UCD GEARY INSTITUTE FOR PUBLIC POLICY
DISCUSSION PAPER SERIES

Worker well-being and quit intentions: is measuring job satisfaction enough?

Diane Pelly
UCD School of Economics & UCD Geary Institute for Public Policy, University College Dublin

Geary WP2022/04
May 17, 2022

Worker well-being and quit intentions: is measuring job satisfaction enough?

Diane Pelly[1]

[1] School of Economics, University College Dublin; diane.pelly@ucdconnect.ie

Worker well-being and quit intentions: is measuring job satisfaction enough?

ABSTRACT

While the links between worker well-being and quit intentions have been well researched, most studies to date rely on a very narrow conceptualisation of well-being, namely job satisfaction, thus ignoring the documented multidimensionality of subjective well-being. This paper explores whether this approach is justified. Using novel survey data, I compare the extent to which hedonic (job satisfaction and affect) and eudemonic (disengagement and basic psychological needs) well-being indicators individually and jointly explain variation in the quit intentions of 994 full-time UK workers. Well-being indicators perform well, explaining four to nine times more variation in quit intentions than wages and hours combined, with the disengagement measure performing best. I find systematic differences in the hedonic and eudemonic well-being profiles of workers who report positive quit intentions and those who do not. A composite model containing all seven well-being indicators offers the best fit, explaining 29.4% of variation in quit intentions versus 24.0% for job satisfaction on its own. My findings suggest that the standard single-item job satisfaction indicator is probably good enough for organisations who are looking for a quick and easy way to identify workers who may be most at risk of forming positive quit intentions. For organisations seeking to develop effective preventative quit strategies however, supplementing single-item job satisfaction with multifaceted well-being indicators is likely to yield valuable additional insights.

Keywords: voluntary turnover; quit intentions; employee retention; worker well-being; experienced utility; decision utility; job satisfaction; engagement; affect

JEL-classification: I31 J280 J220 J260 M5

1. INTRODUCTION

The long-term success of organisations in industries with a high reliance on human capital relies on their ability to attract and retain a stock of high-quality labour. Voluntary turnover, namely a worker's decision to willingly quit an organisation or role through resignation or retirement, disrupts this capacity. While voluntary turnover is not necessarily negative (Robbins & Judge, 2013), 'dysfunctional turnover', or the failure to retain high-performing, highly-valued workers (Zivkovic, Fosic & Starcevic., 2020), is incompatible with long-term profit or performance maximisation (Heavey, Holwerda & Hausknecht., 2013). The cost of replacing a UK worker on the average salary of £27,000 is an estimated £12,000 (45% of total salary), with senior employees costing considerably more (Wright-Whyte, 2019).[2] Voluntary turnover is nonetheless a frequent occurrence. Between January 2017 and December 2018, 26.8 million workers in the UK quit their jobs (ONS, 2019). The average one-year-retention rate across the UK workforce is just 81% (ONS, 2019).[3] In the US, 27% of workers voluntarily quit in 2018, at a cost of $617 billion to the economy ($15,000 per employees) (Work Institute, 2019). 77% of these quits were deemed to be 'preventable' or within the employer's control. Given the prevalence of dysfunctional turnover and its high associated costs, it is imperative to identify the factors that influence a worker's decision to quit. While wages and personal characteristics have some predictive power in explaining quits, effect sizes are small. Attention has thus turned to the role of 'non-pecuniary' factors, non-monetary aspects of the job that influence how workers evaluate and experience working life (Akerlof et al., 1988). Collectively non-pecuniary factors constitute work-related welfare or 'work utility', which is typically captured in the utility function through the latent construct of subjective well-being. With just a few exceptions (e.g., Green, 2010; Nikolova & Cnossen, 2020), economists however typically rely on just one work-related well-being indicator, job satisfaction, to indicate job match strength (Clark, 2001) and to act as a proxy for worker well-being as a whole.

Organisations rely heavily on employee surveys to gauge how their workers feel about their jobs and workplaces (Wiles, 2018). The fact that job satisfaction measures are widely used and reliable predictors of quit intentions, raises questions as to the validity of investigating the case for organisations including other well-being indicators employee

[2] 'Visible' direct costs (e.g., advertising; recruiting etc.) account for just 1/6 of the total cost, with 'invisible' indirect costs (e.g., lost output; erosion of human and social capital etc.) accounting for the bulk of voluntary turnover costs (Zivkovic et al, 2020).
[3] E.g., in 2020, just under 99,000 workers resigned from the NHS, at an estimated cost of £1.2 billion.

surveys. However, worker well-being is incontrovertibly a complex, multidimensional construct that extends far beyond job satisfaction (Bryson, Forth & Stokes, 2014). Employee surveys which rely solely on a job satisfaction measure to proxy for overall worker well-being effectively ignore this multidimensionality and constitute a missed opportunity for organisations to obtain valuable insights into the role that other aspects of the work experience, e.g., meaningfulness, play in shaping voluntary turnover. Furthermore, it is plausible that the current reliance on single-item job satisfaction may, at least partly, reflect the speed and ease with which it can be deployed and / or a lack of awareness on the part of organisations as to the existence of other less well-established well-being indicators which may do as good, or even better, a job of predicting quit intentions amongst their workforces. To date however, very few studies have sought to compare the predictive power of job satisfaction measures to those of other well-being indicators with respect to quit intentions. This study addresses this gap.

I investigate whether a broader conceptualisation of worker well-being should be invoked by organisations who are concerned about dysfunctional turnover. I examine the extent to which well-being indicators that capture not just overall job satisfaction but also the extent to which workers feel happy, engaged, competent, autonomous, socially connected and supported at work, are associated with positive quit intentions and thus, by extension, actual quits.[4] The primary contribution of this study is to help organisations to tackle dysfunctional turnover by assessing the extent to which using additional / alternative well-being measures could provide a valuable 'head start' in identifying a potential turnover problem before it results in actual quits. I use a novel survey dataset specifically designed to measure worker well-being to compare the 'head-to-head' performance of four worker well-being indicators, two hedonic well-being indicators (job satisfaction and global affect) and two eudemonic well-being indicators (disengagement and the extent to which basic psychological needs are satisfied at work). In doing so, I expand on earlier work within labour economics which examines the predictive power of cognitive (job satisfaction) and / or affective (emotions) well-being measures in relation to quits[5], by explicitly introducing eudaimonia into the utility function.

[4] Stated intentions are good predictors of end behaviour (e.g., Steel & Orvalle 1984; Tett & Meyer 1993). Numerous studies testify to the predictive power of quit intentions in relation to actual voluntary turnover (e.g. Cho & Lewis, 2012; Kristensen & Westergård-Nielsen, 2004; Steele & Ovalle, 1984), although the strength of this relationship is contested.

[5] E.g., Blanchflower & Oswald, 1999; Clark, 2001, 2015; Levy-Garboua, Montmarquette & Simonnet, 2007; Green, 2010.

My study also makes several unique contributions to the subjective well-being measurement literature by examining the relationship between well-being indicators and quit intentions at different levels of analysis. Kahneman and Riis (2005 p. 285) characterise humans as having 'two selves' – 'the remembering, evaluating self' (associated with decision utility) and 'the experiencing self' (associated with instant, experienced utility). They argue that, while the two conceptualisations of utility are clearly correlated, in that an individual's current affective state will affect their subjective evaluations and vice versa, they are nonetheless conceptually and empirically distinct.[6] Comprehensive well-being studies should therefore measure decision and experiential utility separately. While the validity of global measures has been called into question due to their susceptibility to recall bias and other heuristics, experiential measures can be logistically challenging and costly to implement and increase respondent burden, which may in turn affect the quality of responses (Lucas, 2021). Kahneman and Riis (2005) concede that the importance of the distinction between the remembering and experiencing self, largely depends on whether the two conceptualisations have different consequences for decision making in a particular context. As far as the formation of quit intentions is concerned, this remains an open question. I contribute to the ongoing debate as to the relative 'superiority' of global or experiential measures by, for the first time, including a wide range of global and experiential satisfaction, affective and eudemonic measures in the same survey and undertake a 'head-to-head' comparison of their individual and joint predictive power in relation to quit intentions. I also measure the extent to which using a multifaceted measure of job satisfaction instead of the standard single-item measure improves predictive power. Finally, given that organisations may be particularly keen to retain certain sub-groups of employees, for example new recruits, I investigate whether particular well-being measures may be better suited to identifying latent quit intentions amongst workers who are female, highly educated, high performers, more senior or recent recruits.

My results reveal systematic differences in the hedonic and eudemonic well-being profiles of workers who intend quitting in the next six months and those who do not. Between-worker well-being differences explain between four to nine times as much variation in quit intentions as differences in wages and hours combined. While all well-

[6] Kahneman & Riis (2005) report a moderate positive correlation between global and experiential affective measures of r=0.38.

being indicators analysed are significantly associated with quit intention formation, predictive power varies widely. In terms of individual indicator effect sizes, I find that job satisfaction outperforms all other measures when controls are included, and that using a multifaceted job satisfaction measure substantially increases this explanatory gap. Well-being measures act as complements, with the introduction of any additional indicator over and above single-item job satisfaction increasing overall explanatory power. This suggests that different well-being indicators are tapping into distinct aspects of the relationship between work utility and voluntary turnover. A composite model containing all seven indicators performs best, explaining 29.4% of variation in quit intentions, as compared to 23.8% for job satisfaction on its own and just 2.7% for wages and hours combined. I find little evidence that using global v experiential measures makes any real difference in terms of predictive power. Finally, with the exception of long-tenured employees, I also find very little evidence that particular well-being indicators may be especially useful for identifying quit intentions amongst the sub-groups of employees examined in this study.

By combining a wide range of well-being indicators in one novel survey, this study addresses several important open questions around the best way to conceptualise and measure worker well-being in quit intention functions. If the decision to quit is, as Green (2010) suggests, primarily an evaluative one, then the current reliance on job satisfaction may indeed be justifiable. If, however, quit intention formation is heavily influenced by transient emotional or psychological factors then it may behove organisations to expand their conceptualisation of worker well-being as it pertains to quits. I address four research questions in this study, all of which have important implications for organisations seeking to identify and prevent dysfunctional voluntary turnover. First, how do other measures of well-being compare to job satisfaction in terms of predicting workers' quit intentions? Second, could the use of an expanded composite wellbeing model benefit organisations who are concerned about dysfunctional turnover? Third, do global well-being measures perform better than experiential measures in terms of predicting quit intentions? Finally, are particular well-being indicators better suited to predicting quits amongst different sub-groups of workers?

The remainder of the paper is organised as follows. Section 2 provides an overview of the conceptual framework and literatures which inform this paper. Section 3 describes the data. Section 4 sets out the empirical framework and robustness checks. Section 5 describes the results. Section 6 discusses the results and concludes.

2. CONCEPTUAL FRAMEWORK

2.1 Conceptualisation and measurement of worker well-being

Worker well-being comprises subjective well-being as it pertains to the domain of work. By specifically referencing the workplace, worker well-being measures provide organisations with a more accurate assessment of how workers are doing at work than more general measures of subjective well-being (e.g. life satisfaction) in isolation (Daniels, 2000).[7] The subjective approach to worker well-being, conceptualises well-being as the extent to which workers themselves feel that that they have a 'good working life', as defined by those individuals, regardless of the objective evidence to the contrary (e.g. Stone & Mackie, 2013). A vast literature (summarised in DeSimone, 2014) supports the notion that worker well-being is multidimensional and includes, at a minimum, two separable and independent constructs - a relatively stable evaluative (cognitive) component and a transient emotional (affective) component (Eid and Diener, 2004). Together, these two components, combine to produce 'hedonic wellbeing', a state in which work-related desires are satisfied and positive emotional states are experienced (Disabato et al., 2016). An individual will report high levels of hedonic worker well-being if he/she is generally satisfied with his/her work-life relative to his/her peers, past experiences, and future expectations and if, on balance, he/she feels happy at work (Bakker & Oerlemans, 2011; Diener and Larsen, 1993).

While worker well-being is a latent construct, it is typically captured using surveys which draw on the standard tripartite model of subjective well-being measurement by gathering self-reported levels of satisfaction, positive affect and negative affect. Work-related satisfaction is typically measured using a modified version of the standard single-item life satisfaction scale in which workers rate their current level of overall job satisfaction from 0 "*Not at all satisfied*" to 10 "*Completely Satisfied*" (Diener et al, 1985)[8]. An alternative approach is to use a multi-faceted measure of job satisfaction, such as the

[7] The Abstract-Specific Hypothesis claims that responses to well-being questions depend on how abstract or specific the measure is (Cummins et al. 2003; Davern et al. 2007). Broader questions trigger the use of cognitive shortcuts (Tversky & Kahneman, 1974), whereas more specific questions induce respondents to attend to the domain of interest, work, and to rely less on heuristic judgements, such as current mood.
[8] The single-item measure forms the baseline measure in this study. However,

Job Descriptive Index (Stanton et al., 2002), which decomposes overall job satisfaction into its constituent parts e.g., satisfaction with pay etc.

Satisfaction measures are relatively stable and correlate highly with enduring life and job circumstances (e.g., Helliwell and Putnam, 2004) and are therefore effective at capturing longer-term evaluations of working life. To capture short-term, context-dependent shifts in well-being, however, affective measures are required to provide a more 'textured tool' for understanding the ups and downs of daily working life (Helliwell and Barrington-Leigh, 2010 p.734). Emotions experienced at work are captured using self-report affective measures. This study adheres to Watson and Tellegen's (1985) well-supported (e.g., Ekkekakis, 2013) 'two domain theory' of affect, which characterises positive and negative emotions as two separate constructs, with largely divergent and non-overlapping determinants. Individuals may experience high or low levels of positive and negative emotions simultaneously (Larsen, McGraw, & Cacioppo, 2001) e.g., they may feel simultaneously inspired and stressed when awarded a major new work project. An individual who is 'happy' at work overall, will experience positive emotions (e.g., joy; excitement; ease) relatively frequently and negative emotions (e.g., anxiety; fear; worry) relatively infrequently.

Hedonic well-being measures can be further decomposed along temporal lines. Global measures capture workers' beliefs about the typical patterns of satisfaction or emotions that they experience at work in general. They are measured on a remembered basis (Bakker & Oerlemans, 2011) and as such represent a considered, overall 'evaluation'. For example, individuals are typically asked to report the extent to which they experienced a list of positive and negative emotions over the 'past month' / 'past few weeks' etc. Global measures have been criticised for being subject to influence by peer comparisons and recall bias, for example peak-end bias (Fredrickson & Kahneman, 1993). As the length of time between the actual experience and the self-report increases, the details may become harder to remember, causing respondents to rely more on semantic knowledge and situation-specific beliefs than episodic memory (Robinson & Clore, 2002). In addition, global measures can be affected by socially pervasive, but frequently erroneous, normative beliefs of what 'should' constitute a good life (e.g., earning a high salary) (Dolan, 2014). Experiential affect measures, on the other hand, capture temporary 'raw', in vivo, emotional states that are triggered by contextual changes, for example the nature of the task; the time of day etc, as they occur.

Respondents are induced to use their recent personal experience as the baseline when rating their current happiness (Reis et al, 2000). Experiential measures thus avoid memory and evaluation biases by measuring emotions in 'real time' (Robinson and Clore, 2002).

In terms of measuring experiential measures, the gold standard is the Experience Sampling Method (ESM) (Larson & Csikszentmihalyi, 2014) which has been successfully used in multiple contexts, including the workplace.[9] Due to the potentially prohibitive time and cost burdens associated with ESM however (see Eisele et al., 2020), Kahneman et al. (2004) developed a 'more efficient' measure, the Day Reconstruction Method (DRM), which captures emotions experienced the previous day. While the DRM stops short of capturing raw feelings 'live' in the exact moment they occur, it uses a structured questionnaire and diary technique designed to induce participants to 'recreate' moments (episodes) from the previous day and to reproduce the same feelings associated with those episodes which they would have reported had they been asked to report them instantaneously. It also incorporates procedures (e.g., obtaining separate estimates of the duration and instant utility of an episode) that reduce the impact of known biases. DRM thus serves as a 'next best' alternative to ESM. DRM self-ratings have been found to substantively replicate those obtained with ESM (e.g., Dockray et al., 2010; Tweten et al., 2016), although a recent study by Lucas et al. (2021) suggests that agreement between the two measures varies depending on the focus of the analysis.[10]

Global and experiential measures have been shown to be separable (Krueger & Schkade, 2008) and differentially determined (Hudson et al.,2016).[11] Nonetheless, despite evidence of considerable within-person variations in the emotions experienced at work (e.g. Fisher, 2000; Ilies & Judge, 2002), and a growing body of research that links experiential well-being with important economic outcomes such as job performance (Binnewies, Sonnentag & Mojza, 2009), global measures continue to dominate the well-being literature. A very small number of worker well-being studies have used experiential measures to date, something which Kahneman and Riis (2005) attribute to the ease with which global measures can be included in national surveys and to the fact that global

[9] Participants are 'pinged' on their mobile phones at random intervals throughout the day for a period of time and are asked to answer questions about their current situation (e.g., who they are with; what they are doing etc..) and to rate their current feelings in that moment.

[10] Dockray et al. (2010) compared ESM and DRM ratings of happiness, tiredness, stress, and anger/frustration over the same 24 hour period and found moderate to high between-person correlations ranged from 0.58 (stress, working day) to 0.90 (happiness, leisure day). Lucas et al. (2021) find high correlations of between .76 and .85 between the 2 methods for average positive and negative affect reported in each situation.

measures are viewed as capturing the cognitive processes underlying individuals' decision making. This study seeks to address this gap.

While hedonic well-being, regardless of how it is measured, forms the core component of worker well-being, empirical research increasingly shows that achieving 'the good working life' is perceived to involve more than just a pleasurable existence. There is growing acknowledgement of the need to explicitly include eudemonic and psychosocial components in the worker well-being model (Martela & Sheldon, 2019). It is not enough for workers to feel happy and satisfied at work. They also need to feel that they have some input and control over their work (Ryff, 1989), that they are performing meaningful work for and with people they like (Baumeister & Leary, 1995) and that they are on a path to personal growth (Deci & Ryan, 2008; Graham & Nikolova, 2015). While hedonic worker well-being comprises workers' cognitive and affective evaluation of their experiences at work, eudemonic worker well-being draws heavily on self-determination theory (Deci & Ryan, 1995; Ryan & Deci, 2000) and reflects workers' subjective evaluation of their capacity to maximise their potential and 'flourish' at work (Bartels, Peterson & Reina, 2019; Steger et al., 2012). This Aristotelian notion of eudemonic well-being as a life lived to its full potential, taken together with hedonic well-being, comprises total worker well-being.

While a multidimensional, expanded conceptualisation of well-being is increasingly becoming the norm, its measurement remains controversial. The argument that hedonia and eudaimonia are independent factors rests largely on the argument that it is possible to experience one without the other. [12] However, the fact that eudemonic and hedonic measures are typically moderately to highly correlated, raises questions about discriminant validity of two-factor model of subjective well-being and about the value-add of measuring both constructs separately (Disabato et al., 2016).[13] While an all-encompassing measure of eudemonic worker well-being unfortunately does not currently exist, eudemonic well-being is typically captured using survey questions which probe respondents' beliefs around the extent to which their jobs are meaningful,

[12] For example, highly valued and meaningful tasks such as childcare have been shown to score highly on purpose but low on pleasure (White & Dolan, 2009) and vice versa. Recent empirical work (Allan et al., 2019; Nikolova & Cnossen, 2020) reveals that, while job satisfaction and meaningful work are correlated, they are distinct concepts.

[13] It is however also possible that the high correlation may, at least partly, reflect the choice of hedonic and / or hedonic measures. Disabato et al. (2016) report a latent correlation of 0.96 between hedonic (Satisfaction with Life Scale, Diener et al., 1985 + Subjective Happiness Scale, Lyubomirsky & Lepper, 1999) and eudemonic well-being (Scales of Psychological Well-Being, Ryff 1989) . They emphasise that several other studies of hedonia and eudaimonia have revealed large correlations ranging from .76 to .92 (e.g. Fredrickson et al, 2013). However, the majority of these studies employ different, often very narrow, measures of hedonia and eudaimonia (for example, Fredrickson et al. 2013 use just one measure of global happiness and one of flourishing)

positively challenge them and allow them to master new skills. Although multiple 'versions' of eudemonic well-being abound, Martela & Sheldon's (2019) meta-analysis reveals that two of the most widely used eudaimonia conceptualisations involve firstly, the extent to which workers experience a strong sense of positive engagement or motivation at work and secondly the extent to which workers feel that their innate psychological needs to feel socially connected, competent and autonomous are being adequately met at work.[14] I therefore use both of these measures as proxies for eudemonic well-being as a whole in this study.

Engagement is an affective-cognitive state of mind that is characterised by absorption, dedication, and vigour (Schaufeli & Bakker, 2004). Low levels of engagement, or disengagement, combined with chronic exhaustion may result in 'work dis-utility' in the form of burnout, a state of work-related psychological distress. The Basic Psychological Needs Satisfaction at Work model (Deci et al., 2001) on the other hand, conceptualises well-being as the extent to which workers feel that they have some input into their jobs and are being facilitated to work towards goals which are congruent with their sense of identity (autonomy) and perceived ability (competence), and to work with and for people with whom they feel a strong personal connection (relatedness) (Deci & Ryan, 2000). Ryan and Deci (2000) contend that the satisfaction of basic psychological needs, like engagement, directly drives a worker's level of motivation and thus (indirectly) his / her productivity. As Nikolova & Cnossen (2020) summarise, workers will be amotivated and unwilling to supply labour at any wage rate if psychological needs go entirely unmet. Partial satisfaction of needs will result in a willingness to work in return for a threshold level of compensation, however workers will lack of a sense of purpose. It is only when psychological needs are satisfied, a state of 'autonomous motivation' (Ryan & Deci, 2000), that workers experience self-efficacy and work becomes meaningful. While most measures of eudaimonia rely on global measures which tap the remembering, evaluative and stable self, it is possible, though far less usual, to measure moment to moment fluctuations[15] To the best of the author's knowledge however, this study represents the first attempt to simultaneously explore the associations between global and experiential eudemonic well-being measures and quit intentions.

[14] Martela & Sheldon (2019) list 63 separate elements used in different operationalisations of eudemonic well-being in the literature.

[15] Csikszentmihalyi's (1990) flow measure captures the extent to which individuals become wholly absorbed in a work task, to the extent that they lose all sense of time. Studies by Sonnentag (2003) and Xanthopoulou et al. (2009), document within-person variations in engagement.

2.2. Quit intentions and well-being measurement in economics

When viewed within a standard labour economics framework, a quit intention is a function of decision utility. Decision utility is inferred from, and is used to explain, choices (Kahneman and Riis, 2005), in this case the choice to quit. A positive quit intention represents the outcome of an evaluative process, in which a worker retrospectively rates his/her overall work experiences over an extended period ('remembered utility') and assesses his/her expected future experiences ('predicted utility') (Kahneman, Wakker & Sarin, 1997; Levy-Garboua, Montmarquette & Simonnet, 2007). Decision utility has an adaptive function by acting as a useful 'utility signal' at the decision-making point (Berridge & Doherty, 2014 p.336). Workers sort into jobs they believe will increase future utility and out of those that drain utility (Blanchflower & Oswald, 1999). Quit intentions thus represent both a mental representation of, and an action plan to realise, a desired future (Shuck, Zigarmi & Owen, 2015) and avoid the negative experiences of the past. Research into the determinants of quit intentions within economics has therefore understandably focused on identifying drivers of decision utility, in particular monetary 'pecuniary factors', namely salary, financial bonuses etc. While pecuniary factors have been found to be consistently negatively correlated with quit intentions, effect sizes tend to be small (Griffith, Hom & Gaertner, 2000; Rubenstein et al., 2018).[16] Similarly, while the predictive role of personal characteristics in relation to quit intentions have also been extensively investigated, effect sizes have also been relatively small.[17] Attention has thus switched to the role of 'non-pecuniary factors' in the utility function e.g., relationships; supervision; type of work; and whether workers can perform, enjoy, and feel positively challenged by their jobs (Akerlof et al., 1988; Lazear & Shaw, 2007). Non-pecuniary factors are typically subsumed under the broad heading of 'worker well-being'.

Worker well-being is characterised as a 'sub-utility function' that captures workers' subjective evaluations of their jobs and the welfare received from all aspects of that job (Clark, 1997 p.191; Clark & Oswald, 1994). Viewed through the decision utility lens, worker well-being reflects workers' 'post-decisional preference' for their current job choice relative to other possibilities (Levy-Garboua, Montmarquette & Simonette,

[16] Griffeth, Hom & Gaertner (2000) and Rubenstein et al. (2018) report average correlations of -.11 and -.17 between pay and quit intentions.

[17]. For example, younger, highly educated, male employees are more likely to intend to quit than older, less educated, female employees (McCarthy, Moonsinghe & Dean, 2020; Grissom, Viano & Selin, 2016). Personality may also shape quit intentions (Woo et al., 2016). For example, Woo (2011) finds a positive association between Big-5 openness and frequent job switching. Workers with longer tenure exhibit reduced quit intention tendencies (Rubenstein et al, 2018). However, seniority is generally positively associated with quit intentions (e.g., McCarthy, Moonsinghe & Dean, 2020).

2007 p.252). Workers are more likely to switch jobs if doing so would increase their total (pecuniary plus non-pecuniary) utility. The issue remains, however, of how best to formally capture worker well-being within the utility function. With some notable exceptions (Green, 2010; Nikolova & Cnossen, 2020), economists have, to date, relied almost exclusively on job satisfaction to proxy for overall worker well-being. This is justified insofar as job satisfaction has been shown to be a reliable predictor of quit intentions (e.g., Ozkan et al.,2020; Rubenstein et al, 2018; Shields and Price, 2002; Sousa-Poza & Sousa-Poza, 2007), particularly within the health sector.[18] [19] However, while job satisfaction has strong predictive power and coheres strongly with the evaluative decision utility framework, it cannot completely capture the full experience of working, notably the lived emotional and psychological reality of everyday working life.

The Benthamite 'experienced utility' framework (Bentham, 1789; Kahneman, Wakker & Sarin, 1997) conceptualises well-being as an indicator of 'raw' affective experiences ('experienced utility'), rather than a comparative, evaluative judgement between alternative opportunities ('decision utility').[20] Kahneman, Wakker & Sarin (1997) caution against using observed choices (decision utility) as the sole measure of the utility of an outcome, on the basis that humans regularly make systematic errors when evaluating past events (e.g., the focusing illusion) and predicting future utility (affective forecasting). Global (evaluative) measures require respondents to both retrieve and emotionally evaluate memories of previous experiences at work. However, numerous experimental findings have highlighted the extent to which recall and forecasting errors (e.g., duration neglect, Redelmeier & Kahneman, 1996) may distort the hedonic quality of the original (recalled) experience, on which predictive utility and therefore quit intentions, are based, leading to sub-optimal decisions. To prevent such errors of judgement, Kahneman et al. advocate for in-the-moment, or 'instant utility', to be explicitly included in choice functions. This requires the use of direct self-report measures that instantaneously capture the 'sign' (valence) and intensity of transient affective experiences. In this model, 'total utility' comprises the integral of discrete moments of experienced utility, weighted by duration, over an extended period of time.

[18] Ozkan et al's. (2020) meta-analysis of the antecedents of turnover intention in the US reports an average negative correlation of -.54 between job satisfaction and turnover intention.
[19] Shields & Ward (2001) find that nurses who are dissatisfied with their jobs are 65% more likely to intend quitting than their more satisfied counterparts. Scott et al. (2006) find that particular job satisfaction domains have a direct effect on general practitioners' intentions to quit, in addition to their indirect effect via the overall job satisfaction measure.
[20] Whether or not experienced utility influences the quit decision directly or indirectly (via decision utility) remains contested. However, the idea that workers' experiences at work shape quit intentions, and therefore actual quits, is uncontentious.

Kahneman and Riis (2005) argue that total utility measures elicit ‘action tendencies’ insofar as experienced emotions trigger an instinctual desire to exit (avoid) the current work situation or to remain (approach). In the context of quit intentions, total utility can therefore be interpreted as a measure of a worker’s average preference to stay in his/her current job or to pursue alternative career opportunities.

With the notable exception of Green (2010) however, the role of emotions in determining quit intentions / quits, is largely bypassed in the economics literature. Green uses a pre-existing dataset to compare the relative predictive power of job satisfaction and emotions in relation to quits 15 months later. He finds that while positive and negative affect measures both predict quits, they are outperformed by job satisfaction. He attributes this finding to the fundamentally evaluative nature of job satisfaction which renders it more suitable for capturing the cognitive processes engaged when a worker considers quitting.

While Green’s (2010) work played an important role in highlighting the potential role of emotions experienced at work in shaping quits, it is limited to the extent that it relies exclusively on global affective measures. The fact that global affective measures also contain an evaluative component, could potentially partly explain the positive association between affective measures and quits in Green’s study if the affective measures were tapping into the same cognitive process as the job satisfaction measure, albeit to a lesser extent. If the predictive power of well-being measures in relation to quits depends, as Green claims, on their relative evaluative strength, then non-cognitive, ‘purer’ experiential measures of raw emotions experienced at work should presumably be even less able to compete with job satisfaction in terms of capturing quit intentions. Conversely, if the in vivo lived reality of day to day working life is, in fact, a key determinant of quit intentions, experiential measures should be better placed than global measures to capture this. To date, however the links between instant utility and quit intentions have not been examined.

With some notable exceptions detailed below, quit intentions research has also tended to largely ignore the links between ‘psychological’ or eudemonic aspects of the work experience and quit intentions that have been documented in other disciplines (see Sousa-Posa & Henneberger, 2004 for a summary). In relation to the two eudemonic measures used in this study, disengagement has been shown to be positively associated with quit intentions (see Sandhaya & Sulphey, 2020), as has the failure to satisfy basic psychological needs. Van den Broeck et al.'s (2016) meta-analysis reports negative correlations between quit intentions and the psychological needs of relatedness (-.21), competence (-.05) and autonomy (-.31). Böckerman & Ilmakunnas (2009) find that 'job disamenities', or adverse working conditions, positively predict quit intentions and actual quits amongst Finnish workers, a finding which supports earlier work by Shields and Price (2002). Dur and van Lent (2019) show that individuals who rate their jobs as 'socially useless' jobs are more likely to want to switch jobs if they could. Nikolova & Cnossen (2020) use three waves of the European Working Conditions Survey to show that the satisfaction (or not) of basic psychological needs work explains 60% of the variation in work meaningfulness perceptions, with relatedness, emerging as the most important factor. While they do not specifically investigate the links between eudemonic well-being and quits, they reveal a significant positive association between low meaningfulness, absenteeism and the intention to retire.[21] Their findings suggests that eudemonic well-being measures may play an important role in predicting quit intentions, a possibility that I explore further in this study.

3. DATA

3.1 Survey Design and Data Collection

I employ a novel in-depth survey which I designed with the specific aim of capturing the multidimensionality of worker well-being. The survey was piloted using a convenience sample (n=30) to inform the development of the protocol. The final survey was issued online to 994 participants sourced by Prolific Academic, a specialist online survey-panel provider.[22] The survey was completed online between 25/11/2019 and 19/2/2020.[23] Due to the study's focus on worker well-being, the sample comprises full-time workers based in the UK. [24] [25] Standard Prolific pre-screening criteria were used to recruit respondents between 18 and 65 years, who were engaged in full-time paid employment for more than 2 months, in organisations with 5 or more workers, for at least 21 hours

[21] A ten-point increase in meaningfulness raises the intended retirement age by 2.5 years, on average.
[22] 1,514 Prolific panel members met the pre-screening criteria and were invited by Prolific to participate. Of these, 994 panel members elected to participate in the survey, corresponding to a response rate of 65.6%.The Prolific UK database at the time of data collection comprised mainly white, full-time workers. 55% of the panel were female (v 66% in this sample). 75% were aged 20-40 (v 67% in this sample) and 50% held university degrees (v 60% in this sample). Participants were paid £5.30 to complete the survey. Average completion time was 32 minutes.
[23] Data collection was paused for 1 month to mitigate the distortionary well-being impact of Christmas and/or January back-to-work-blues.
[24] Shift-/ part-time and self-employed workers are excluded due to evidence of systematic differences in quit motivations between part-time v full-time workers (McBey & Karakowsky, 2001). The self-employed are excluded due to evidence of a 'self-employed job satisfaction premium' (Van der Zwan, Hessels & Rietfeld, 2018). The self-employed enjoy better mental health and well-being compared to similar employees (Benz and Frey, 2008; Binder and Coad, 2013; Hessels et al., 2018; Nikolova, 2019;). This well-being premium is often attributed to the utility of being your own boss and having autonomy and flexibility (Benz and Frey, 2008).
[25] The data included 8 respondents from Ireland. Excluding these workers from the analysis does not affect the results materially.

per week. The sample characteristics are depicted in **S1** in the Online Supplementary Materials. S1 also compares the key demographic variables of the workers in the sample to a worker sub-sample from the nationally representative UK Understanding Society dataset used in Wheatley (2021). Compared to Wheatley, the current sample contains a higher proportion of women, university graduates and workers in the 25-39 age bracket. Seven observations with missing values are excluded from the base analysis (65 observations when controls are included). **S2** provides further information on the missing value distribution for independent and control variables. No discernible pattern is detectable.

3.2 Measures

S3 in the Supplementary Materials contains a detailed description of all variables. The outcome variable is Quit Intentions. Respondents are asked the following question "*Are you actually planning to leave your job within the next six months?*". Possible responses are *yes* (17.5%), *no* (59.9%) and *not sure* (22.6%).

3.2.1 Independent Variables

Hedonic well-being – global measures

Job satisfaction measures workers' evaluations of the overall state of their working lives using the standard question *Overall, how satisfied are you with your job?* where 0 = *completely dissatisfied* and 10 = *completely satisfied*. Mean satisfaction is 5.8.[26] [27] Global affect is measured using the Institute of Work Psychology (IWP) Multiaffect Indicator (Warr and Parker, 2010; 2016). Respondents use a 7 point Likert scale to indicate the extent to which they experienced 8 negative and 8 positive emotions at work during the past month (1 =*Never* and 7 = *Always*). For ease of comparison with the DRM scores, IWP scores are recoded using a 0-6 scale. Global positive (negative) affect is the mean of the 8 positive (negative) feeling scores. Cronbach's alphas for positive and negative affect are 0.89 and 0.91. Given evidence that multi-faceted measures may reduce social acceptability bias (Groot & Van den Brink, 1999) and that single-item indicators of subjective well-being may be less reliable than multi-item scales (e.g., Ryff, 1989), I follow Bakker and Oerleman's (2011) recommendation and also employ a multifaceted job

[26] Mean job satisfaction in the UK was 7.4 in 2010 (ONS, 2019). The lower figure found here likely reflects sample composition, in particular the relatively high proportion of private sector workers (63%) and workers in the education (13.7%), retail (8.8%) and health (10.8%) sectors.

satisfaction, the validated (Kinicki et al, 2002) 6-item Abridged Job Descriptive Index (JDI) (Stanton et al, 2002). The JDI measures workers' satisfaction with the job in general (mean: 16.7 out of 24); work itself (mean: 10.0 out of 18); pay (mean: 10.9 out of 18); promotion opportunities (mean: 5.9 out of 18); people (mean:12.9 out of 18) and supervision (mean:11.8 out of 18). Cronbach's alpha ranges from 0.79 to 0.89.

<u>Hedonic well-being – experiential measures</u>

Experiential job satisfaction and affect are measured using the Day Reconstruction Method (DRM) (Kahneman et al., 1994). Workers use diary entries to 'reconstruct' three consecutive 'episodes' from the previous working day. The time-of-day starting point for the episodes is randomly generated. Participants record when each episode started and ended; where they were; who they were with and what they were doing. They are asked *How did you feel during this episode?* and instructed to rate the extent to which they experienced 16 emotions (the same emotions used to measure global affect) during this episode, where 0 = *Did not experience that feeling at all* and 6 = *That feeling was an important part of the experience*. Experiential affect is the average of the positive (2.85) and negative (2.11) affect scores for the 3 episodes after 20 observations with missing values for one or more episodes have been removed. Cronbach's alpha scores for positive and negative experiential emotions are .893 and .824 respectively. Experiential job satisfaction is measured by asking participants to use a 0-10 scale to answer the question *All things considered how satisfied were you with this episode?* Their average score for the three episodes constitutes experiential job satisfaction (mean: 6.66).

<u>Eudemonic well-being – global measures</u>

Engagement is captured using the disengagement measure from the English-version validated (Halbesleben & Demerouti, 2005) 16-item **Oldenburg-Burnout Inventory (OLBI)** (Demerouti & Bakker, 2008) which includes two dimensions, disengagement and exhaustion. For the disengagement section, respondents rate their agreement with four positive (e.g. "*This is the only type of work I can imagine doing*") and four negative statements (e.g. *'I talk about work negatively")* using a 1 (*Strongly Agree*) to 4 (*Strongly Disagree*) scale. Negative statements are recoded so that a high score indicates a high level of disengagement. Mean disengagement is 2.4, with a reliable Cronbach's alpha of 0.83. The 21-item **Basic Psychological Needs Satisfaction at Work Scale** (Deci et al, 2001) measures the extent to which workers' innate needs for relatedness (feeling socially connected*)*, competence (feeling capable of attaining desired work-related outcomes*)* and autonomy (feeling that work is compatible with one's self-identity) are met in the workplace. Respondents use a 1-7 scale to rank the trueness of statements e.g. *I really like the people I work with*. Mean scores are 4.92 (relatedness), 4.94 (competence) and 4.43 (autonomy). Cronbach's alpha scores are 0.88, 0.71 and 0.78 respectively.

Eudemonic well-being – experiential measures

Experiential eudemonic well-being is captured using the DRM. Participants are asked to use a 0-6 scale to rate how well each of two statements describes how they were feeling during that episode, with a score of 0 meaning that they did not experience the feeling at all and a score of 6 meaning that the feeling was a very important part of the experience. I employ the self-generated statements *I felt like people cared about me* and *I felt a sense of accomplishment* as the experiential equivalents of the global relatedness and competence measures, with mean scores of 3.7 and 4.4 respectively.

3.2.2 Control Variables

I control for personal and work characteristics which are supported by an Imai, Keele & Tingley (2010) causal mediation analysis.[28] The results of the analysis are set out in **S4**. Demographic covariates comprise age; gender; education and parental status. Personality is assessed using the validated (Lovik, Verbeke & Molenborghs, 2017) 10-item Big-5 Inventory-10 (Rammstedt & John, 2007) which assesses five dimensions: neuroticism; openness to experience; agreeableness; conscientiousness and extraversion. Work-related covariates include net monthly salary (GBP '000); total self-reported hours worked the previous month; seniority (0-5 self-rating scale, where 5 = "most senior") and tenure (years in the organisation). I also measure other variables (life satisfaction, self-rated mental health, self-rated performance, relationship status) which are not used as controls but which I use in the descriptive analysis.[29]

4. EMPIRICAL FRAMEWORK

[28] Controls which are significant at the 10% or above level for any of the 7 well-being 'treatments' using the Stata *medeff* command (Hicks & Tingley, 2011) are included in the regression analysis. While self-rated mental health is significant, I do not control for it due to the risk of it acting as a collider or 'bad' control (Pearl, 2009).

[29] Life satisfaction measures workers' overall satisfaction with their lives, all things considered (0-10 scale); Self-rated mental health is measured using a 1-5 scale (1=Very Bad; 5 = Very Good). Self-rated performance measures workers' self-rated performance over the previous month relative to the best job that anyone could do at that job using a 0-10 scale.

I adopt the standard approach used in the economics literature (e.g., Shields & Ward, 2001; Clark & Oswald, 1996) and specify quit intentions as a function of personal and work characteristics and of work utility. Work utility is in turn a function of the total non-pecuniary benefits derived from work. It is proxied by worker well-being and is assumed to guide the quit decision (Green, 2010). Equation 1 is estimated to isolate the impact of worker well-being on quit intention formation:

$$\boldsymbol{Q_i = \beta_0 + \beta_1 WWB_i + \beta_2 X_i + \beta_3 \lambda_i + \varepsilon_i} \quad (1)$$

where Q_i is the probability of worker i intending to quit within the next 6 months; β_0 is the intercept; WWB_i is a proxy for work-utility, namely the self-reported work-related well-being (hedonic, eudemonic or both, depending on the specification) of worker i; X_i is a vector of personal characteristics; λ_i is a vector of work characteristics which includes wages and hours and ε_i is an error term. The parameter β_1 captures the change in the probability of worker i intending to quit which is associated with a one standard-deviation increase in WWB_i. In line with the criterion validity test of a well-being indicator, I hypothesize that β_1 is negative for 'positive' indicators (e.g., job satisfaction) and positive for 'negative' indicators (e.g., disengagement). Rather than use a single latent factor of worker well-being for WWB_i, I examine four different proxies for worker well-being (two subjective well-being and two eudemonic well-being indicators) in order to identify those indicators which are likely to prove most helpful for organisations who are seeking to assess and prevent voluntary turnover.

In line with the majority of studies which use quit intentions as the dependent variable, I employ a cross-sectional design. As such, I cannot rule out the existence of unobserved individual level factors which predict both well-being and quit intentions (e.g., risk preferences; beliefs around gendered family roles etc.) and I make no claims to a causal interpretation of the results. While the analysis would obviously benefit from the use of a panel dataset which controls for time invariant unobserved heterogeneity and which includes a similarly wide range of well-being measures, unfortunately no such dataset currently exists. However, by way of endogeneity mitigation, I estimate the results controlling and not controlling for a wide range of covariates, including work-related factors such as seniority and personality traits.[30] For ease of interpretability, in my main analysis I use a multivariate linear probability model to estimate a baseline specification (Equation 1 excluding X_i and λ_i) which isolates the effect of well-being on quit intentions holding all other variables constant at their means. Following Green (2010), I merge *yes* and *not sure* responses (coded 1) to the quit intentions question.[31] *No* responses are coded 0. The alternative is to exclude the '*not sures*' or to analyse them as a third outcome. The impact of adopting these approaches is depicted in **S5** and **S6**.[32] I use the Huber-Sandwich-White correction to ensure standard errors are robust to heteroskedasticity. The Benjamini-Hochberg (1995) multiple inference method is used to control the false discovery rate (the proportion of significant results that represent false positives).[33] For all models, I investigate which well-being indicator (job satisfaction; affect; disengagement or basic psychological needs satisfaction) best fits the data by comparing explanatory power (R^2) and goodness of fit (Bayesian Information Criterion, abbreviated BIC), with and without controls (X_i and λ_i).

Next, I examine whether a composite multi-dimensional well-being model outperforms the commonly used unidimensional job satisfaction model. I employ a hierarchical (stepwise) regression model comparison framework, in which a composite regression model is built by gradually adding well-being indicators to the previous model at each step. The hypothesis is that additional specifications should significantly increase the explanatory power (R^2) and goodness of fit by capturing a larger proportion of variance in the outcome variable than a model which relies solely on the base measure, job satisfaction plus controls. I use the Stata *hireg* command (Bern, 2005) to formally test the null hypothesis that there will be no difference in the explanatory power offered by a composite model (job satisfaction + additional well-being indicators) versus the base model (job satisfaction only). If the R^2 of the later model is significantly higher than the R^2 in the earlier model, then the later model is assumed to offer a better fit. Starting with the standard measure, single-item global job satisfaction, I add additional well-being indicators, changing the order of inclusion each time to take account of potential sequence sensitivity (Gelbach, 2016). Additional indicators are added as follows:

- M1: Job satisfaction + Affect + Disengagement + Psychological Needs

[31] I combine *Yes* and *Not Sure* responses on the basis that a *Not sure* response suggests that the formation of a future quit intention is at least a possibility, whereas a *No* response definitively rules out any such possibility. Analysis of the ordered logit results also indicates that the *Not Sure* responses are closer to the *Yes* responses in terms of sign and magnitude than the *No* responses.
[32] Excluding the *Not Sure* responses increases the explanatory power (R^2) of all well-being models substantially. While effect sizes are marginally lower than in the binary model, the coefficients are identically signed, with similar p-values. See S5.
[33] P-values controlling for multiple testing are generated as follows: (1) The p-values are ranked from smallest to largest; (2) each p-value is compared to a critical value ($[i/m]*Q$), where i is the rank, m the total number of tests, and Q is the false discovery rate of 0.1; (3) p-values are deemed significant if they are smaller than the p-value Benjamini-Hochberg critical value at the relevant threshold.

- M2: Job satisfaction + Affect + Psychological Needs + Disengagement
- M3: Job satisfaction + Disengagement + Affect + Psychological Needs
- M4: Job satisfaction + Disengagement + Psychological Needs + Affect
- M5: Job satisfaction + Psychological Needs + Affect + Disengagement
- M6: Job satisfaction + Psychological Needs + Disengagement + Affect

I also investigate the impact of changing the base measure from job satisfaction to disengagement as follows. I then replace the global well-being indicators used in the main analysis with their experiential equivalents and re-run the main analysis. Finally, I examine the extent to which using a multi-faceted measure of job satisfaction, the JDI, improves explanatory power in the main model.

4.1. Robustness Checks

I perform a number of robustness checks. First, I relax the assumption of linearity, assume that the error terms of Equation 1 are normally distributed and estimate a logit regression.[34] Next I drop the binary model assumption by unbundling 'yes' and 'not sure' responses and run an ordered logistic model using all 3 category responses ('yes', 'not sure', 'no') (Long & Freese, 2006).[35] Drawing on Boes & Winkelmann (2006), I then relax the parallel regression assumption and run a generalised ordered logit model instead of a standard ordered logit model which assumes that the relative magnitudes of the effects of each of the explanatory variables are constant across the distribution of single-scale responses.[36]

5. RESULTS

5.1 Descriptive Statistics

17.5% of workers report positive quit intentions, 59.9% report negative quit intentions and 22.6% are not sure.[37] Descriptives for the independent variables and Bonferonni-adjusted bivariate correlations are provided in **S9**. All of the correlation coefficients are signed in line with standard well-being theory. Global job satisfaction is highly correlated

[34] The results of the logit model (marginal effects) are reported in S7. There are no differences in the signs, although effect sizes are generally smaller and explanatory power lower in the logit model than in the OLS model. Disengagement has the strongest effect in the logit model, whereas job satisfaction has the strongest effect in the OLS model.
[35] The ordered logit marginal effects are set out in S6. The binary logit model appears to fit the data better than the ordered logit model in that it produces higher R^2 values and lower log likelihood figures for all measures. Furthermore, the coefficients for the *Not Sure* responses have the same sign (but a smaller magnitude) as the *Yes* coefficients across all measures, providing support for the merging of these two categories.
[36] The generalised ordered logit marginal effects are set out in **S8**. I find no material differences in the sign or magnitude of the marginal effects as compared to the ordered logit model. *Yes*, and *Not Sure* responses are signed the same (opposite to *No* responses) for all well-being measures. In general, the model has more predictive power for *Yes* and *No* responses than *Not Sure* responses and fits the data marginally better than the ordered logit model.
[37] No is coded 1. Not sure is coded 2 and Yes is coded 3. Mean=1.57 (sd=0.77).

with global positive (.591) and negative (-.536) affect; disengagement (-.653); competence (.536) and autonomy (.541). It is moderately correlated with relatedness (.395), experiential positive affect (.404), experiential competence (.335), experiential disengagement (.408) and experiential relatedness (.364). The correlation between global job satisfaction and experiential negative affect is low (-.191). In general, global measures are just moderately correlated with their experiential counterparts, providing support for the notion that they are tapping into different aspects of the work experience.

5.1.1 Quitters v Stayers

Following Green (2010), I investigate systematic differences in the demographic and well-being profiles of 'Quitters' (workers who respond 'yes' or 'not sure' to the quit intentions question) and 'Stayers' (workers who respond 'no'). **S10** in the Supplementary Materials sets out the differences in the demographic profiles between Quitters and Stayers. Quitters are on average younger (35.7 v 37.6; p=.002), less likely to be parents (38.9% v 54.3%; p <.001) and more likely to have net household income of less than £2,000 per month (37.9% v 27.7%; p=.003) than Stayers. In terms of personality profile, they are more likely to score highly on openness (3.5 v 3.4; p=.03) and neuroticism (3.19 v 2.88; p<.001) and lower on extraversion (2.8 v 2.9: p=.05), conscientiousness (3.75 v 3.94; p<.001) and agreeableness (3.4 v 3.6; p=.013). They are more likely to report lower self-rated mental health scores (3.3 v 3.7; p<.001) and to have a mental health condition (30% v 23%; p=.012) and to report being less senior (2.1 v 2.5; p<.001) than Stayers. They are less likely to rate themselves as high performers (52.3% v 63.8%; p<.001) and to earn salaries of over £2,000 per month (27.1% v 42.5%; p<.001) and are more likely to have worked fewer hours the previous month (146 v 151; p=.08).

Table 1 sets out differences between the well-being profiles of Quitters and Stayers. It follows Clark (1997) and shows the result of cross-tabulations between Quitter status and all well-being indicators. As the well-being variables are ordinal rather than cardinal e.g., disengagement scores of 4 cannot be interpreted as being twice as high as scores of 2), columns 2 and 3 of the bottom half of the table show the percentage of Quitters and Stayers who report 'high' levels in respect to each of the outcomes (as described in the table). 'High' levels are assumed to be equivalent to the 75th percentile or higher for all measures.[38] Column 4 reports the *p*-value from the test of identical means. [39]

Table 1
Quitters v Stayers – Well-being profiles

	All workers (n=840)	Quitters (n=381)	Stayers (n=543)	p-value
Mean reported score				
Subjective well-being				
Overall life satisfaction (0-10)	6.49	5.89	6.92	<.001
Global overall Job Satisfaction (0-10)	5.82	4.64	6.66	<.001
JDI Satisfaction with job in general (0-24)	16.52	12.34	19.55	<.001
JDI Satisfaction with work itself (0-18)	9.87	7.17	11.82	<.001
JDI Satisfaction with pay (0-18)	10.83	8.84	12.27	<.001
JDI Satisfaction with promotion opps (0-18)	5.92	3.33	7.79	<.001
JDI Satisfaction with supervision (0-18)	11.78	9.48	13.44	<.001
JDI Satisfaction with people (0-18)	12.87	11.27	14.03	<.001
Experiential job satisfaction (0-10)	6.36	6.04	7.06	< .001
Global Positive Emotions (0-6)	2.51	2.16	2.76	<.001
Global Negative Emotions (0-6)	1.59	1.99	1.29	<.001
Experiential Positive Emotions (0-6)	2.86	2.62	3.03	<.001
Experiential Negative Emotions (0-6)	2.13	2.28	2.02	<.001
Eudaimonic well-being				
Disengagement (1-7)	2.50	2.81	2.27	<.001
Global Competence (1-7)	4.93	4.59	5.17	<.001
Global Relatedness (1-7)	4.91	4.62	5.12	<.001
Global Autonomy (1-7)	4.40	4.02	4.67	<.001
Experiential Relatedness (1-7)	3.73	3.37	3.99	<.001
Experiential Competence (1-7)	4.43	4.07	4.69	<.001
Percentage (%) in 'high' category				
Subjective well-being				
Overall Life Satisfaction (>=7.0)	60.6%	47.2%	63.9%	<.001
Global overall Job Satisfaction (>=7.0)	48.7%	24.7%	65.6%	<.001
Satisfaction with job in general (>=24.0)	28.1%	11.4%	40.1%	<.001
Satisfaction with work itself (>=16.0)	25.9%	15.1%	33.5%	<.001
Satisfaction with pay (>=18.0)	24.2%	13.6%	31.8%	<.001
Satisfaction with promotion opps (>=10.0)	25.1%	10.5%	35.8%	<.001
Satisfaction with supervision (>=18.0)	28.5%	16.5%	37.2%	<.001
Satisfaction with people (>=18.0)	34.8%	23.6%	43.2%	<.001
Experiential job satisfaction (>=8.0)	34.2%	23.6%	41.7%	<.001
Global Positive Emotions (>=3.4)	22.1%	12.8%	28.8%	<.001
Global Negative Emotions (>=2.2)	26.3%	39.0%	17.0%	<.001

[38] Molodynski et al. (2021) use a lower (clinical) cut-off for disengagement (2.1 v 2.8 used here). Using these cut-offs, 93.4% of quitters v 63.7% of Stayers are disengaged (*p*<.001).

[39] For robustness, I re-run this analysis with Quitters decomposed into those workers who respond *Yes*, designated "Definite Quitters" and workers who respond *Not Sure*, designated "Possible Quitters". The results are set out in **S11** and **S12.** Definite Quitters are younger, less likely to be parents and more likely to have been with their organisations for less than 5 years than Possible Quitters. Definite Quitters report a lower level of worker well-being than Possible Quitters across all measures. The raw differences are all significant, with the exception of global and experiential positive emotions and experiential negative emotions.

Experiential Positive Emotions (>3.5)	27.1%	18.5%	33.5%	<.001
Experiential Negative Emotions (>2.5)	23.6%	31.9%	17.9%	<.001
<u>*Eudaimonic well-being*</u>				
Disengagement (>=2.8)	30.4%	50.7%	15.8%	<.001
Global Competence (>=5.6)	27.9%	16.2%	36.4%	<.001
Global Relatedness (>=5.7)	26.1%	18.2%	31.8%	<.001
Global Autonomy (>=5.2)	24.4%	13.1%	32.3%	<.001
Experiential relatedness (>=5.3)	19.0%	24.4%	11.4%	<.001
Experiential competence (>=5.6)	26.3%	19.0%	31.2%	<.001

** Observations with missing values for any of the well-being variables are omitted. Quitters are workers who respond Yes or Not Sure when asked if they are intending to quit in the next 6 months. Stayers are workers who respond No. 'High' thresholds correspond to 75% percentile levels. P-values refer to t-test / chi-squared tests of identical means between Quitters and Stayers.154 observations with missing values excluded.*

Table 1 shows that Quitters report more negative well-being overall than Stayers. Quitters report lower scores for all positive well-being indicators and higher scores for all negative well-being indicators than Stayers. In addition, a higher percentage of Quitters are in the top (bottom) quartile of all negative (positive) well-being indicator scores. I find the largest raw differences between Quitters and Stayers in relation to overall job satisfaction (24.7% v 65.6%), disengagement (50.7% v 15.8%) and satisfaction with promotion opportunities (10.5% v 34.8%). With the sole exception of experiential competence, all raw differences are statistically significant at the 1% level.

5.2 Main Regression analysis

5.2.1 Main regression analysis – individual indicators

Next, I formally test the relationship between worker well-being indicators and quit intentions using multivariate regression analysis. I compare the extent to which the following 4 (global) well-being indicators explain variations in quit intentions, with and without controls: 1) single-item job satisfaction; 2) affect (2 measures: positive + negative affect); 3) disengagement and 4) basic psychological needs satisfaction (3 measures: relatedness + competence + autonomy). A positive coefficient implies that a one-unit standard deviation increase in the well-being measure increases the probability of quit intentions. The results (with controls) are set out in **Table 2.** **<u>S13</u>** in the Supplementary materials provides the results without controls.

With the exception of the relatedness measure, all of the well-being measures are significantly associated with quit intentions at the 1% level adjusted for multiple inference. All coefficients are in the expected direction, with higher levels of well-being associated with a reduced probability of quit intentions. Effect sizes range from .068

(competence) to .215 (job satisfaction). Following Mehmetoglu and Jakobsen (2016)[40] I find significant large effects for job satisfaction and disengagement, a medium effect for negative affect and small effects for positive emotions, competence, and autonomy. The single-item job satisfaction measure has the largest individual effect, with a one standard deviation (2.2 unit) increase associated with a 21.5 percentage point decrease in the probability of quit intentions. However, the disengagement measure produces a similar effect size of .200 in the with-controls specification and a higher effect size than job satisfaction (-.232 v .225) in the no-controls specification. By way of comparison, a one standard deviation rise in monthly salary (£1,000) reduces the probability of quit intentions by 7.9 percentage points.

All of the well-being models have more predictive power than wages and hours combined, which explain just 2.7% of variation in quit intentions (see **S14).** In relation to the covariates, consistent with previous studies, I find that earning a higher salary, working longer hours the previous month, being a parent, not being university educated and scoring lower on the Big-5 openness trait, are all negatively associated with the formation of positive quit intentions. A one standard deviation increase in any of these covariates, reduces the probability of quit intentions by three or four percentage points.

I next analyse the sub-scale items for all measures to see if certain aspects of individual measures are more important determinants of quit intentions than others. In relation to positive affect (see **S15**), just three of the eight emotions measured appear to be driving the negative relationship with quit intentions, namely *enthusiastic* (-.091; p<.001), *inspired* (-.028; p=.092) and *at ease* (-.036; p=.025). Similarly, in relation to negative affect, the positive relationship with quit intentions is being driven by the emotions *depressed* (.063; p<.001), *dejected* (.058; p=.001) and *despondent* (.039; p=.018). In relation to disengagement (see **S16**), the extent to which workers *talk about their work in a negative way* (-.173, p=.020), find their work to be a *positive challenge* (.064; p=.016), *can't imagine doing any other type of work* (.055; p=.002)

[40] β_1 <= .09 = 'small' effect; 0.1< β_1< 0.19 = 'medium' effect; β_1 >= 0.2 = 'large' effect

Table 2
Comparison of links between worker well-being indicators and the probability of quit intentions (binary outcome; standardised scores)

	(1) **Job Satisfaction**	(2) **Affect**	(3) **Disengagement**	(4) **Basic Psychological Needs**
Global Job Satisfaction	-.215*** (.014)			
Global Positive Emotions		-.070*** (.018)		
Global Negative Emotions		.125*** (.019)		
Disengagement			.200*** (.017)	
Global Relatedness				-.026 (.019)
Global Competence				-.068*** (.021)
Global Autonomy				-.090*** (.021)
Age	-.008 (.014)	-.004 (.017)	-.002 (.017)	-.014 (.017)
Gender	.011 (.016)	.014 (.016)	.009 (.016)	.001 (.016)
Parent	-.035** (.015)	-.051*** (.017)	-.032** (.017)	-.046*** (.017)
Education	.029* (.015)	.033** (.016)	.039***(.015)	.038** (.016)
Openness	.027* (.015)	.035** (.016)	.035** (.014)	.043*** (.015)
Extraversion	.007 (.014)	-.004 (.017)	-.001 (.015)	.006 (.016)
Agreeableness	-.005 (.015)	-.015 (.016)	-.001 (.015)	-.005 (.016)
Conscientiousness	-.006 (.014)	-.028* (.017)	-.001 (.016)	-.015 (.017)
Neuroticism	.005 (.017)	-.011** (.018)	-.005 (.017)	.006 (.017)
Tenure	-.000 (.015)	.006 (.017)	-.017 (.015)	.010 (.017)
Seniority	.001 (.016)	-.007 (.018)	.004 (.016)	.018 (.019)
Salary	-.034** (.017)	-.064*** (.017)	-.031* (.016)	-.050*** (.017)
Hours last month	-.068** (.031)	-.071** (.034)	-.066** (.031)	-.064** (.035)
Constant	.399*** (.014)	.399*** (.015)	.396*** (.014)	.399*** (.015)
Controls	**YES**	**YES**	**YES**	**YES**
Observations	**929**	**929**	**929**	**929**
McFadden R^2	**.2382**	**.1622**	**.2566**	**.1585**
RMSE	**.4317**	**.4529**	**.4267**	**.4542**
BIC	**1163.18**	**1258.25**	**1147.27**	**1269.23**

*Notes:*** p<0.01, ** p<0.05, * p<0.1. Benjamini-Hochberg p-values adjusted for multiple inference. Robust standard errors in parentheses. Dependent Variable is binary quit Intentions, namely stated intention to quit the job within the next 6 months, with Yes and Not Sure categories merged (0 = No; 1 = Yes / Not Sure). Standardised scores are used throughout. 60 observations with missing well-being or control observations are dropped.*

and *feel more and more engaged* in their work (.096; p<.001) appear to be particularly relevant for quit intention formation.[41]In relation to the BPN of competence (see **S17**), workers who report feeling a *sense of accomplishment* (-.045; *p*<.001), and who *get a chance to show how capable they are* (-.032; *p*=.002) are significantly less likely to form positive quit intentions. Finally, with regard to autonomy, workers who that their *feelings are taken into consideration* at work (-.068; *p*<.001) are less likely to form positive quit intentions.[42] Somewhat surprisingly, I also find that workers who *are told that they are good at their job* (.024; *p*=.038) and who *feel free to express their opinions* on the job (.030, *p*=.038) are more, rather than less, likely to form positive quit intentions. This may reflect a greater sense of self-confidence, which could in turn be independently positively associated with positive quit intentions.

In terms of overall explanatory power (R^2), the disengagement indicator outperforms the standard single-item job satisfaction measure, explaining 25.6% of variation in quit intentions (versus 23.8% for job satisfaction) and exhibiting a lower BIC (1147.3 v 1163.2) and RMSE (.427 V .432) than job satisfaction. Furthermore, when controls are excluded (see S13), it produces a larger effect size. The well-being indicators are thus ranked as follows in terms of explanatory power and fit: 1) disengagement; 2) job satisfaction; 3) affect and 4) basic psychological needs satisfaction. The top 2 models each explain approximately 1/4 of the variation in quit intentions.

5.2.2 Hierarchical step-wise regression model comparison

I next examine whether using a composite model increases explanatory power in relation to quit intentions. **Table 3** depicts the results. Starting with the standard well-being measure, single-item job satisfaction (column 1), I gradually introduce three additional well-being indicators containing six additional well-being measures (positive and negative affect, disengagement, relatedness, competence and autonomy), changing the order each time in order to control for sequence sensitivity, as outlined in Section 3. I also change the baseline measure from job satisfaction to disengagement in the final two

[41] 1=Strongly Agree and 4= Strongly Disagree, therefore a negative relationship between negative items and quit intentions is expected.
[42] 1=Not at all true and 7= Very True, therefore a negative relationship between positive items and quit intentions is expected.

specifications. **S18** in the Supplementary Materials contains the results of this analysis. To identify the 'best' model, I

Table 3
Hierarchical Regression Model Comparison Framework (Quit Intentions binary) – M1

	(Model 1) **JS**	**(Model 2)** **JS + A**	**(Model 3)** **JS + A + D**	**(Model 4)** **JS + A + D + BPN**
Job Satisfaction	-.215***	-.195***	-.121***	-.123***
	(.014)	(.016)	(.021)	(.019)
Positive Emotions		.014	.012	.012
		(.019)	(.016)	(.016)
Negative Emotions		.058**	.031**	.030**
		(.020)	(.014)	(.014)
Disengagement			.145***	.155***
			(.019)	(.020)
Relatedness				-.011
				(.018)
Competence				.037*
				(.021)
Autonomy				-.011
				(.021)
Controls	**YES**	**YES**	**YES**	**YES**
Observations	**929**	**929**	**929**	**914**
McFadden R^2	**.238**	**.246**	**.292**	**.294**
Change in R^2		**.006***	**.046*****	**.003**
RMSE	**.4317**	**.4299**	**.4164**	**.4173**
BIC	**1163.18**	**1167.03**	**1113.42**	**1118.43**

*Notes *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. Dependent Variable is binary Quit Intentions, namely stated intention to quit the job within the next 6 months, with Yes and Not Sure categories merged (0 = No; 1 = Yes / Not Sure). The significance of changes in R^2 is tested using the Stata hireg command. Standardised scores are used throughout. 65 observations with missing well-being observations are dropped.*

use the Stata *hireg* command (Bern, 2005) to test for significant differences in R^2 across models. Based on the criteria of highest R^2 and lowest RMSE and BIC, Model 3 (job satisfaction + affect + disengagement) is optimal, explaining 29.2% of variation in quit intentions, versus 24.0% for single-item job satisfaction alone. Using a composite model increases explanatory power by 5.2 percentage points. [43] I do not find much evidence of sequence sensitivity. However, combing global affect with any other measure reverses the sign of global positive affect and renders it non-significant, thus reducing its diagnostic power.

5.2.3. Heterogeneity Analysis

Organisations may be concerned about retaining particular sub-groups of workers. I thus re-run the main regression analysis incorporating interaction terms to investigate heterogeneity in the predictive power of different well-being measures for particular sub-groups of measures, namely university educated workers, women, high self-rated performers, recent hires and senior workers. **S19** in the Supplementary Materials outlines the results. I find limited evidence of heterogeneity. Both the job satisfaction and disengagement measures appear to have greater predictive power in relation to employees who have been with the organisation for longer. The effect sizes are similar (small) but are, as expected, oppositely signed. I find a larger effect for competence for longer serving and more senior workers, but interestingly, the interaction coefficients for the two groups are oppositely signed (positive for workers of longer tenure and negative for more senior workers).

5.2.4 Single-item job satisfaction v multifaceted job satisfaction

Finally, I investigate the extent to which using a multifaceted job satisfaction measure could assist organisations who are concerned about voluntary turnover by increasing explanatory power. The results are set out in **S20**. Using a multifaceted measure, the Job Descriptive Index (JDI), increases R^2 by 6.2 percentage points (from 24.2% to 30.4%), reduces BIC (by 38.3) and RMSE and moves the job satisfaction model into first place ahead of disengagement in the well-being indicator rankings. In addition, the facet coefficients provide organisations with valuable insights into the interaction between quit intention formation and how workers evaluate specific aspects of their jobs. For

[43] While incorporating basic psychological need measures marginally raises R^2, the increase is not significant, and it increases BIC and RMSE.

example, a one standard deviation rise in satisfaction with promotion opportunities reduces the probability of quit intentions by 8.8 percentage points (<.001), an effect size that is almost three times as large as that associated with an equivalent rise in pay satisfaction (-3.3%; *p*=.026).

Table 4 Main regression analysis (without controls) : Head to head (Global v Experiential)
Comparison of links between experiential worker well-being models and the probability of quit intentions (binary outcome; standardised scores)

	Global Job Satisfaction	**Experiential Job Satisfaction**	**Global Affect**	**Experiential Affect**	**Global Psychological Needs**	**Experiential Psychological Needs**
Global Job Satisfaction	-.221*** (.012)					
Experiential Job Satisfaction		-.114*** (.015)				
Global Positive Affect			-.076*** (.018)			
Global Negative Affect			.107*** (.018)			
Experiential Positive Affect				-.088*** (.016)		
Experiential Negative Affect				.062*** (.016)		
Global Disengagement						
Global Competence					-.057** (.022)	
Global Relatedness					-.024 (.019)	
Global Autonomy					-.096*** (.022)	
Experiential Competence						-.070*** (.019)
Experiential Relatedness						-.054*** (.018)
Constant	.408*** (.014)	.410*** (.016)	.411*** (.015)	.410*** (.016)	.410*** (.015)	.410*** (.016)
Controls	**NO**	**NO**	**NO**	**NO**	**NO**	**NO**
Observations	877	877	877	877	877	877
McFadden R^2	.2060	.0552	.1085	.0565	.1030	.0507
RMSE	.4390	.4789	.4654	.4788	.4671	.4803
BIC	1056.49	1208.97	1164.84	1214.51	1177.01	1219.93

*Notes:*** p<0.01, ** p<0.05, * p<0.1. Benjamini-Hochberg p-values adjusted for multiple inference. Robust standard errors in parentheses. Dependent Variable is binary quit Intentions, namely stated intention to quit the job within the next 6 months, with Yes and Not Sure categories merged (0 = No; 1 = Yes / Not Sure). Standardised scores are used throughout. 70 observations with missing well-being or control observations are dropped.*

In summary, there is strong evidence in support of using the JDI job satisfaction measure instead of the standard single-item job satisfaction measure.

5.2.5. Global v Experiential well-being indicators: head-head comparison

Finally, I directly compare the relative predictive power of global and experiential measures. **Table 4** sets out the results. While all experiential measure coefficients are highly significant and are signed the same as their global equivalents, although with the exception of positive affect and relatedness, substantially smaller, they are strongly outperformed by global measures across the board in terms of the standard criteria (higher R^2, lower BIC, lower RMSE etc.). A full composite model containing all experiential measures explains just 13.3% of variation in quit intentions versus 29.4% for the global measure equivalent (see **S21**). Interestingly however, the experiential affective measures appear to be more stable than their global counterparts when combined with other well-being measures, with positive affect remaining significant and negatively signed throughout. As a final piece of analysis, I therefore investigate whether using experiential affective measures instead of global affective measures in the best-performing composite model improves explanatory power. The results are contained in **S22**. I find no material differences in the two specifications (Table 3 v S22), with the all-global measures marginally outperforming the global plus experiential affect model.

6. DISCUSSION

The current study uses novel survey data to address two simple questions with far-reaching practical implications for organisations concerned about voluntary turnover, namely can well-being measures be used to predict quit intentions and, if so, which measures perform best?

In relation to the first question, my results clearly highlight the crucial role played by worker-being in shaping quit intentions. Well-being models individually explain 15.8% - 23.8% of variation in quit intentions, compared to just 2.7% for wages and working hours combined. I find highly significant differences in the well-being profiles of Quitters and Stayers across all well-being measures examined, with Quitters reporting consistently lower well-being scores than Stayers. Furthermore, there is evidence of progression, with Definite Quitters reporting consistently lower well-being scores than (possible) Quitters. This is encouraging for organisations as it supports the interpretation of a reported quit intention as the end point of a gradual withdrawal process, which could potentially be halted, or even reversed, through the judicious use of targeted interventions aimed at improving worker well-being. Conversely, my findings that workers who score higher on the Big-5 openness trait and who are not parents or university educated are significantly more likely to form positive intentions is of questionable value for organisations, given that these are not factors over which they have any influence.

In relation to the second question, the relatively wide variation in explanatory power found across the different well-being indicators suggests that the choice of well-being measure does indeed matter. Global measures outperform experiential measures across the board, particularly in relation to satisfaction. This finding, together with the relatively low effect sizes found for all affective measures, lends support to Green (2010)'s conclusion that (global) evaluative measures may inherently be better suited to serve as inputs in quit intention functions than experiential measures. The results appear to suggest that what workers think about their jobs matters more for quit intention formation than how workers actually experience their jobs day-to-day. It is, however, also possible that this finding might reflect the medium-term temporal framing of the quit intention question used in this study[44] and that experiential measures might have played a larger role had a more immediate, or indeed no, timeframe been employed. It is also plausible that this finding holds only up to a certain emotional 'threshold' level, and that if the day-to-day lived reality of working were to become sufficiently miserable and / or lacking in pleasure, that work would become intolerable, forcing workers to follow their hearts and exit.

In terms of individual well-being indicators, I find that the best-performing single measure in terms of quit intentions is disengagement. It outperforms the single-item job satisfaction in terms of effect size in the no-controls specification, (.23 v -.22) and offers a better overall fit than job satisfaction, explaining a larger portion of variation in quit intentions (25.7% v 23.8%), while lowering RMSE and BIC. In addition, in contrast to single-item job satisfaction which just produces a single figure by way of output, the disengagement measure provides organisations with the added advantage of being able to analyse its eight sub-scale items which may reveal valuable, and potentially actionable, insights into aspects of the work experience which are particularly problematic for particular staff cohorts. Interestingly, despite the fact that job satisfaction and

[44] Participants are asked if they are actually thinking of quitting "within the next 6 months"

disengagement are highly negatively correlated, combining the two measures explains a substantially higher proportion of variation in quit intentions than either measure on its own, suggesting that, while the two measures undoubtedly overlap, the disengagement measure appears to be capturing additional aspects of the work experience. Analysing the disengagement sub-scale items suggests that the added value provided by the disengagement measure may reflect the fact that it causes workers to focus more specifically on the nature of the work itself than single-item job satisfaction. This would explain why substituting the multifaceted JDI job satisfaction measure erodes most of this value-add, a finding which likely reflects the relatively high correlation found between many of the disengagement sub-scale items and the JDI work measure.[45]

The results in general suggest that well-being measures may act as complements by tapping into distinct aspects of the quit intentions-worker well-being relationship. Combining job satisfaction with *any* additional well-being measure increases overall explanatory power, with the optimal model (job satisfaction + disengagement + affect) increasing explanatory power by six percentage points relative to the baseline job satisfaction model. Organisations may, however, need to trade increased explanatory power for pragmatism. Multi-faceted measures such as disengagement and the JDI are more burdensome on respondents (e.g., the satisfaction of basic psychological needs at work scale has 21 questions versus a single question for job satisfaction), increasing survey length (and cost) but also the risk of non- or incomplete responses. If the organisation's sole aim is to merely to identify potential quitters than this trade-off may not make sense. However, where organisations are not constrained or are keen to obtain more nuanced insights which can be used to design targeted interventions however, incorporating additional measures, in particular, disengagement is probably justified.

Voluntary turnover only becomes problematic for organisations if they start to lose employees who they are particularly keen to retain, for example high performers. Knowing that certain well-being measures are likely do a better job than others in terms of identifying potential Quitters in sub-groups of interest would therefore be extremely valuable for organisations. Unfortunately, however, I find very limited evidence that any well-being measure, including single-item job satisfaction, may systematically

[45] Substituting the JDI for the standard single-item job satisfaction measure in the current study increased explanatory power by a further two percentage points relative to the model which combines single-item job satisfaction and disengagement. The JDI measure also provides additional information on sources of worker dissatisfaction which too can be used to inform the design of preventative quit strategies. For example, the results of the current study suggest that, contrary to standard economic theory, dissatisfaction with promotion opportunities and supervision are more reliable predictors of quit intentions than pay dissatisfaction.[45]

outperform any other indicator in terms of identifying quit intentions amongst high-performing workers, or indeed any other groups of workers, assuming that workers' self-reports are an accurate reflection of their true performance, seniority etc. Future research which ideally incorporated independent third-party data may however yield fresh insights in this regard.

The paper has a number of limitations which could be addressed by future research. The sample is by design a non-representative, online sample. While the evidence that 'professional' survey participants differ demographically and attitudinally from other survey participants is mixed (Huff and Tingley, 2015; Hillygus et al., 2014), my participants may differ systematically from the 'average' worker (e.g., higher proportion of women and graduates), which detracts from wider generalisability. An obvious direction for future research is to target a more diverse online sample and/or to extend our survey to a field setting. Secondly, the outcome variables are subjective, self-rated scales, which may raise concerns about self-report and recall bias. While subjective data is essential to uncovering subjective perceptions of how well one is doing at work, carrying out this analysis in a setting which uses multiple data points and / or links quit intention data to actual quit data would undoubtedly strengthen validity. Finally, the conclusions which can be drawn from the study are limited to conditional correlations due to the reliance on cross-sectional data.

That said, my findings have important practical implications for organisations seeking to proactively identify and prevent dysfunctional turnover. They highlight the important role played by worker well-being in determining quit intentions, and therefore the potential for organisations to use non-pecuniary factors which are under their control to improve worker well-being, thereby reducing the risk of future quits. The findings also highlight the benefits for organisations of using more nuanced multi-faceted indicators when assessing quit risk in order to obtain 'early warning' indicators of a potential quit problem, which may give them a valuable 'head start' in terms of designing appropriate quit prevention strategies.

SUPPLEMENTARY MATERIALS

Supplementary material referenced in this article can be found at Supplementary materials.

ACKNOWLEDGEMENTS

I would like to thank Orla Doyle, Liam Delaney, Michael Daly and Margaret Samahita for their extremely helpful comments on this paper. I am also grateful to Benjamin Elsner, Aisling Reynolds-Feighan, Tiziana Brancaccio, the participants of the PhD economics seminar series, University College Dublin and the 2021 HESG Summer meeting, University of Cambridge for their suggestions. This study is approved by the UCD Human Research Ethics Committee. Funding from the Irish Research Council (GOIPG/2020/59) and the UCD Behavioural Science Group is gratefully acknowledged.

REFERENCES

Akerlof, G.A., Rose, A.K., Yellen, J.L., Ball, L., and Hall, R.E., 1988. Job switching and job satisfaction in the US labor market. *Brookings papers on economic activity*, *1988*(2), pp.495-594.

Allan, B.A., Tebbe, E.A., Bouchard, L.M. and Duffy, R.D., 2019. Access to decent and meaningful work in a sexual minority population. *Journal of Career Assessment*, *27*(3), pp.408-421.

Bakker, A.B. and Oerlemans, W., 2011. Subjective well-being in organizations. *The Oxford handbook of positive organizational scholarship*, *49*, pp.178-189.

Bartels, A.L., Peterson, S.J. and Reina, C.S., 2019. Understanding well-being at work: Development and validation of the Eudemonic workplace well-being scale. *PLoS One*, *14*(4), p.e0215957.

Baumeister, R. F., and Leary, M. R. 1995. The need to belong: Desire for interpersonal attachments as a fundamental human motivation. *Psychological Bulletin, 117*(3), 497–529. https://doi.org/10.1037/0033-2909.117.3.497

Benjamini, Y. and Hochberg, Y., 1995. Controlling the false discovery rate: a practical and powerful approach to multiple testing. *Journal of the Royal statistical society: series B (Methodological)*, *57*(1), pp.289-300.

Bentham, J., 1789. *An introduction to the principles of morals*. London: Athlone.

Benz, M. and Frey, B.S., 2008. The value of doing what you like: Evidence from the self-employed in 23 countries. *Journal of Economic Behavior & Organization*, *68*(3-4), pp.445-455.

Bern, P., 2005. *HIREG: Stata module for hierarchical regression*.

Berridge, K.C. and O'Doherty, J.P. 2014. From experienced utility to decision utility. *Neuroeconomics,* 335-351. Academic Press

Binder, M. and Coad, A., 2013. Life satisfaction and self-employment: A matching approach. *Small business economics*, *40*(4), pp.1009-1033.

Binnewies, C., Sonnentag, S. and Mojza, E.J., 2009. Daily performance at work: Feeling recovered in the morning as a predictor of day-level job performance. *Journal of Organizational Behavior: The International Journal of Industrial, Occupational and Organizational Psychology and Behavior*, *30*(1), pp.67-93.

Blanchflower, D.G. and Oswald, A.J., 1999. Well-being, insecurity and the decline of American job satisfaction. *NBER working paper*, *7487*.

Böckerman, P. and Ilmakunnas, P., 2009. Job disamenities, job satisfaction, quit intentions, and actual separations: Putting the pieces together. *Industrial Relations: A Journal of Economy and Society*, *48*(1), pp.73-96.

Boes, Stefan, and Rainer Winkelmann. 2006. Ordered Response Models. In *Modern Econometric Analysis: Survey on Recent Developments*, ed. Olaf Hübler and Jachim Frohn, 167-181. Berlin: Springer. http://dx.doi.org/10.1007/3-540-32693-6_12

Bryson, A., Forth, J. and Stokes, L., 2014. Does worker wellbeing affect workplace performance?. *London: UK Government Department of Business Innovation and Skills*.

Cho, Y.J. and Lewis, G.B., 2012. Turnover intention and turnover behavior: Implications for retaining federal employees. *Review of public personnel administration*, *32*(1), pp.4-23.

Clark, A.E., 1997. Job satisfaction and gender: why are women so happy at work?. *Labour economics*, *4*(4), pp.341-372.

Clark, A.E., 2015. What makes a good job? Job quality and job satisfaction. *IZA World of Labor*.

Clark, A.E., 2001. What really matters in a job? Hedonic measurement using quit data. *Labour economics*, *8*(2), pp.223-242.

Clark, A.E. and Oswald, A.J., 1994. Unhappiness and unemployment. *The Economic Journal*, *104*(424), pp.648-659.

Clark, A.E. and Oswald A.J., 1996. Satisfaction and comparison income. *Journal of public economics*, *61*(3), pp.359-381.

Csikszentmihalyi, M. and Csikzentmihaly, M., 1990. *Flow: The psychology of optimal experience* (Vol. 1990). New York: Harper & Row.

Cummins, R.A., Eckersley, R., Pallant, J., Van Vugt, J. and Misajon, R., 2003. Developing a national index of subjective wellbeing: The Australian Unity Wellbeing Index. *Social indicators research*, *64*(2), pp.159-190.

Daniels, K., 2000. Measures of five aspects of affective well-being at work. *Human Relations*, *53*(2), pp.275-294.

Davern, M.T., Cummins, R.A. and Stokes, M.A., 2007. Subjective wellbeing as an affective-cognitive construct. *Journal of Happiness Studies*, *8*(4), pp.429-449.

Deci, E.L. and Ryan, R.M., 1995. Human autonomy. In *Efficacy, agency, and self-esteem* (pp. 31-49). Springer, Boston, MA.

Deci, E. L., Ryan, R.M., Gagné, M., Leone, D., Usunov, J., and Kornazheva. B., 2001. "Need satisfaction, motivation, and well-being in the work organizations of a former eastern bloc country: A cross-cultural study of self-determination." *Personality and social psychology bulletin* 27(8): 930-942.

Deci, E.L. and Ryan, R.M., 2000. The" what" and" why" of goal pursuits: Human needs and the self-determination of behavior. *Psychological inquiry*, *11*(4), pp.227-268.

Deci, E.L. and Ryan, R.M., 2008. Self-determination theory: A macrotheory of human motivation, development, and health. *Canadian psychology/Psychologie canadienne*, *49*(3), p.182.

Demerouti, E. and Bakker, A. B. 2008. The Oldenburg Burnout Inventory: A good alternative to measure burnout and engagement. *Handbook of stress and burnout in health care*.

De Simone, S., 2014. Conceptualizing wellbeing in the workplace. *International journal of business and social science*, *5*(12).

Diener, E.D., Emmons, R.A., Larsen, R.J. and Griffin, S., 1985. The satisfaction with life scale. *Journal of personality assessment*, *49*(1), pp.71-75.

Diener, E.D. and Larsen, R.J. 1993. *The experience of emotional well-being*

Dimotakis, N., Scott, B.A. and Koopman, J., 2011. An experience sampling investigation of workplace interactions, affective states, and employee well-being. *Journal of Organizational Behavior*, *32*(4), pp.572-588.

Disabato, D.J., Goodman, F.R., Kashdan, T.B., Short, J.L. and Jarden, A., 2016. Different types of well-being? A cross-cultural examination of hedonic and eudaimonic well-being. *Psychological assessment*, *28*(5), p.471.

Dockray, S., Grant, N., Stone, A.A., Kahneman, D., Wardle, J. and Steptoe, A., 2010. A comparison of affect ratings obtained with ecological momentary assessment and the day reconstruction method. *Social Indicators Research*, *99*(2), pp.269-283.

Dolan, P., 2014. *Happiness by design: Change what you do, not how you think*. Penguin.

Dur, R. and Van Lent, M., 2019. Socially useless jobs. *Industrial Relations: A Journal of Economy and Society*, *58*(1), pp.3-16.

Eid, M. and Diener, E., 2004. Global judgments of subjective well-being: Situational variability and long-term stability. *Social indicators research*, *65*(3), pp.245-277.

Eisele, G., H. Vachon, G. Lafit, P. Kuppens, M. Houben, I. Myin-Germeys and W. Viechtbauer 2020. The effects of sampling frequency and questionnaire length on perceived burden, compliance, and careless responding in experience sampling data in a student population. Preprint. PsyArXiv. https://doi.org/10.31234/osf.io/zf4nm

Ekkekakis, P., 2013. *The measurement of affect, mood, and emotion: A guide for health-behavioral research*. Cambridge University Press.

Fisher, C. D. (2000). Mood and emotions while working: Missing pieces of job satisfaction? Journal of Organizational Behavior, 185–202.

Fredrickson, B.L. and Kahneman, D., 1993. Duration neglect in retrospective evaluations of affective episodes. *Journal of personality and social psychology*, *65*(1), p.45.

Fredrickson, B.L., Grewen, K.M., Coffey, K.A., Algoe, S.B., Firestine, A.M., Arevalo, J.M., Ma, J. and Cole, S.W., 2013. A functional genomic perspective on human well-being. *Proceedings of the National Academy of Sciences*, *110*(33), pp.13684-13689.

Gelbach, J.B., 2016. When do covariates matter? And which ones, and how much?. *Journal of Labor Economics*, *34*(2), pp.509-543.

Gordon, S., Tang, C.H.H., Day, J. and Adler, H., 2019. Supervisor support and turnover in hotels: does subjective well-being mediate the relationship?. *International Journal of Contemporary Hospitality Management*.

Graham, C. and Nikolova, M., 2015. Bentham or Aristotle in the development process? An empirical investigation of capabilities and subjective well-being. *World development*, *68*, pp.163-179.

Green, F. 2010. Well-being, job satisfaction and labour mobility. *Labour Economics.* 17 (6), 897-903.

Griffeth R. W., Hom, P. W. and Gaertner, S. 2000 A metanalysis of antecedents and correlates of employee turnover: Update, moderator tests, and research implications for the next millennium. *Journal of Management*, 26(3), 463-488.

Grissom, J.A., Viano, S.L. and Selin, J.L., 2016. Understanding employee turnover in the public sector: Insights from research on teacher mobility. *Public Administration Review*, *76*(2), pp.241-251.

Groot, W. and van den Brink, H.M., 1999. Job satisfaction of older workers. *International Journal of Manpower*.

Halbesleben J. R. and Demerouti, E. 2005. The construct validity of an alternative measure of burnout: Investigating the English translation of the Oldenburg Burnout Inventory. *Work & Stress*, 19 (3). 208-220.

Heavey, A.L., Holwerda, J.A. and Hausknecht, J.P., 2013. Causes and consequences of collective turnover: A meta-analytic review. *Journal of Applied Psychology*, *98*(3), p.412.

Helliwell, J.F. and Barrington-Leigh, C.P., 2010. Measuring and understanding subjective well-being. *Canadian Journal of Economics/Revue canadienne d'économique*, *43*(3), pp.729-753.

Helliwell, J.F. and Putnam, R.D., 2004. The social context of well–being. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*, *359*(1449), pp.1435-1446.

Hessels, J., Arampatzi, E., van der Zwan, P. and Burger, M., 2018. Life satisfaction and self-employment in different types of occupations. *Applied Economics Letters*, *25*(11), pp.734-740.

Hicks, R. and Tingley, D., 2011. Causal mediation analysis. *The Stata Journal*, *11*(4), pp.605-619.

Hillygus, D. Sunshine, Natalie Jackson, and M. Young. 2014. "Professional respondents in non-probability online panels." *Online panel research: A data quality perspective* 1: 219-237.

Hudson, N.W., Lucas, R.E., Donnellan, M.B. and Kushlev, K., 2016. Income reliably predicts daily sadness, but not happiness: A replication and extension of Kushlev, Dunn, and Lucas (2015). *Social psychological and personality science*, *7*(8), pp.828-836.

Huff, C. and Tingley, D. 2015. "“Who are these people?” Evaluating the demographic characteristics and political preferences of MTurk survey respondents." *Research & Politics* 2(3)

Ilies, R. and Judge, T.A., 2002. Understanding the dynamic relationships among personality, mood, and job satisfaction: A field experience sampling study. *Organizational behavior and human decision processes*, *89*(2), pp.1119-1139.

Imai, K., Keele, L. and Tingley, D., 2010. A general approach to causal mediation analysis. *Psychological methods*, *15*(4), p.309.

Kahneman, D. and Riis, J., 2005. Living, and thinking about it: Two perspectives on life. *The science of well-being*, *1*, pp.285-304.

Kahneman, D., Krueger, A.B., Schkade, D.A., Schwarz, N. and Stone, A.A., 2004. A survey method for characterizing daily life experience: The day reconstruction method. *Science*, *306*(5702), pp.1776-1780.

Kahneman, D., Wakker, P.P. and Sarin, R., 1997. Back to Bentham? Explorations of experienced utility. *The quarterly journal of economics*, *112*(2), pp.375-406.

Kinicki, A.J., McKee-Ryan, F.M., Schriesheim, C.A. & Carson, K.P. 2002. Assessing the construct validity of the job descriptive index: a review and meta-analysis. *Journal of applied psychology*, 87(1), p.14.

Kristensen, N. and Westergård-Nielsen, N., 2004. Does low job satisfaction lead to job mobility? *Institute of Labor Economics (IZA).* No. 1026.

Krueger, A.B. and Schkade, D.A., 2008. The reliability of subjective well-being measures. *Journal of public economics*, *92*(8-9), pp.1833-1845.

Larsen, J.T., McGraw, A.P. and Cacioppo, J.T., 2001. Can people feel happy and sad at the same time?. *Journal of personality and social psychology*, *81*(4), p.684.

Larson, R. and Csikszentmihalyi, M., 2014. The experience sampling method. In *Flow and the foundations of positive psychology* (pp. 21-34). Springer, Dordrecht.

Lazear, E.P. and Shaw, K.L., 2007. Personnel economics: The economist's view of human resources. *Journal of economic perspectives*, *21*(4), pp.91-114.

Lévy-Garboua, L., Montmarquette, C. and Simonnet, V., 2007. Job satisfaction and quits. *Labour Economics*, *14*(2), pp.251-268.

Long, J.S. and Freese, J., 2006. *Regression models for categorical dependent variables using Stata* (Vol. 7). Stata press.

Lovik A., Verbeke, G. and Molenberghs, G. 2017. Evaluation of a very short test to measure the big five personality factors on a Flemish sample. *Journal of Psychological & Educational Research, 25 (2).*

Lucas, R.E., Wallsworth, C., Anusic, I. and Donnellan, M.B., 2021. A direct comparison of the day reconstruction method (DRM) and the experience sampling method (ESM). *Journal of personality and social psychology*, *120*(3), p.816.

Lyubomirsky, S. and Lepper, H.S., 1999. A measure of subjective happiness: Preliminary reliability and construct validation. *Social indicators research*, *46*(2), pp.137-155.

Martela, F. and Riekki, T.J., 2018. Autonomy, competence, relatedness, and beneficence: A multicultural comparison of the four pathways to meaningful work. *Frontiers in psychology*, *9*, p.1157.

Martela, F. and Sheldon, K.M., 2019. Clarifying the concept of well-being: Psychological need satisfaction as the common core connecting eudaimonic and subjective well-being. *Review of General Psychology*, *23*(4), pp.458-474.

McBey, K. and Karakowsky, L., 2001. Examining sources of influence on employee turnover in the part-time work context. *Career Development International*.

McCarthy, I.O., Moonesinghe, R. and Dean, H.D., 2020. Association of employee engagement factors and turnover intention among the 2015 US Federal Government workforce. *SAGE Open*, *10*(2), p.2158244020931847.

Mehmetoglu, M. and Jakobsen, T.G., 2016. *Applied statistics using Stata: a guide for the social sciences*. Sage.

Molodynski, A., Lewis, T., Kadhum, M., Farrell, S.M., Lemtiri Chelieh, M., Falcão De Almeida, T., Masri, R., Kar, A., Volpe, U., Moir, F. and Torales, J., 2021. Cultural variations in wellbeing, burnout and substance use amongst medical students in twelve countries. *International Review of Psychiatry*, *33*(1-2), pp.37-42.

Nikolova, M., 2019. Switching to self-employment can be good for your health. *Journal of Business Venturing*, *34*(4), pp.664-691.

Nikolova, M. and Cnossen, F., 2020. What makes work meaningful and why economists should care about it. *Labour Economics*, *65*, p.101847.

ONS (Office for National Statistics), 2019. *Annual Population Survey (APS).* Release dates 17/6/2019 and 14/10/2019

Ozkan AH, Elci M, Karabay ME, Kitapci H and Garip C. 2020. Antecedents of turnover intention: a meta-analysis study in the united states. *E+M Ekonomie a Management*. 23(1):93-110.

Pearl, J., 2009. Causal inference in statistics: An overview. *Statistics surveys*, *3*, pp.96-146.

Rammstedt, B. and John, O.P., 2007. Measuring personality in one minute or less: A 10-item short version of the Big Five Inventory in English and German. *Journal of research in Personality*, *41*(1), pp.203-212.

Redelmeier, D.A. and Kahneman, D., 1996. Patients' memories of painful medical treatments: Real-time and retrospective evaluations of two minimally invasive procedures. *pain*, *66*(1), pp.3-8.

Reis, H.T., Reis, H.T. and Judd, C.M. eds., 2000. *Handbook of research methods in social and personality psychology*. Cambridge University Press.

Robbins, S.P. and Judge, T.A., 2013. *Organisational Behaviour*: Global Edition.

Robinson, M.D. and Clore, G.L., 2002. Episodic and semantic knowledge in emotional self-report: evidence for two judgment processes. *Journal of personality and social psychology*, *83*(1), p.198.

Rubenstein, A.L., Eberly, M.B., Lee, T.W. and Mitchell, T.R., 2018. Surveying the forest: A meta-analysis, moderator investigation, and future-oriented discussion of the antecedents of voluntary employee turnover. *Personnel Psychology*, *71*(1), pp.23-65.

Ryan, R.M. and Deci, E.L., 2000. Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American psychologist*, *55*(1), p.68.

Ryff, C.D., 1989. Happiness is everything, or is it? Explorations on the meaning of psychological well-being. *Journal of personality and social psychology*, *57*(6), p.1069.

Sandhya, S. and Sulphey, M.M., 2020. Influence of empowerment, psychological contract and employee engagement on voluntary turnover intentions. *International Journal of Productivity and Performance Management*.

Schaufeli, W.B. and Bakker, A.B., 2004. Job demands, job resources, and their relationship with burnout and engagement: A multi-sample study. *Journal of Organizational Behavior: The International Journal of Industrial, Occupational and Organizational Psychology and Behavior*, *25*(3), pp.293-315.

Scott, A., Gravelle, H., Simoens, S., Bojke, C. and Sibbald, B., 2006. Job satisfaction and quitting intentions: a structural model of British general practitioners. *British journal of industrial relations*, *44*(3), pp.519-540.

Shields, M.A. and Price, S.W., 2002. Racial harassment, job satisfaction and intentions to quit:evidence from the British nursing profession. *Economica*, *69*(274), pp.295-326.

Shields, M.A. and Ward, M., 2001. Improving nurse retention in the National Health Service in England: the impact of job satisfaction on intentions to quit. *Journal of health economics*, *20*(5), pp.677-701.

Shuck, B., Zigarmi, D. and Owen, J., 2015. Psychological needs, engagement, and work intentions: A Bayesian multi-measurement mediation approach and implications for HRD. *European Journal of Training and Development*.

Sonnentag, S., 2003. Recovery, work engagement, and proactive behavior: a new look at the interface between nonwork and work. *Journal of applied psychology*, *88*(3), p.518.

Sousa-Poza, A. & Henneberger, F. (2004). Analyzing Job Mobility with Job Turnover Intentions: An International Comparative Study. Journal of Economic Issues, 38(1), 113-137.

Sousa-Poza, A. and Sousa-Poza, A.A., 2007. The effect of job satisfaction on labor turnover by gender: An analysis for Switzerland. *The Journal of Socio-Economics*, *36*(6), pp.895-913.

Stanton, J. M., Sinar, E. F., Balzer, W. K., Julian, A. L., Thoresen, P., Aziz, S., Fisher, G. G. & Smith, P. C. 2002. Development of a compact measure of job satisfaction: The abridged Job Descriptive Index. *Educational and Psychological Measurement*, 62 (1), 173-191.

Steel, R.P., and Orvalle, N. K. 1984. A review and meta-analysis of research on the relationship between behavioral intentions and employee turnover. *Journal of Applied Psychology*, 69, 673–686.

Steger, M.F., 2012. Making meaning in life. *Psychological Inquiry*, *23*(4), pp.381-385.

Stone, A.A. and Mackie, C.E., 2013. *Subjective well-being: measuring happiness, suffering, and other dimensions of experience*. National Academies Press.

Stone, A.A., Kessler, R.C. and Haythomthwatte, J.A., 1991. Measuring daily events and experiences: Decisions for the researcher. *Journal of personality*, *59*(3), pp.575-607.

Tett, R.P. and Meyer, J.P., 1993. Job satisfaction, organizational commitment, turnover intention, and turnover: path analyses based on meta-analytic findings. *Personnel psychology*, *46*(2), pp.259-293.

Tversky, A. and Kahneman, D., 1974. Judgment under Uncertainty: Heuristics and Biases: Biases in judgments reveal some heuristics of thinking under uncertainty. *science*, *185*(4157), pp.1124-1131.

Tweten, C., Anusic, I., Lucas, R.E. and Donnellan, M.B., 2016. A direct comparison of the Experience Sampling Method (ESM) and the Day Reconstruction Method (DRM). *Retrieved from osf. io/5mjys*.

Van den Broeck, A., Ferris, D.L., Chang, C.H. and Rosen, C.C., 2016. A review of self-determination theory's basic psychological needs at work. *Journal of Management*, *42*(5), pp.1195-1229.

Van der Zwan, P., Hessels, J. and Rietveld, C.A., 2018. Self-employment and satisfaction with life, work, and leisure. *Journal of Economic Psychology*, *64*, pp.73-88.

Warr, P. 2016 (Previous version 2010 in conjunction with Parker, S.). IWP Multi-Affect Indicator. Institute of Work Psychology, University of Sheffield

Watson, D. and Tellegen, A., 1985. Toward a consensual structure of mood. *Psychological bulletin*, *98*(2), p.219.

Wheatley, D., 2021. Workplace location and the quality of work: The case of urban-based workers in the UK. *Urban Studies*, *58*(11), pp.2233-2257.

White, M. P. and Dolan, P. 2009. Accounting for the richness of daily activities. *Psychological science*, 20 (8), 1000-1008.

Wiles, J. 2018. *Is it Time to Toss Out Your Old Employee Engagement Survey?* www.gartner.com. Accessed online 2/8/2021. Is It Time To Toss Out Your Old Employee Engagement Survey

Woo, S.E., 2011. A study of Ghiselli's hobo syndrome. *Journal of Vocational Behavior*, *79*(2), pp.461-469.

Woo, S.E., Chae, M., Jebb, A.T. and Kim, Y., 2016. A closer look at the personality-turnover relationship: Criterion expansion, dark traits, and time. *Journal of Management*, *42*(2), pp.357-385.

Work Institute, 2019. *2019 Retention Report.* Accessed online June 2021. Work Institute 2019 Retention Report final-1.pdf

Wright-Whyte, K. 2019. Employee cost revealed: Average employee costs SMEs £12,000 to replace. *Accounts and Legal Small Business Advice.* Accessed online June 2021. Average Employee Replacement Cost is £12,000 for SMEs | Accounts and Legal

Xanthopoulou, D., Bakker, A.B., Demerouti, E. and Schaufeli, W.B., 2009. Work engagement and financial returns: A diary study on the role of job and personal resources. *Journal of occupational and organizational psychology*, *82*(1), pp.183-200.

Zivkovic, A., Fosic, I. and Starcevic, D.P., 2020. Employee Turnover Trends in Croatia. *Economic and Social Development: Book of Proceedings*, pp.155.