. Consistent with Topel (1982), firms that have an available pool of labor are relatively more likely to lay off employees, because they can more readily reverse their decision. Unemployment levels are increasing in the availability of labor. Therefore, firms operating in industries with lower unemployment have higher adjustment costs and may be less likely to restructure based on expected aggregate demand shocks. Similarly, firms with union employees incur higher layoff costs and are more likely to have restructurings blocked by unions, increasing labor adjustment costs for the firm (Chen et al., 2011). This may significantly affect the likelihood of restructuring in expectation of negative aggregate demand shocks.

I measure unemployment using the BLS industry unemployment rate data.[7] I find the

[7] I use the "Unemployed Persons by Occupation and Sex" or "Unemployed Persons by Industry, Class of Worker, and Sex" table, depending on availability for each year. For example, the data from 2020 are from

time-series average unemployment for each industry and split the sample cross-sectionally by industry at the median. Similarly, I obtain the BLS data on the percent of employed workers represented by unions in each industry and split the sample based on annual median union representation.[8] I match industry data to firms using two-digit NAICS industries.

3.2. The restructuring-based measure of systematic risk

Restructuring, as an indication of labor divestment, is by itself insufficient to determine whether a firm is exposed to systematic risk. The firm may be reducing its investment in labor because of an expected demand shock that is either economy-wide or specific to the firm. The context in which the firm takes the restructuring expense can help determine which is the case. If the firm terminates employees when macroeconomic employment growth is also low, the firm is likely exposed to an expected aggregate demand shock affecting a large fraction of the economy.

Following this logic, employment beta is calculated as β_i^{EMPL} from the Tobit regression of:

$$restr_{i,t} = \alpha_i + \beta_i^{EMPL} \times EMPL_t + \varepsilon_{i,t}, \tag{2}$$

where $restr_{i,t}$ is as defined above, $EMPL_t$ is macroeconomic employment growth as defined above, i is the firm, and t is the quarter. As in the panel regression of Equation (1), using a Tobit regression to estimate this relation allows β_i^{EMPL} to describe the relation between $EMPL_t$ and the latent variable representing firm change in labor investment. The measure of labor investment, $restr_{i,t}$, is censored at zero because of the accounting rules

https://www.bls.gov/cps/cps_aa2020.htm. I use data from 2003 through 2020, spanning a vast majority of the sample period. I assign each industry a 2012 two-digit NAICS code based on industry name.

[8] I use the BLS table "Percent of employed, Private wage and salary workers, Members of unions – Unadjusted series" for the percent of union participation in each industry. Series ID LUU0204906600 provides the overall rates across all industries. I assign the two-digit NAICS code based on industry name.

for restructuring expense.[9] To ensure a sufficient sample to estimate β_i^{EMPL}, I require 40 quarters of data for each firm.

The higher the β_i^{EMPL}, the more the firm is affected by expected aggregate demand shocks as indicated by its labor divestment. This regression approach follows the pattern of estimating a market beta, where firm returns are regressed on market returns, and the coefficient from the regression is the measure of systematic risk.

As further evidence that employment beta is related to the timing of divestment in labor, I provide some additional descriptive analysis. If firms cut labor in expectation of a demand shock, it is likely that labor is a substantial cost to the firm. Therefore, if the average firm is affected by aggregate demand shocks, the firms that cut labor in expectation of demand shocks should be those for which labor is a substantial cost.

Considering this relation, I obtain measures of labor leverage, that is, operating leverage that is generated from the use of labor in production (Donangelo et al., 2019; Lev, 1974; Levhari and Weiss, 1974; Rosett, 2001, 2003). Specifically, I select measures from Donangelo et al. (2019) and Rosett (2001) that indicate labor leverage:

- Sales per employee, $SperEmp_i$, the ratio of firm sales revenue divided by the number of employees. Labor leverage is decreasing in $SperEmp_i$.[10]
- Employees, Emp_i, which is the number of employees in the firm divided by total assets as of the beginning of the fiscal year. Labor leverage is increasing in Emp_i.
- Extended labor share, ELS_i, which is the ratio of labor expenses to the sum of labor expenses, operating profits, and the change in finished goods inventories. Because

[9] In the data, some values for restructuring expense are greater than zero, which represent reversals of prior restructuring charges. These reversals comprise 2.3% of the observations of $restr_{i,t}$. For estimation of β_i^{EMPL}, positive values are assigned a value of zero.

[10] This is not used directly in Donangelo et al. (2019) or Rosett (2001), but is a modification of the measure of employees, Emp_i, with a focus on output per employee instead of assets per employee.

labor expenses are not disclosed by most firms, they are estimated as the number of employees times the industry average labor expenses. Labor leverage is increasing in ELS_i.

- Debt-to-equity, DE_i, the book value of firm debt divided by the market value of firm equity. Labor leverage is decreasing in DE_i.
- Labor to capital, LK_i, which is the number of employees divided by the book value of net property, plant, and equipment. Labor leverage is increasing in LK_i.
- Total assets, AT_i, the log of total assets. Labor leverage is decreasing in AT_i.
- Tangibility, $Tang_i$, which is the book value of net property, plant, and equipment divided by total assets. Labor leverage is decreasing in $Tang_i$.

All measures are firm means of annual observations because the restructuring-based measure of systematic risk, β_i^{EMPL}, is time-invariant by firm in the main sample.

There is also the concern that restructuring reflects the current performance of the firm or is an expense that firms take when performance is poor as part of a "big bath" that accompanies macroeconomic downturns (Bens and Johnston, 2009). To address this concern, tests include an operating earnings-based alternative measure of systematic risk. Substituting restructuring with the growth operating earnings in Equation (2) provides the following:

$$oigrow_{i,t} = \alpha_i + \beta_i^{OI} \times EMPL_t + \varepsilon_{i,t}, \tag{3}$$

where $oigrow_{i,t}$ is the quarterly operating earnings growth relative to the same quarter a year ago, scaled by total assets as of the beginning of the 12-month period. The measure identifies firms that have earnings fluctuating in concert with macroeconomic employment.[11]

3.3. Risk measurement

3.3.1. Firm-specific approach

I measure systematic risk using the beta on the market returns from the Fama-French-Carhart four-factor model (Carhart, 1997; Fama and French, 1993). This is widely used as a conventional measure of systematic risk. For each firm, I estimate the annual market beta using a regression of firm returns, less the risk-free rate, on the aggregate market returns, less the risk-free rate, and the returns for the SMB, HML, and UMD portfolios over a historical 60-month window:

$$\begin{aligned}[R_{i,s} - RF_s] = \alpha_{i,t} + \beta_{i,t}^{FF} \times \left[R_s^{mkt} - RF_s\right] + \beta_{i,t}^{SMB} \times R_s^{SMB} + \\ \beta_{i,t}^{HML} \times R_s^{HML} + \beta_{i,t}^{UMD} \times R_s^{UMD} + \varepsilon_{i,s}\end{aligned} \tag{4}$$

where $R_{i,s}$ is the stock return for month s and firm i; RF_s is the risk-free rate for month s; and R_s^{mkt}, R_s^{SMB}, R_s^{HML}, and R_s^{UMD} are the returns of the aggregate market, size, value, and momentum portfolios for month s. The $\beta_{i,t}^{FF}$ is the level of systematic risk exposure for firm i for the year t. Because employment beta is at a firm level, and not a firm-year level, I calculate the systematic risk of the firm as the time-series mean of $\beta_{i,t}^{FF}$, β_i^{FF}.

To test whether the firms that reduce labor when macroeconomic labor growth is low are exposed to higher systematic risk, I follow Rosett (2001) and regress the returns-based measure of risk, β_i^{FF}, on the restructuring-based measure of systematic risk, β_i^{EMPL}:

$$\beta_i^{FF} = \alpha_0 + \gamma_1 \times \beta_i^{EMPL} + \gamma_2 \times \beta_i^{OI} + Controls + \varepsilon_i, \tag{5}$$

[11] In this paper, and in Ball et al. (2022) and Ellahie (2021), operating earnings does not include restructuring expense.

where the controls are the measures of labor leverage, $SperEmp_i$, Emp_i, ELS_i, DE_i, LK_i, AT_i, and $Tang_i$. The controls also include firm characteristics that are linked to risk, specifically, firm size, $Size_i$, and the market-to-book ratio, mb_i. Size is the time-series mean of the log of the firm equity market value. Market-to-book is the time-series mean of the firm equity market value divided by the book value of equity. I also substitute β_i^{EMPL} with the quintile rank of β_i^{EMPL}, $\check{\tilde{\beta}}_i^{EMPL}$, in the regression because β_i^{EMPL} is highly skewed and prone to outliers (a result of the relatively short time-series over which β_i^{EMPL} is estimated for each firm).[12]

To the extent that firms are affected by aggregate demand shocks and reduce labor in expectation of such shocks, they should have a higher restructuring-based measure of systematic risk, β_i^{EMPL}, and a higher returns-based measure of systematic risk, β_i^{FF}. Therefore I expect γ_1 to be positive. Because the earnings-based alternative measure of systematic risk and the measures of labor leverage are included as controls, a significant positive coefficient suggests that restructuring provides information about systematic risk that is distinct from these other measures.

3.3.2. Portfolio approach

As an alternative approach, this study employs portfolios constructed based on employment beta, β_i^{EMPL}. This approach provides a more direct association between the firm characteristics represented by β_i^{EMPL} and return characteristics, because the returns-based measure of systematic risk is estimated for each portfolio specifically. Also, this approach can reveal any non-linearities in the relation between β_i^{EMPL} and systematic risk as indicated by the returns-based measure.

I construct portfolios of employment beta, β_i^{EMPL}, based on cross-sectional quintile

[12]The skewness of β_i^{EMPL} is -4.62.

rank. Portfolio membership is time-invariant as is β_i^{EMPL}. For each portfolio, I estimate:

$$[R_{i,s} - RF_s] = \alpha_p + \beta_p^{FF} \times \left[R_s^{mkt} - RF_s\right] + \beta_p^{SMB} \times R_s^{SMB} + \beta_p^{HML} \times R_s^{HML} + \beta_p^{UMD} \times R_s^{UMD} + \varepsilon_{i,s}, \tag{6}$$

where the variables are defined above in Equation (4), and the subscript p indicates portfolio. Because I expect that firms that are more exposed to systematic risk will record their restructuring expense when aggregate labor growth is lower, the relation between restructuring and macroeconomic employment growth, β_i^{EMPL}, increases with systematic risk. Therefore, I expect that portfolios that have higher levels of β_i^{EMPL} also have higher systematic risk as measured by the returns-based measure, β_p^{FF}.

The inclusion of returns to the size, value, and momentum portfolios, R_s^{SMB}, R_s^{HML}, and R_s^{UMD}, controls for common risk factors that may be associated with the restructuring based measure, β_i^{EMPL}. To ensure that the information provided by restructuring expense is distinct from that of operating earnings, I form 25 portfolios based on the quintiles of the restructuring-based measure, β_i^{EMPL}, and the earnings-based alternative, β_i^{OI}. To the extent that β_i^{EMPL} provides information about systematic risk that is distinct from that of operating earnings, the returns-based measure of systematic risk, β_p^{FF}, should be higher for higher levels of β_i^{EMPL} at all levels of β_i^{OI}.

3.3.3. Out-of-sample portfolio approach

Because employment beta, β_i^{EMPL}, is estimated in the time-series, as is the returns-based measure, β_p^{FF}, the estimation windows overlap and systematic risk is measured as a time-invariant characteristic. As an alternative, this study employs a test that uses returns observed after the determination of employment beta.

To do this, I use use quarterly restructuring, $restr_{i,t}$, and macroeconomic employment growth, $EMPL_t$, to estimate employment beta, β_i^{EMPL}, for each firm for each year from 2010 through 2020. Specifically, β_i^{EMPL} is estimated using a growing window of quarterly observations starting from 2001 and ending in each of the years from 2010 through 2020. I construct annual quintile portfolios based on the levels of the restructuring-based measure, β_i^{EMPL}. Firm returns are associated with each portfolio starting from June of the year subsequent to portfolio construction.

I estimate Equation (6) by portfolio. Because employment beta, β_i^{EMPL}, is intended to identify firms that are exposed to aggregate demand shocks, I expect that portfolios with higher levels of β_i^{EMPL} will provide higher estimations of returns-based systematic risk, β_p^{FF}.

4. Data and Sample

4.1. Sample

I collect restructuring expense from the quarterly Compustat file. The file provides restructuring expense starting in 1996; however, the data are sparsely populated until 2001 (Hann et al., 2021). Therefore, my sample starts in 2001 and ends in 2020. Firm stock returns are from the CRSP monthly stock return file. I collected the Fama-French-Carhart portfolio returns from Kenneth French's website at Dartmouth College and quarterly macroeconomic employment growth from the BLS website.[13] Firms that do not record restructuring throughout the sample period are excluded because the determination of employment beta,

[13]Fama-French-Carhart returns are available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html. I obtained the data from the BLS's Labor Productivity and Cost Measures, Major Sectors table from https://www.bls.gov/productivity/tables/. The data are as of March 3, 2023. I use the percentage change in employment for the same quarter a year ago for all workers in the nonfarm business sector.

β_i^{EMPL}, requires variation in restructuring to calculate the measure.[14] Macroeconomic employment growth is provided by calendar quarter and I match it to the Compustat fiscal quarter that ends on or within three months after the calendar quarter end. As a reference, all variable definitions are provided in Appendix A.

Table 1 provides descriptive statistics for restructuring, $restr_{i,t}$, operating earnings growth, $oigrow_{i,t}$, and macroeconomic employment, $EMPL_t$. Restructuring is reported as a negative number, so lower numbers indicate more restructuring expense. The mean of restructuring is -0.0040 and the median is 0, indicating a left-skewed distribution. This is consistent with other special items, which are recorded occasionally to report expected bad news (Basu, 1997; Hayn and Hughes, 2006). Operating income growth also appears left-skewed with a mean of -0.0022 and a median of 0.0013, again potentially reflecting the conservatism in earnings. Macroeconomic employment growth, $EMPL_t$, is less skewed, with a mean of 0.0003 and a median of 0.0014. The positive mean and median are consistent with the general growth in employment occurring economy-wide over the 20 years in the sample.

4.2. Validation of restructuring as a measure of labor divestment

The first test assessing restructuring as a plausible measure of labor divestment involves calculating the correlation between the growth in the number of employees and restructuring expense. Firms report their employee numbers annually, so I collect this data from the Compustat annual file. The untabulated significant (p-value < 0.0001) Pearson (Spearman) correlation between restructuring as a fraction of beginning total assets and employee growth scaled by beginning total assets is 0.05 (0.22), indicating that firms record more restructuring expense when their own employee growth is low. This is consistent with

[14] About 37% of the Compustat observations of $restr_{i,t}$ are associated with firms that have no variation in restructuring during the sample period. I discuss this further in section 6.4.

restructuring providing information about firm divestment in labor. Because restructuring only indicates labor divestment, the correlation has an upper bound that is likely well below one. To account for this, I also perform a Tobit regression of restructuring expense, $restr_{i,t}$, on the change in the firm's number of employees. The untabulated coefficient on the change in employees is 0.385 (t-statistic = 13.98), again consistent with restructuring expense providing information about labor divestment.

Table 2 provides the bivariate correlations of restructuring, $restr_{i,t}$, operating earnings, $oigrow_{i,t}$, and macroeconomic employment growth, $EMPL_t$. The Pearson (Spearman) correlation between restructuring, $restr_{i,t}$, and macroeconomic employment growth, $EMPL_t$, is 0.04 (0.07). The significantly positive association indicates a systematic component to restructuring expense, as the average firm in the sample is likely to have more restructuring expense when macroeconomic employment growth is low. Operating earnings growth, $oigrow_{i,t}$, has a lower Pearson (Spearman) correlation with macroeconomic employment, $EMPL_t$, of 0.00 (-0.00), which is not significantly above zero, consistent with a weaker relation.

Panel A of Table 3 provides the summary statistics from the Tobit regression of Equation (1) testing the relation between restructuring expense, $restr_{i,t}$, and macroeconomic employment growth, $EMPL_t$. Operating income growth, $oigrow_{i,t}$, controls for the information in operating income. Column 1 shows that $EMPL_t$ has a coefficient of 0.596 with a t-statistic of 3.99, indicating a significant relation between restructuring and aggregate unemployment growth. Column 2 (Column 3) performs the same estimation for firms that have below (above) median workforce union participation. Results are consistent with Column 1, suggesting that, in this sample, union membership does not present an adjustment cost that inhibits firms from recording restructuring related to aggregate shocks. Similarly, Column 4 (Column 5) provides the same regression for below (above) median unemployment firms. Again, the coefficient on $EMPL_t$ is consistently positive and significant, providing results similar to Column 1. This provides evidence that, in this sample, worker scarcity does not provide a sufficient adjustment cost to inhibit observation of the systematic component of restructuring expense.[15]

Panel B of Table 3 provides summary statistics from the OLS time-series regression of Equation (1). This analysis aggregates restructuring information cross-sectionally by quarter to structurally align the data with the macroeconomic employment variable, $EMPL_t$. Consistent with Panel A, Panel B provides statistics supporting the conclusion that restructuring expense has a systematic component and that firms record restructuring in response to expected aggregate shocks. Specifically, Column 1 indicates a positive coefficient on the measure of macroeconomic employment, $EMPL_t$, of 0.237 (t-statistic = 2.62), consistent with restructuring moving in concert with macroeconomic employment changes. Columns 2 and 3 (Columns 4 and 5) provide similar coefficients on $EMPL_t$, indicating that workforce union participation (worker scarcity) does not, in this sample, inhibit observation of the systematic component of restructuring.[16]

5. Results

5.1. The risk relevance of restructuring expense

Table 4 provides descriptive statistics for the 2,730 firms for which the restructuring-based measure of systematic risk can be constructed. The restructuring-based measure, β_i^{EMPL}, has a mean of -1.7380 and a median of 0.0961, indicating substantial left-skewness in the

[15] In untabulated analyses, I test the difference between the coefficients for high and low union membership and high and low unemployment. The coefficients are not significantly different.

[16] As an alternative aggregate measure of restructuring, I calculate the percentage of firms that take annual restructuring expense as of a given quarter. Using this as the dependent variable in the regressions in Panel B provides similar significant results.

distribution, consistent with the presence of outliers in the left tail of the distribution. Further, the 25th percentile is -0.7861, indicating that a fraction of the sample has restructuring expenses that move counter-cyclically with macroeconomic employment growth. This is consistent with industries drawing labor resources from a variety of labor pools, not all of which may correlate with macroeconomic employment statistics (Neal, 1995). Because the raw restructuring-based measure of systematic risk, β_i^{EMPL}, is potentially affected by outliers, I primarily use the quintile-ranked version of the measure, $\check{\check{\beta}}_i^{EMPL}$, which reduces the influence of outliers and provides a uniform distribution. The returns-based measure of systematic risk, β_i^{FF}, has a mean and median around one, consistent with what would be expected for an average market beta across a diversified sample. The operating earnings-based alternative measure, β_i^{OI}, has a mean of 0.0959 and a median of 0.2137, and a 25th percentile of -0.6853, consistent with a portion of the sample having a countercyclical relation between operating earnings and macroeconomic employment. The labor leverage measures and risk controls are available for a majority of the sample.

Table 5 provides the Pearson correlations between the employment betas, β_i^{EMPL} and $\check{\check{\beta}}_i^{EMPL}$, the returns-based measure, β_i^{FF}, and the operating earnings-based alternative measure, β_i^{OI}, with each other and the controls for Equation (5). The ranked employment beta, $\check{\check{\beta}}_i^{EMPL}$, has a significant and positive correlation with the returns-based measure, β_i^{FF}, of 0.11, consistent with $\check{\check{\beta}}_i^{EMPL}$ increasing with the systematic risk of the firm. The operating earnings-based alternative measure has a lower correlation with β_i^{FF} of 0.05. The ranked restructuring-based measure of systematic risk, $\check{\check{\beta}}_i^{EMPL}$, also has a correlation in the expected direction with several of the measures of labor leverage from the literature, including sales per employee, $SperEmp_i$, number of employees, Emp_i, extended labor share, ELS_i, debt-to-equity ratio, DE_i, labor-to-capital ratio, LK_i, and tangibility, $Tang_i$.[17]

[17] The Pearson correlations between $\check{\check{\beta}}_i^{EMPL}$ and Emp_i, ELS_i, and DE_i are not significant, but the untabulated Spearman correlations are significant in the same direction.

This is evidence that firms that have higher dependence on labor as a factor of production are also more likely to record restructuring at times of lower macroeconomic employment growth, consistent with ranked employment beta, $\check{\check{\beta}}_i^{EMPL}$, being more relevant for firms with higher labor costs.

The summary statistics from the estimation of Equation (5) are tabulated in Table 6. The the results in Column 1 indicate that employment beta, β_i^{EMPL}, has a significant association with the returns-based measure of systematic risk, β_i^{FF}, with a coefficient of 0.002 (t-statistic = 2.24). The operating earnings-based alternative measure, β_i^{OI}, controls for operating earnings information that may substitute for restructuring expense. The results indicate that labor flows provide systematic risk information that is not otherwise conveyed by operating earnings. This is evidence consistent with Hypothesis 1, that firms that reduce labor investments when macroeconomic employment growth is lower carry more systematic risk than firms that reduce labor investments at other times; this highlights the risk-relevance of restructuring. Column 2 provides similar results for $\check{\check{\beta}}_i^{EMPL}$ (coefficient = 0.031, t-statistic = 5.56). Columns 3 and 4 also provide consistent information (β_i^{EMPL} coefficient = 0.002, t-statistic = 2.46; $\check{\check{\beta}}_i^{EMPL}$ coefficient = 0.028, t-statistic = 4.76), and because these Columns include the measures of labor leverage, they also provide evidence that the risk information conveyed by employment beta is distinct from that provided by traditional measures of labor dependence.

Table 7 provides the summary statistics from the estimation of Equation (6) by quintile of employment beta, β_i^{EMPL}. The results are consistent with those reported in Table 6, and indicate that systematic risk monotonically increases with the level of β_i^{EMPL}. The lowest portfolio of β_i^{EMPL} has an estimated β_p^{FF} of 0.933, while the highest portfolio has an estimated β_p^{FF} of 1.085. The third, fourth, and fifth highest portfolios have estimations of β_p^{FF} that are significantly higher than the lowest portfolio. The presence of the size, value, and momentum portfolio returns ensures that employment beta is not a function of these characteristics. The results are consistent with Hypothesis 1, that firms that divest labor at times of lower macroeconomic employment growth carry more systematic risk than firms that divest labor at other times.[18]

Table 8 provides the estimation of Equation (6) by quintile of employment beta, β_i^{EMPL}, and the operating earnings-based alternative measure, β_i^{OI}. The results are consistent with those in Table 7, in that the level of β_p^{FF} is significantly higher for the highest portfolio of β_i^{EMPL} relative to the lowest portfolio at all levels of β_i^{OI}, with the estimations for the highest portfolio β_p^{FF} being between 1.032 and 1.136, and those for the lowest portfolio being between 0.847 and 0.998. The results support the conclusion that the risk-relevant information in restructuring is not subsumed by that in operating earnings.

The out-of-sample estimations of Equation (6) by quintile of employment beta, β_i^{EMPL}, are in Table 9. The results are largely consistent with those in Table 7. The levels of the returns-based measure of systematic risk, β_p^{FF}, increase from portfolio 1 to portfolio 5. The increase is monotonic to portfolio 4, which has a slightly higher measure of β_p^{FF} relative to portfolio 5 (a difference of 0.039). Portfolios 2 through 5 have significantly higher levels of β_p^{FF} relative to the lowest portfolio. The results provide assurance that the results in Table 7 are not attributable to the overlapping estimation of β_i^{EMPL} and the returns for estimating β_p^{FF}. This is additional evidence that firms with restructuring charges that increase when macroeconomic employment growth is lower have higher systematic risk relative to those with restructuring expenses that are uncorrelated with macroeconomic employment growth.

[18]Results reported in Table 7 are similar when employing the Fama and MacBeth (1973) regression.

6. Additional Analyses

6.1. Post-restructuring outcomes

To further explore the characteristics of firms with high restructuring-based measures of systematic risk, I investigate differences in post-restructuring outcomes. The tests in section 5 provide evidence that firms that divest labor when macroeconomic employment growth is lower are more systematically risky. The premise is that firms reduce their labor if they expect a negative demand shock. If the shock is economy-wide, it will affect a broad cross-section of firms, reducing macroeconomic employment growth. Therefore, firms that reduce labor assets when macroeconomic employment growth is low are likely exposed to the aggregate demand shock. In this way, the timing of the labor divestment reveals the nature of the firm's risk.

Systematically risky firms are exposed to aggregate demand shocks, and those firms should realize the effect of the demand shocks on output and inputs at the firm level. In other words, if systematically risky firms restructure in expectation of an aggregate demand shock, then they should have lower outputs and inputs after restructuring, as the aggregate demand shock manifests. I test whether this is the case by determining whether firms with higher β_i^{EMPL} have lower output (measured by sales) and inputs (measured by expenses) after restructuring. This would be the case if high β_i^{EMPL} firms experience outsized effects from the aggregate demand shock.[19]

Also, if systematically risky firms restructure in expectation of aggregate demand shocks, then the demand shocks following their restructuring should affect a broad cross-section of the economy. That is, negative aggregate demand shocks should follow the

[19]Embedded in this test is the assumption that, on average, aggregate demand shocks are harder for the firm to recover from than idiosyncratic demand shocks because the source of an aggregate shock is unrelated to business decisions. Therefore firms with higher exposure to aggregate demand shocks will have lower demand and lower labor needs for longer than other firms.

restructuring activities by systematically risky firms, but not necessarily other firms. To test this, I determine whether economy-wide performance, measured by GDP growth and aggregate sales growth, is lower following restructuring activities by higher β_i^{EMPL} firms.

For each quintile of employment beta, β_i^{EMPL}, I calculate the means of two firm characteristics, sales growth and expense growth, and two aggregate characteristics, aggregate sales growth and GDP growth, for the years that firms take (do not take) a restructuring charge. I expect that the difference in the means of each the four measures will increase as β_i^{EMPL} increases. That is, I expect that firms with higher systematic risk demonstrate larger drops in firm and aggregate growth following restructuring, relative to firms with lower β_i^{EMPL}, as firms with higher employment beta are more likely to restructure in expectation of an aggregate demand shock.

I measure the effects of demand shocks on the firm via two-year post-restructuring sales growth, $SalesGrow_{i,t}$. Specifically, $SalesGrow_{i,t}$ is the level of firm sales for the year after year t less the level as of the year before year t, divided by total assets as of the end of the year prior to year t, where year t is the year with or without restructuring. I measure the effect on expenses as the two-year post-restructuring expense growth, $ExpGrow_{i,t}$. Specifically, $ExpGrow_{i,t}$ is the difference between operating expenses in the year after year t and the year prior to year t, scaled by total assets as of the beginning of the two-year period. Operating expenses are calculated as sales revenue less operating income before depreciation and amortization and exclude restructuring expense. If firms with higher employment beta, β_i^{EMPL}, are more affected by demand shocks and reduce their labor expenses in response, then firms with higher levels of β_i^{EMPL} will have lower levels of sales growth, $SalesGrow_{i,t}$, and expense growth, $ExpGrow_{i,t}$, following restructuring relative to other years.

I measure subsequent aggregate demand shocks via aggregate sales growth, $AggSaleGrow_t$, and GDP growth, $GDPgrow_t$. Aggregate sales growth is the cross-sectional average of the four-quarter change in sales, divided by total assets as of the beginning of the period, weighted by the market value of firm equity at the beginning of the period. Aggregate sales growth is measured monthly and includes all firms with quarters ending in that month. $AggSalesGrow_t$ is the time-series mean of this aggregate sales growth over the 24 months starting at the beginning of year t. GDP growth is the percent change in the seasonally adjusted GDP from the same quarter in the prior year.[20] $GDPgrow_t$ is the time-series mean of quarterly GDP growth over the four quarters starting in the first quarter after year t.[21] If firms with higher employment beta, β_i^{EMPL}, are more likely to take restructuring in expectation of aggregate demand shocks, then I expect that $AggSaleGrow_t$ and $GDPgrow_t$ will be lower for years after restructuring for those firms.

Table 10 presents the means of post-restructuring sales growth, $SalesGrow_{i,t}$, post-restructuring expense growth, $ExpGrow_{i,t}$, aggregate sales growth, $AggSaleGrow_t$, and GDP growth, $GDPgrow_t$, by whether firms took restructuring charges and quintile of the restructuring-based measure of systematic risk. The Column indicating the difference between years with or without restructuring shows that, for all quintiles of β_i^{EMPL}, the measures are lower for the years of restructuring versus otherwise.[22] However, the differences increase in magnitude from the lowest quintile to the highest quintile of β_i^{EMPL} for all of the firm and aggregate measures of growth. Specifically, the difference in $SalesGrow_{i,t}$ ($ExpGrow_{i,t}$) changes from -0.166 (-0.162) in the lowest portfolio to -0.260 (-0.250)

[20]GDP data are obtained from the BEA's table 1.1.5.

[21]I use only the quarters after year t because GDP lags aggregate accounting information by one quarter to one year (Hann et al., 2021; Konchitchki and Patatoukas, 2014a,b).

[22]The results are consistent with John et al. (1992), who show that restructuring firms quickly cut cost of goods sold, labor, research and development, and debt expenses. Atiase et al. (2004) find that firm performance improves post-restructuring, but only relative to the restructuring year. Post-restructuring performance is comparable to pre-restructuring years in their study. My findings suggest that performance is generally lower in the post-restructuring year relative to the pre-restructuring year, but they are not directly comparable because I investigate different measures of performance and use a different research design more relevant to my research objectives.

in the highest portfolio, and the difference in differences is statistically significant at a 1% level. The increase is monotonic, with the exception of portfolio 3 (2 and 3) for $SalesGrow_{i,t}$ ($ExpGrow_{i,t}$). For the aggregate measures, the difference increases in magnitude for $GDPgrow_t$ ($AggSalesGrow_t$) from -0.002 (-0.010) in the lowest portfolio to -0.010 (-0.013) in the highest portfolio, and the difference in differences is statistically significant at a 1% level. The increase is monotonic for $GDPgrow_t$ and monotonic through portfolio 4 for $AggSalesGrow_t$. Overall, the results are consistent with expectations, providing evidence that firms with higher levels of β_i^{EMPL} are more exposed to aggregate demand shocks, and that they take restructuring charges in expectation of these shocks.

6.2. Restructuring reversals

Firms can reverse restructuring expenses. Restructuring is an accrual made in expectation of future costs, and as information regarding these costs arrives, prior estimates may need revision. Naturally, if restructuring accruals are made under more uncertain conditions, then they are more likely to be reversed.

This study's prior results suggest that restructuring may arise in expectation of either aggregate or firm-specific demand shocks, and that firms with higher employment betas are more likely to restructure in response to aggregate demand shocks. This distinction is important, as managers are primarily experts in their own firms, and demonstrate less knowledge about the aggregate economy (Hutton et al., 2012). Therefore, managers restructuring in response to expected aggregate shocks are operating with more uncertainty than if they were restructuring in response to firm-specific shocks.

To investigate this hypothesis, I test whether firms that restructure in response to expected aggregate shocks later reverse more of their restructuring expenses. Specifically, I test the association between $\check{\check{\beta}}_i^{EMPL}$ and the incidence and magnitude of restructuring reversals. I measure the incidence of restructuring reversals, μ_i^{Rev}, as the firm-level mean of the number of quarters with $restr_{i,t}$ greater than zero. I measure the magnitude of restructuring reversals, $\mu_i^{Rev\$}$, as the firm-level mean of all values of $restr_{i,t}$ that are greater than zero, multiplied by 1,000. If firms that restructure in response to an aggregate demand shock do so under higher uncertainty, then I expect a positive association between the measures of reversal and $\check{\breve{\beta}}_i^{EMPL}$.[23]

The results of the test are presented in Table 11. Panel A shows that the bivariate Pearson correlation between μ_i^{Rev} ($\mu_i^{Rev\$}$) and $\check{\breve{\beta}}_i^{EMPL}$ is 0.126300 (0.08489) and significant at a 0.01 level. Panel B estimates an OLS regression of μ_i^{Rev} and $\mu_i^{Rev\$}$ on $\check{\breve{\beta}}_i^{EMPL}$ and controls. I include β_i^{OI}, the alternative operating income measure of systematic risk, as a control for other information in the firm's income statement, size, $size_i$, to control for factors related to the scope and magnitude of firm operations, and two measures of restructuring to control for the frequency and magnitude of the firm's overall restructuring behavior. The frequency of restructuring, $restrF_i$, is the percentage of quarters for which the firm's measure of restructuring, $restr_{i,t}$, is less than zero, indicating that the firm recorded restructuring expense. The magnitude of restructuring is the firm-level mean of restructuring expense, excluding reversals, calculated as the mean of $restr_{i,t}$ conditional on it being less than or equal to zero. Column 1 (2) provides the summary statistics for the regression of μ_i^{Rev} ($\mu_i^{Rev\$}$), and in both cases the coefficient on $\check{\breve{\beta}}_i^{EMPL}$ is positive and significant, consistent with the idea that firms that restructure in response to expected aggregate demand shocks do so with more uncertainty and therefore are more likely to reverse restructuring. Column 3 (4) presents the regression of μ_i^{Rev} ($\mu_i^{Rev\$}$) including controls. The coefficient on $\check{\breve{\beta}}_i^{EMPL}$ remains positive and significant, indicating that the results in Columns 1 and 2 are not attributable to the firm's size, restructuring behavior, or the information in operating

[23]Moehrle (2002) finds that firms use restructuring reversals opportunistically to manage earnings. My results suggest a different rationale for reversals by certain firms. In all likelihood both reasons exist.

earnings.

6.3. VIX as a measure of expected demand shock

I use macroeconomic employment growth to measure expected aggregate demand shock because labor is an important input to production that has observable changes at both the firm and aggregate level. The symmetry provided by using measures of labor divestment at both levels provides alignment that is intuitive and logical. However, while demand shocks likely play a substantial role in macroeconomic employment growth, there are other factors that can affect macroeconomic employment. For example, the real business cycle literature proposes that technology shocks can reduce employment by making workers redundant, although the direction and magnitude of this effect is debated (Gali, 1999). Labor supply has generally been considered to have a limited effect on macroeconomic employment, although research continues (Hall, 1979; Prescott and Wallenius, 2012).

While I do not have evidence that these factors affect my interpretation that declines in labor investment are a reflection of expected negative demand shocks, I provide additional evidence to support this assertion. As an alternative measure for expected aggregate demand shocks, I use the CBOE volatility index (VIX). VIX is calculated from the 30-day implied volatilities of options traded on the S&P 500 components and provides an aggregate market expectation for volatility. It is often referred to as the "fear index," and increases in VIX are associated with aggregate demand shocks and lower subsequent growth (Foerster et al., 2014; Leduc and Liu, 2016).

As an initial test to confirm the appropriateness of macroeconomic employment growth as a measure of expected demand shock, I assess whether firms with higher $\check{\check{\beta}}_i^{EMPL}$ are more likely to restructure at times when VIX is high. If so, then firms that restructure under low macroeconomic employment growth also restructure under high aggregate expected volatility, an alternative measure of aggregate demand shock. I measure the level of VIX during restructuring, VIX_t, as the mean annual level of VIX as of the end of quarter of restructuring, t, and estimate its correlation with $\check{\check{\beta}}_i^{EMPL}$.

I also calculate an alternative employment beta using VIX instead of macroeconomic employment growth, $EMPL_t$. Specifically, I estimate a Tobit regression of restructuring, $restr_{i,t}$, on annual VIX as of quarter t by firm. The coefficient on VIX is β_i^{VIX}, the alternative employment beta. Because VIX increases with expected demand shocks, in contrast to macroeconomic employment, $EMPL_t$, which decreases in the same expectation, lower levels of β_i^{VIX} are associated with higher levels of systematic risk. Therefore, I expect that $\check{\check{\beta}}_i^{EMPL}$ and β_i^{VIX} should have a negative correlation. Similarly, I expect that lower levels of β_i^{VIX} should have higher levels of β_p^{FF}, indicating higher systematic risk.

The results of these tests are in Table 12. Panel A provides the correlation between VIX during periods of restructuring, VIX_t, and ranked employment beta, $\check{\check{\beta}}_i^{EMPL}$. The Pearson correlation is 0.13246, consistent with the idea that firms that restructure during low macroeconomic employment growth also restructure during high aggregate expected volatility. Similarly, alternative employment beta, β_i^{VIX}, is strongly negatively correlated with ranked employment beta, $\check{\check{\beta}}_i^{EMPL}$. This is consistent with the notion that declines in $EMPL_t$ appropriately measure expected aggregate demand shocks.

Panel B of Table 12 presents the estimation of Equation (6), but using portfolios based on alternative employment beta, β_i^{VIX}, instead of β_i^{EMPL}. Consistent with β_i^{VIX} measuring systematic risk, the estimations of β_p^{FF} are declining over the five portfolios. The decline is monotonic, with the exception of portfolio 3, which is 0.008 lower than portfolio 4. Portfolios 3, 4, and 5 are all significantly lower than portfolio 1, consistent with β_i^{VIX} measuring systematic risk. Overall, these results reinforce the interpretation of prior results and indicate that firms that divest labor during times of expected demand shock have higher systematic risk.

6.4. Industry restructuring-based systematic risk

While the above analyses provide consistent evidence of the risk-relevance of restructuring, one drawback is that, to determine employment beta, firms need to have recorded restructuring expense over the period of interest. This may limit the usefulness of β_i^{EMPL} for many firms. One potential solution is to instead generate an industry-level version of β_i^{EMPL}. This provides two benefits. First, the aggregation of data within an industry provides a more granular view of the time-series variation in restructuring charges. Second, the firms without restructuring expense can be included in the analysis. There is evidence that labor markets are relatively similar within industries, as are stock returns, making industry groupings a natural choice (Chan et al., 2007; Neal, 1995; Topel, 1982).

To construct the industry employment beta, β_{ind}^{EMPL}, I calculate the quarterly mean of $restr_{i,t}$ within two-digit NAICS industries, $restr_{I,t}$. I estimate Equation (3) using $restr_{I,t}$ instead of $restr_{i,t}$.[24] The coefficient on macroeconomic employment growth, $EMPL_t$, is the industry employment beta, β_{ind}^{EMPL}. This measure is identical for all firms in the same industry.

I estimate the Fama-French-Carhart regression, Equation (6), by quintile portfolio of industry employment beta, β_{ind}^{EMPL}. I exclude all firms for which I am able to calculate a firm-specific employment beta, β_i^{EMPL}, to ensure that the results are not attributable only to those firms. The results are presented in Table 13. Consistent with prior results, β_p^{FF} increases monotonically across the five portfolios, with a value of 0.658 in portfolio 1 and a value of 1.112 in portfolio 5. Portfolios 2 through 5 have a value of β_p^{FF} that is significantly larger than portfolio 1. Overall, these findings are consistent with prior results

[24] I use OLS estimation because $restr_{I,t}$ is uncensored.

and demonstrate the usefulness of β_i^{EMPL} across a broader cross-section of firms.

7. Conclusion

This study investigates the information content of the timing of labor flows out of a firm. Labor is an important, but expensive, input to production. When firms expect a negative demand shock, they are likely to reduce their dependence on labor until demand recovers. These demand shocks may be macroeconomic or idiosyncratic. If they are macroeconomic, the firm will be divesting labor at the same time as many other firms and macroeconomic labor growth will be low. Following this logic, this study tests whether firms that divest labor when macroeconomic labor growth is low have more exposure to macroeconomic demand shocks and therefore higher systematic risk.

To do this, I employ a specific accounting expense related to human capital: restructuring. Restructuring is often excluded from measures of earnings because it is not indicative of the continuing operations of the company, that is, it is not persistent. However, this study's findings provide evidence that restructuring is a value-relevant component of earnings, specifically with regard to risk assessment. The premise is that restructuring is defined by GAAP to include costs of eliminating or relocating employees, and tests in this study provide empirical support for that notion.

The tests in this study validate restructuring as an indication of divestment in labor at the firm level, and they demonstrate that restructuring has a systematic component that is associated with economy-wide movements in employment growth. I develop a restructuring-based measure that quantifies the degree to which a firm reduces its investment in labor when macroeconomic employment growth is lower. This employment beta is positively correlated with the use of labor as a productive input and is uncorrelated with the degree to which operating earnings move with macroeconomic employment growth, supporting the inference that restructuring charges provide information that is not in operating earnings. A series of tests shows that employment beta is positively associated with market beta, the conventional measure of systematic risk.

Additional tests provide further insights. Firms with higher employment betas show lower firm-level and aggregate-level performance after restructuring, consistent with these firms experiencing aggregate demand shocks. Also, an alternative measure of aggregate demand shock, VIX, creates similar results, consistent with labor growth offering insight regarding expected aggregate demand. Finally, industry-level employment betas provide information relevant to firms that do not engage in restructuring during the sample period.

Overall, this study aims to contribute in three ways. The first is to demonstrate how labor flows can provide systematic risk information. To my knowledge, this is the first study to use the timing of labor divestment as a signal of exposure to undiversifiable macroeconomic shocks, and the results shed light on how firms that are exposed to such shocks take actions in response. Second, because this study is focused on restructuring expense, the results highlight the usefulness of transitory accruals for risk assessment. Finally, this study emphasizes the call for more quantitative mandatory disclosure regarding investments and divestments of human capital assets by demonstrating the usefulness of the limited information currently disclosed.

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A. Variable definitions

Variable	Description
$restr_{i,t}$	Firm restructuring expense over the prior four quarters, scaled by total assets as of the beginning of the four-quarter period.
$oigrow_{i,t}$	Firm operating earnings growth from the same quarter a year ago, scaled by total assets as of the beginning of the four-quarter period.
$EMPL_t$	The percentage change in macroeconomic employment from the same quarter in the prior year, divided by 1000.
$AGGrestr_t$	The mean of $restr_{i,t}$ across firms by calendar quarter.
OI_t	The mean of $oigrow_{i,t}$ across firms by calendar quarter.
β_i^{EMPL}	The restructuring-based measure of systematic risk, calculated as the coefficient from firm-level regressions of restructuring ($restr_{i,t}$) on macroeconomic employment ($EMPL_t$).
$\check{\beta}_i^{EMPL}$	The cross-sectional quintile rank of β_i^{EMPL}.
β_i^{FF}	The coefficient on the return on the market less the risk free rate in the Fama-French-Carhart four-factor regression specified in Equation (4) using rolling five-year monthly returns.
β_i^{OI}	The coefficient from firm-level regressions of operating income growth ($oigrow_{i,t}$) on macroeconomic employment ($EMPL_t$).
$size_i$	The firm-level time-series mean of the market value of equity.
mb_i	The firm-level time-series mean of the market to book ratio.
$SperEmp_i$	The firm-level time-series mean of the ratio of firm sales revenue divided by the number of employees.
Emp_i	The firm-level time-series mean of the number of employees divided by beginning of year total assets.
ELS_i	The firm-level time-series mean of extended labor share as in Donangelo et al. (2019). Extended labor share is calculated as the ratio of labor expenses to the sum of labor expenses, operating profits, and the change in finished goods inventories. Labor expenses are estimated for the firm as the number of employees times the industry average labor expenses.
DE_i	The firm-level time-series mean of the book value of firm debt divided by the market value of firm equity.
LK_i	The firm-level time-series mean of the number of employees divided by the book value of net property, plant, and equipment.

AT_i	The firm-level time-series mean of the log of total assets.
$Tang_i$	The firm-level time-series mean of the book value of net property, plant, and equipment divided by total assets.
β_p^{FF}	The coefficient on the return on the market less the risk free rate in the Fama-French-Carhart four-factor regression specified in Equation (6) for the portfolio of β_i^{EMPL}.
β_p^{SMB}	The coefficient on the size portfolio returns in the Fama-French-Carhart four-factor regression specified in Equation (6) for the portfolio of β_i^{EMPL}.
β_p^{HML}	The coefficient on the value portfolio returns in the Fama-French-Carhart four-factor regression specified in Equation (6) for the portfolio of β_i^{EMPL}.
β_p^{UMD}	The coefficient on the momentum portfolio returns in the Fama-French-Carhart four-factor regression specified in Equation (6) for the portfolio of β_i^{EMPL}.
$SalesGrow_{i,t}$	Sales growth for the two-year period starting in year t calculated as the two-year change in annual sales from the end of the year prior to year t divided by total assets as of the beginning of the two-year period.
$ExpGrow_{i,t}$	Total expense growth for the two-year period starting in year t, calculated as the two-year change in annual operating expenses from the end of the year prior to year t divided by total assets as of the beginning of the two-year period. Expenses are calculated as firm sales revenue minus operating income before depreciation expenses.
$GDPgrow_t$	The mean GDP growth over a four-quarter period starting immediately after year t. Aggregate GDP growth is calculated quarterly as the percent change in seasonally-adjusted GDP from the same quarter the year before.
$AggSalesGrow_t$	The mean aggregate sales growth over the two-year period starting in year t. Aggregate sales growth is the weighted cross-sectional average of the four-quarter change in firm sales divided by total assets as of the beginning of the period. Aggregate sales growth is weighted by the market value of firm equity as of the beginning of the four-quarter period and is calculated monthly based on the quarter-end date.
μ_i^{Rev}	The time-series mean by firm of the number of observations for which $restr_{i,t}$ is > 0, indicating a reversal of prior restructuring charges.

$\mu_i^{Rev\$}$	The time-series mean by firm of $restr_{i,t}$ conditional on it being > 0, indicating the amount of reversed prior restructuring charges, multiplied by 1000.
$restrF_i$	The percent of quarters for which $restr_{i,t}$ is less than 0.
$restr\$_i$	The mean of $restr_{i,t}$ at the firm level, conditional on $restr_{i,t} \leq 0$.
VIX_t	The average annual level of VIX as of the quarter t.
β_i^{VIX}	An alternative restructuring-based measure of systematic risk, measured as the coefficient from firm-level regressions of restructuring ($restr_{i,t}$) on aggregate uncertainty, (VIX_t).
β_{ind}^{EMPL}	The restructuring-based measure of systematic risk calculated the same way as β_i^{EMPL}, but using industry-level restructuring. The measure is the same for all firms in the same industry.

Table 1: Descriptive statistics for firm-year restructuring, operating income growth, and macroeconomic employment growth

Variable	N	Mean	SD	25P	Med	75P
$restr_{i,t}$	244,318	−0.0040	0.0105	−0.0026	0	0
$oigrow_{i,t}$	244,318	−0.0022	0.0314	−0.0059	0.0013	0.0097
$EMPL_t$	244,318	0.0003	0.0026	−0.0004	0.0014	0.0019

Table 1: Descriptive statistics for the firm-quarter measures of restructuring and operating earnings and macroeconomic employment growth. Macroeconomic employment does not vary across firms for fiscal quarters ending in the same calendar quarter. The table includes observations for which all variables are present for the years 2001–2020. The variable definitions appear in appendix A. All continuous variables are winsorized at 1% and 99%.

Table 2: Correlations for firm-year restructuring, operating income growth, and macroeconomic employment growth

		$restr_{j,t}$	$oigrow_{j,t}$	$EMPL_t$
1	$restr_{i,t}$		-0.07^{*}	0.07^{*}
2	$oigrow_{i,t}$	−0.00		-0.00^{*}
3	$EMPL_t$	0.04^{*}	0.00	

Table 2: Bivariate correlations for the 244,318 firm-quarter observations of restructuring, operating income growth, and macroeconomic employment growth. Macroeconomic employment growth does not vary across firms for fiscal quarters ending in the same calendar quarter. The table includes observations for which all variables are present for the years 2001–2020. Significance at the p<0.1 level is indicted with *. The variable definitions appear in appendix A. All continuous variables are winsorized at 1% and 99%. Pearson (Spearman) correlations are above (below) the diagonal.

Table 3: Restructuring charges and aggregate labor productivity growth

Panel A: Tobit estimations using firm-quarter observations

	(1)	(2)	(3)	(4)	(5)
	All obs	Low Union	High Union	Low Unemp	High Unemp
VARIABLES	$restr_{i,t}$	$restr_{i,t}$	$restr_{i,t}$	$restr_{i,t}$	$restr_{i,t}$
$EMPL_t$	0.596***	0.587***	0.588***	0.540**	0.577***
	(3.99)	(3.05)	(4.13)	(2.66)	(4.96)
$oigrow_{i,t}$	−0.044***	−0.050***	−0.041***	−0.034	−0.031***
	(−3.75)	(−3.42)	(−3.96)	(−1.43)	(−3.76)
Constant	0.009***	0.013***	0.005***	0.011***	0.006***
	(7.55)	(7.29)	(6.18)	(7.23)	(5.81)
Obs	244,318	112,997	130,828	85,069	139,817
Prob>F	0.0006	0.0018	0.0003	0.0489	0.0000
Clusters	firm, year	firm, year	firm, year	firm, year	firm, year

Panel B: OLS estimations using a time-series of observations					
	(1)	(2)	(3)	(4)	(5)
	All obs	Low Union	High Union	Low Unemp	High Unemp
VARIABLES	$AGGrestr_t$	$AGGrestr_t$	$AGGrestr_t$	$AGGrestr_t$	$AGGrestr_t$
$EMPL_t$	0.237**	0.230***	0.241**	0.198**	0.250***
	(2.62)	(2.71)	(2.59)	(2.30)	(3.03)
OI_t	−0.115*	−0.166**	−0.077	−0.162**	−0.029
	(−1.81)	(−2.42)	(−1.57)	(−2.50)	(−0.72)
Constant	−0.004***	−0.003***	−0.005***	−0.002***	−0.005***
	(−18.65)	(−16.87)	(−20.36)	(−12.08)	(−22.24)
Obs	81	81	81	81	81
Prob>F	0.0208	0.0232	0.0185	0.0336	0.0113
R-squared	0.33	0.37	0.31	0.35	0.31

Table 3: Summary statistics from the Tobit (Panel A) and OLS (Panel B) regressions of firm restructuring on macroeconomic employment growth and operating income growth for the years 2001–2020. The t-statistics are below the coefficients in parentheses. Panel B reports t-statistics using Newey-West standard errors with lags for four observations. The variable definitions appear in Appendix A. All continuous variables are winsorized at 1% and 99%. Column 1 in Panel A (B) uses all available firm-quarter (time-series) observations. Columns 2 and 3 present the same estimation for industries with low and high union membership. Columns 4 and 5 present the same estimation for firms in industries with low and high unemployment across the sample period. The statistical significance of coefficients is indicated as: *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Descriptive statistics for firm-level variables

	N	Mean	SD	25P	Median	75P
β_i^{EMPL}	2730	−1.7380	9.2414	−0.7861	0.0961	0.9362
$\check{\beta}_i^{EMPL}$	2730	2.0000	1.4145	1.0000	2.0000	3.0000
β_i^{FF}	2688	1.0463	0.4156	0.7584	1.0193	1.2976
β_i^{OI}	2730	0.0959	2.3330	−0.6853	0.2137	1.1593
$size_i$	2691	13.2847	1.7292	12.0366	13.2610	14.4503
mb_i	2691	2.7108	3.4693	1.3786	2.0884	3.3991
$SperEmp_i$	2678	489.5484	801.8777	174.3428	258.0524	450.3649
Emp_i	2688	0.0062	0.0083	0.0015	0.0037	0.0072
ELS_i	2538	0.4939	0.7073	0.3535	0.5648	0.7372
DE_i	2691	1.3330	4.5823	0.1071	0.3035	0.8251
LK_i	2622	−3.8936	1.3983	−4.4606	−3.6851	−3.0254
AT_i	2691	6.6848	1.9645	5.2775	6.6459	7.9951
$Tang_i$	2661	0.2363	0.2162	0.0683	0.1661	0.3370

Table 4: Descriptive statistics for employment beta and firm characteristics. All measures are time-invariant. The table includes observations for the years 2001–2020. The variable definitions appear in Appendix A. All continuous variables are winsorized at 1% and 99%.

Table 5: Pearson correlations for firm-level variables

		β_i^{EMPL}	$\check{\beta}_i^{EMPL}$	β_i^{FF}	β_i^{OI}
1	$\check{\beta}_i^{EMPL}$	0.51			
2	β_i^{FF}	0.04*	0.11*		
3	β_i^{OI}	−0.00	−0.02	0.05*	
4	$size_i$	0.16*	0.07*	0.11*	0.10*
5	mb_i	−0.03	0.01	0.02	−0.07*
6	$SperEmp_i$	−0.00	−0.06*	−0.00	0.08*
7	Emp_i	−0.04*	0.02	−0.07*	−0.01
8	ELS_i	0.04*	0.02	−0.07*	0.06*
9	DE_i	0.02	−0.02	0.05*	0.04*
10	LK_i	−0.01	0.08*	−0.06*	−0.19*
11	AT_i	0.18*	0.03	0.06*	0.16*
12	$Tang_i$	−0.01	−0.05*	0.02	0.18*

Table 5: Bivariate correlations for employment beta and firm characteristics. Significance at the $p<0.1$ level is indicted with *. All measures are time-invariant. The table includes observations for the years 2001–2020. The variable definitions appear in Appendix A. All continuous variables are winsorized at 1% and 99%.

Table 6: Regression of the returns-based measure of systematic risk on employment beta and controls

VARIABLES	(1) β_i^{FF}	(2) β_i^{FF}	(3) β_i^{FF}	(4) β_i^{FF}
β_i^{EMPL}	0.002**		0.002**	
	(2.24)		(2.46)	
$\check{\check{\beta}}_i^{EMPL}$		0.031***		0.028***
		(5.56)		(4.76)
β_i^{OI}	0.008**	0.009**	0.010***	0.010***
	(2.44)	(2.53)	(2.89)	(2.84)
$size_i$			0.103***	0.098***
			(8.81)	(8.41)
mb_i			−0.003	−0.003
			(−1.37)	(−1.31)
$SperEmp_i$			0.000	0.000
			(0.45)	(0.45)
Emp_i			−5.009***	−4.905***
			(−3.29)	(−3.24)
ELS_i			−0.030**	−0.029**
			(−2.51)	(−2.46)
DE_i			0.014***	0.014***
			(6.49)	(6.32)
LK_i			0.017	0.014
			(1.20)	(0.99)
AT_i			−0.080***	−0.075***
			(−7.36)	(−6.98)
$Tang_i$			0.098	0.092
			(1.28)	(1.21)
Constant	1.049***	0.983***	0.300***	0.260**
	(128.73)	(71.12)	(2.88)	(2.51)
Observations	2,688	2,688	2,495	2,495
R-squared	0.004	0.014	0.050	0.057

Table 6: Summary statistics from the regressions of Equation (5). The t-statistics are below the coefficients in parentheses. The variable definitions appear in Appendix A. All continuous variables are winsorized at 1% and 99%. The statistical significance of coefficients is indicated as: *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Estimation of returns-based systematic risk by portfolio of employment beta

Portfolio of β_i^{EMPL}	Lowest (1)	(2)	(3)	(4)	Highest (5)
Mean β_i^{EMPL}	−12.308	−0.527	0.109	0.723	3.462
β_p^{FF}	0.933***	0.943***	0.983***,‡	1.081***,‡	1.085***,‡
	(79.10)	(101.02)	(120.63)	(117.00)	(94.77)
β_p^{SMB}	0.782***	0.647***	0.547***	0.679***	0.841***
	(43.13)	(45.26)	(43.78)	(48.13)	(48.42)
β_p^{HML}	−0.100***	0.131***	0.261***	0.104***	−0.095***
	(−5.84)	(9.69)	(22.03)	(7.78)	(−5.80)
β_p^{UMD}	−0.139***	−0.061***	−0.075***	−0.114***	−0.194***
	(−12.64)	(−6.98)	(−9.79)	(−13.14)	(−18.41)
Constant	0.000	0.002***	0.002***	0.002***	−0.000
	(0.19)	(5.93)	(6.75)	(5.60)	(−0.03)
Observations	100,394	103,732	111,320	108,979	101,577
R-squared	0.133	0.179	0.218	0.216	0.180

Table 7: Summary statistics from the estimation of Equation (6). The t-statistics are below the coefficients in parentheses. The variable definitions appear in Appendix A. All continuous variables are winsorized at 1% and 99%. The statistical significance of coefficients is indicated as: *** p<0.01, ** p<0.05, * p<0.1. Significant positive differences in β^{FF} from the lowest portfolio of β_i^{EMPL} at a p<0.10 level is indicated with ‡.

Table 8: Estimation of the returns-based measure of systematic risk by portfolio of employment beta conditional on the earnings-based alternative measure

β_i^{EMPL} portfolio	(1)	(2)	(3)	(4)	(5)
β_i^{OI} portfolio					
(1)	0.938***	0.884***	1.088***,‡	1.108***,‡	1.032***,‡
(2)	0.912***	0.891***	0.879***	0.933***	1.079***,‡
(3)	0.847***	0.868***	0.869***	0.969***,‡	1.046***,‡
(4)	0.932***	1.076***,‡	1.033***,‡	1.141***,‡	1.119***,‡
(5)	0.998***	1.087***,‡	1.232***,‡	1.228***,‡	1.136***,‡

Table 8: This table provides the estimates of β_p^{FF} from the estimation of Equation (6) by portfolios determined by the level of employment beta, β_i^{EMPL}, and the level of the operating income alternative measure, β_i^{OI}. The variable definitions appear in Appendix A. All continuous variables are winsorized at 1% and 99%. The statistical significance of coefficients is indicated as: *** p<0.01, ** p<0.05, * p<0.1. Significant positive differences in β_p^{FF} from the lowest portfolio of β_i^{EMPL} at a p<0.10 level are indicated with ‡.

Table 9: Estimation of returns-based systematic risk using out-of-sample returns by portfolio of employment beta

Portfolio of β_i^{EMPL}	Lowest (1)	(2)	(3)	(4)	Highest (5)
	$R_{i,t} - RF_t$	$R_{i,t} - RF_t$	$R_{i,t} - RF_t$	$R_{i,t} - RF_t$	$R_{i,t} - RF_t$
β_p^{FF}	0.901***	0.931***,‡	0.934***,‡	1.007***,‡	0.968***,‡
	(59.04)	(74.73)	(85.99)	(84.46)	(67.55)
β_p^{SMB}	0.754***	0.536***	0.458***	0.445***	0.672***
	(30.78)	(26.76)	(26.27)	(23.26)	(29.19)
β_p^{HML}	0.033*	0.193***	0.283***	0.194***	0.010
	(1.67)	(12.12)	(20.42)	(12.71)	(0.53)
β_p^{UMD}	−0.075***	−0.123***	−0.103***	−0.086***	−0.096***
	(−3.83)	(−7.69)	(−7.40)	(−5.57)	(−5.22)
Constant	−0.002***	−0.000	0.000	0.000	−0.001**
	(−3.14)	(−0.82)	(0.95)	(0.44)	(−2.16)
Obs	47,627	48,406	49,221	48,793	47,136
R-squared	0.139	0.190	0.228	0.208	0.164

Table 9: Summary statistics from the estimation of Equation (6) using returns measured after the determination of β_i^{EMPL}. The t-statistics are below the coefficients in parentheses. The variable definitions appear in Appendix A. All continuous variables are winsorized at 1% and 99%. The statistical significance of coefficients is indicated as: *** p<0.01, ** p<0.05, * p<0.1. Significant positive differences in β_p^{FF} from the lowest portfolio of β_i^{EMPL} at a p<0.10 level are indicated with ‡.

Table 10: Post-restructuring firm sales and expense growth, and aggregate sales and GDP growth, by portfolio of employment beta

$restr_{i,t} < 0$		No	Yes	Difference
	β_i^{EMPL} portfolio			
$SalesGrow_{i,t}$	(1)	0.249	0.083	−0.166
	(2)	0.271	0.099	−0.173
	(3)	0.239	0.079	−0.160
	(4)	0.297	0.084	−0.213‡‡‡
	(5)	0.286	0.026	−0.260‡‡‡
$ExpGrow_{i,t}$	(1)	0.229	0.066	−0.162
	(2)	0.241	0.081	−0.160
	(3)	0.206	0.066	−0.140
	(4)	0.259	0.066	−0.193‡‡
	(5)	0.361	0.011	−0.250‡‡‡
$GDPgrow_t$	(1)	0.044	0.042	−0.002
	(2)	0.046	0.041	−0.004‡‡‡
	(3)	0.046	0.041	−0.005‡‡‡
	(4)	0.047	0.040	−0.008‡‡‡
	(5)	0.047	0.037	−0.010‡‡‡
$AggSalesGrow_t$	(1)	0.028	0.018	−0.010
	(2)	0.030	0.018	−0.012‡‡‡
	(3)	0.029	0.017	−0.012‡‡‡
	(4)	0.031	0.017	−0.014‡‡‡
	(5)	0.031	0.017	−0.013‡‡‡

Table 10: Means of $SalesGrow_{i,t}$, $ExpGrow_{i,t}$, $GDPgrow_t$, and $AggSalesGrow_t$ by β_i^{EMPL} portfolio and whether the firm incurred restructuring in the fiscal year. Differences in means are presented in the rightmost column. The ‡, ‡‡, and ‡‡‡, indicate that the difference is lower than the difference in the lowest β_i^{EMPL} portfolio at a p<0.1, p<0.05, and p<0.01 level of statistical significance with errors clustered by fiscal year. The variable definitions appear in Appendix A. All continuous variables are winsorized at 1% and 99%.

Table 11: Restructuring reversal and employment beta

Panel A: Means by portfolio of β_i^{EMPL}						
Portfolio of β_i^{EMPL}	Lowest (1)	(2)	(3)	(4)	Highest (5)	Correlation with: $\check{\check{\beta}}_i^{EMPL}$
μ_i^{Rev}	0.01260	0.02028	0.01665	0.02424	0.02772	0.12630***
$\mu_i^{Rev\$}$	0.04158	0.04104	0.02681	0.05597	0.09706	0.08489***

Panel B: Regression of μ_i^{Rev} and $\mu_i^{Rev\$}$				
	(1)	(2)	(3)	(4)
VARIABLES	μ_i^{Rev}	$\mu_i^{Rev\$}$	μ_i^{Rev}	$\mu_i^{Rev\$}$
$\check{\check{\beta}}_i^{EMPL}$	0.003***	0.013***	0.002***	0.009***
	(6.65)	(4.45)	(4.23)	(3.03)
β_i^{OI}			−0.000	−0.000
			(−0.45)	(−0.23)
$restrF_i$			0.025***	−0.017
			(7.11)	(−0.90)
$restr\$_i$			−0.703***	−7.478***
			(−3.90)	(−7.50)
$size_i$			0.000	−0.006**
			(0.97)	(−2.37)
Constant	0.013***	0.027***	−0.002	0.090***
	(10.69)	(3.94)	(−0.31)	(2.79)
Observations	2,730	2,730	2,691	2,691
R-squared	0.016	0.007	0.075	0.039

Table 11: Panel A provides the means of the measures of restructuring expense reversal, μ_i^{Rev} and $\mu_i^{Rev\$}$, by portfolio of employment beta, β_i^{EMPL}, and the correlations between the reversal measures and ranked employment beta. Panel B provides the summary statistics from the regression of restructuring expense reversal on ranked employment beta. The t-statistics are below the coefficients in parentheses. The variable definitions appear in Appendix A. All continuous variables are winsorized at 1% and 99%. The statistical significance of coefficients is indicated as: *** p<0.01, ** p<0.05, * p<0.1.

Table 12: Aggregate uncertainty and the timing of restructuring charges

Panel A: Means of aggregate uncertainty by portfolio of β_i^{EMPL}

Portfolio of β_i^{EMPL}	Lowest (1)	(2)	(3)	(4)	Highest (4)	Correlation with: $\check{\check{\beta}}_i^{EMPL}$
VIX_t	3.99663	7.65347	7.34578	9.43442	8.14575	0.13246***
β_i^{VIX}	0.00206	0.00027	−0.00000	−0.00022	−0.00128	−0.59532***

Panel B: Estimation of returns-based systematic risk by portfolio of the alternative restructuring measure of systematic risk

Portfolio of β_i^{VIX}	Lowest (1)	(2)	(3)	(4)	Highest (5)
	$R_{i,t} - RF_t$	$R_{i,t} - RF_t$	$R_{i,t} - RF_t$	$R_{i,t} - RF_t$	$R_{i,t} - RF_t$
β_p^{FF}	1.092***	1.082***	0.950***,‡	0.958***,‡	0.944***,‡
	(95.89)	(118.18)	(113.23)	(104.86)	(80.70)
β_p^{SMB}	0.817***	0.620***	0.588***	0.648***	0.816***
	(47.26)	(44.34)	(45.89)	(46.40)	(45.12)
β_p^{HML}	−0.148***	0.126***	0.300***	0.102***	−0.072***
	(−9.06)	(9.48)	(24.68)	(7.70)	(−4.23)
β_p^{UMD}	−0.192***	−0.107***	−0.073***	−0.074***	−0.137***
	(−18.27)	(−12.50)	(−9.31)	(−8.62)	(−12.43)
Constant	0.001*	0.002***	0.002***	0.002***	−0.000
	(1.91)	(4.95)	(5.64)	(6.55)	(−0.70)
Observations	103,558	106,543	107,548	106,631	101,722
R-squared	0.177	0.217	0.212	0.185	0.138

Table 12: Panel A provides the means of the measure of aggregate uncertainty, VIX_t, during the quarters of restructuring by portfolio of β_i^{EMPL}, and the means of employment beta, which uses aggregate uncertainty levels instead of macroeconomic employment changes as the aggregate signal, β_i^{VIX}, by portfolio of β_i^{EMPL}. Panel B provides summary statistics from the estimation of Equation (6), but uses the alternative employment beta, β_i^{VIX}. The t-statistics are below the coefficients in parentheses. The variable definitions appear in Appendix A. All continuous variables are winsorized at 1% and 99%. The statistical significance of coefficients is indicated as: *** p<0.01, ** p<0.05, * p<0.1. Significant negative differences in β^{FF} from the lowest portfolio of β_i^{VIX} at a p<0.10 level are indicated with ‡.

Table 13: Estimation of the returns-based measure of systematic risk by portfolio of industry employment beta

Portfolio of β_{ind}^{EMPL}	Lowest (1)	(2)	(3)	(4)	Highest (5)
	$R_{i,t} - RF_t$	$R_{i,t} - RF_t$	$R_{i,t} - RF_t$	$R_{i,t} - RF_t$	$R_{i,t} - RF_t$
β_p^{FF}	0.658***	0.966***,‡	1.022***,‡	1.054***,‡	1.112***,‡
	(105.50)	(81.93)	(75.36)	(85.80)	(81.11)
β_p^{SMB}	0.528***	0.680***	0.922***	0.864***	0.729***
	(58.29)	(37.82)	(46.65)	(50.17)	(38.34)
β_p^{HML}	0.471***	0.276***	−0.126***	−0.138***	−0.469***
	(54.11)	(16.30)	(−6.71)	(−8.27)	(−25.46)
β_p^{UMD}	−0.045***	−0.126***	−0.115***	−0.179***	−0.294***
	(−7.99)	(−11.27)	(−9.10)	(−16.54)	(−24.27)
Constant	0.002***	−0.003***	−0.004***	−0.003***	−0.002***
	(8.27)	(−6.97)	(−8.89)	(−5.82)	(−4.58)
Observations	195,766	93,696	101,586	115,011	92,909
R-squared	0.140	0.150	0.129	0.149	0.171

Table 13: Summary statistics from the estimation of Equation (6) using industry employment beta, β_{ind}^{EMPL}. Observations with restructuring during the sample period are excluded from the sample. The t-statistics are below the coefficients in parentheses. The variable definitions appear in Appendix A. All continuous variables are winsorized at 1% and 99%. The statistical significance of coefficients is indicated as: *** p<0.01, ** p<0.05, * p<0.1. Significant positive differences in β^{FF} from the lowest portfolio of β_i^{EMPL} at a p<0.10 level are indicated with ‡.